Preface

This textbook is designed to teach the university mathematics student the basics of the subject of linear algebra. There are no prerequisites other than ordinary algebra, but it is probably best used by a student who has the “mathematical maturity” of a sophomore or junior.

The text has two goals: to teach the fundamental concepts and techniques of matrix algebra and abstract vector spaces, and to teach the techniques of developing the definitions and theorems of a coherent area of mathematics. So there is an emphasis on worked examples of nontrivial size and on proving theorems carefully.

This book is copyrighted. This means that governments have granted the author a monopoly — the exclusive right to control the making of copies and derivative works for many years (too many years in some cases). It also gives others limited rights, generally referred to as “fair use,” such as the right to quote sections in a review without seeking permission. However, the author licenses this book under the terms of the GNU Free Documentation License (GFDL), which gives you more rights than most copyrights. Loosely speaking, you may make as many copies as you like at no cost, and you may distribute these copies if you please. You may modify the book for your own use. The catch is that if you make modifications and you distribute the modified version, you must also license the new version with the GFDL. So the book has lots of inherent freedom, and no one is allowed to distribute a modified version that restricts these freedoms. (See the license itself for all the exact details of the rights you have been granted.)

Notice that initially most people are struck by the notion that this book is free (the French would say gratuit, at no cost). And it is. However, it is more important that the book has freedom (the French would say liberté, liberty). It will never go “out of print” nor will updates be designed to frustrate the used book market. Those considering teaching a course with this book can examine it thoroughly in advance. Adding new exercises or new sections has been purposely made very easy, and the hope is that others will contribute these modifications back for incorporation into the book for all to benefit.

Topics The first half of this text (through Chapter M [179]) is basically a course in matrix algebra, though the foundation of some more advanced ideas is also being laid in these early sections. Vectors are presented exclusively as column vectors (since we also have the typographic freedom to avoid the cost-cutting move of displaying column vectors inline as the transpose of row vectors), and linear combinations are presented very early. Spans, null spaces and column spaces are also presented early, simply as sets, saving most of their vector space properties for later, so they are familiar objects before being scrutinized carefully.

You cannot do everything early, so in particular matrix multiplication comes later than usual. However, with a definition built on linear combinations of column vectors, it should seem more natural than the usual definition using dot products of rows with columns. And this delay emphasizes that linear algebra is built upon vector addition and scalar
multiplication. Of course, matrix inverses must wait for matrix multiplication, but this
does not prevent nonsingular matrices from occurring sooner. Vector space properties
are hinted at when vectors and matrices are first defined, but the notion of a vector
space is saved for a more axiomatic treatment later. Once bases and dimension have
been explored in the context of vector spaces, linear transformations and their matrix
representations follow. The goal of the book is to go as far as canonical forms and matrix
decompositions in the Core, with less central topics collected in a section of Topics.

Linear algebra is an ideal subject for the novice mathematics student to learn how
to develop a topic precisely, with all the rigor mathematics requires. Unfortunately,
much of this rigor seems to have escaped the standard calculus curriculum, so for many
university students this is their first exposure to careful definitions and theorems, and
the expectation that they fully understand them, to say nothing of the expectation that
they become proficient in formulating their own proofs. We have tried to make this text
as helpful as possible with this transition. Every definition is stated carefully, set apart
from the text. Likewise, every theorem is carefully stated, and almost every one has a
complete proof. Theorems usually have just one conclusion, so they can be referenced
precisely later. Definitions and theorems are cataloged in order of their appearance in
the front of the book, and alphabetical order in the index at the back. Along the way,
there are discussions of some more important ideas relating to formulating proofs (Proof
Techniques), which is advice mostly.

Origin and History  This book is the result of the confluence of several related events
and trends.

• Math 232 is the post-calculus linear algebra course taught at the University of Puget
  Sound to students majoring in mathematics, computer science, physics, chemistry
  and economics. Between January 1986 and June 2002, I taught this course sev-
  enteen times. For the Spring 2003 semester, I elected to convert my course notes
to an electronic form so that it would be easier to incorporate the inevitable and
nearly-constant revisions. Central to my new notes was a collection of stock ex-
amples that would be used repeatedly to illustrate new concepts. (These would
become the Archetypes, Chapter A [559].) It was only a short leap to then decide
to distribute copies of these notes and examples to the students in the two sections
of this course. As the semester wore on, the notes began to look less like notes and
more like a book.

• I used the notes again in the Fall 2003 semester for a single section of the course.
  Simultaneously, the textbook I was using came out in a fifth edition. A new chapter
  was added toward the start of the book, and a few additional exercises were added
  in other chapters. This demanded the annoyance of reworking my notes and list
  of suggested exercises to conform with the changed numbering of the chapters and
  exercises. I had an almost identical experience with the third course I was teaching
  that semester. I also learned that in the next academic year I would be teaching a
course where my textbook of choice had gone out of print. There had to be a better
  alternative to having the organization of my courses buffeted by the economics of
  traditional textbook publishing.

• I had used \LaTeX\ and the Internet for many years, so there was little to stand in the
  way of typesetting, distributing and “marketing” a free book. With recreational
and professional interests in software development, I had long been fascinated by the open-source software movement, as exemplified by the success of GNU and Linux, though public-domain TeX might also deserve mention. Obviously, this book is an attempt to carry over that model of creative endeavor to textbook publishing.

• As a sabbatical project during the Spring 2004 semester, I embarked on the current project of creating a freely-distributable linear algebra textbook. (Notice the implied financial support of the University of Puget Sound to this project.) Most of the material was written from scratch since changes in notation and approach made much of my notes of little use. By August 2004 I had written half the material necessary for our Math 232 course. The remaining half was written during the Fall 2004 semester as I taught another two sections of Math 232. I taught a single section of the course in the Spring 2005 semester, while my colleague, Professor Martin Jackson, graciously taught another section from the constantly shifting sands that was this project. His many suggestions have helped immeasurably.

However, much of my motivation for writing this book is captured by H.M. Cundy and A.P. Rollet in their Preface to the First Edition of *Mathematical Models* (1952), especially the final sentence,

This book was born in the classroom, and arose from the spontaneous interest of a Mathematical Sixth in the construction of simple models. A desire to show that even in mathematics one could have fun led to an exhibition of the results and attracted considerable attention throughout the school. Since then the Sherborne collection has grown, ideas have come from many sources, and widespread interest has been shown. It seems therefore desirable to give permanent form to the lessons of experience so that others can benefit by them and be encouraged to undertake similar work.

**How To Use This Book**  Chapter, Theorems, etc. are not numbered in this book, but are instead referenced by acronyms. This means that Theorem XYZ will always be Theorem XYZ, no matter if new sections are added, or if an individual decides to remove certain other sections. Within sections, the subsections are acronyms that begin with the acronym of the section. So Subsection XYZ.AB is the subsection AB in Section XYZ. Acronyms are unique within their type, so for example there is just one Definition B, but there is also a Section B. At first, all the letters flying around may be confusing, but with time, you will begin to recognize the more important ones on sight. Furthermore, there are lists of theorems, examples, etc. in the front of the book, and an index that contains every acronym. If you are reading this in an electronic version (PDF or XML), you will see that all of the cross-references are hyperlinks, allowing you to click to a definition or example, and then use the back button to return. In printed versions, you must rely on the page numbers. However, note that page numbers are not permanent! Different editions, different margins, or different sized paper will affect what content is on each page. And in time, the addition of new material will affect the page numbering.

Chapter divisions are not critical to the organization of the book. Sections are the main organizational unit. Sections are designed to be the subject of a single lecture or classroom session, though there is frequently more material than can be discussed and illustrated in a fifty-minute session. Consequently, the instructor will need to be selective about which topics to illustrate with other examples and which topics to leave
to the student’s reading. Many of the examples are meant to be large, such as using five or six variables in a system of equations, so the instructor may just want to “walk” a class through these examples. The book has been written with the idea that some may work through it independently, so the hope is that students can learn some of the more mechanical ideas on their own.

The highest level division of the book is the three Parts: Core, Topics, Applications. The Core is meant to carefully describe the basic ideas required of a first exposure to linear algebra. In the final sections of the Core, one should ask the question: which previous Sections could be removed without destroying the logical development of the subject? Hopefully, the answer is “none.” The goal of the book is to finish the Core with the most general representations of linear transformations (Jordan and rational canonical forms) and perhaps matrix decompositions (LU, QR, singular value). Of course, there will not be universal agreement on what should, or should not, constitute the Core, but the main idea will be to limit it to about forty sections. Topics is meant to contain those subjects that are important in linear algebra, and which would make profitable detours from the Core for those interested in pursuing them. Applications should illustrate the power and widespread applicability of linear algebra to as many fields as possible. The Archetypes (Chapter A [559]) cover many of the computational aspects of systems of linear equations, matrices and linear transformations. The student should consult them often, and this is encouraged by exercises that simply suggest the right properties to examine at the right time. But what is more important, they are a repository that contains enough variety to provide abundant examples of key theorems, while also providing counterexamples to hypotheses or converses of theorems.

I require my students to read each Section prior to the day’s discussion on that section. For some students this is a novel idea, but at the end of the semester a few always report on the benefits, both for this course and other courses where they have adopted the habit. To make good on this requirement, each section contains three Reading Questions. These sometimes only require parroting back a key definition or theorem, or they require performing a small example of a key computation, or they ask for musings on key ideas or new relationships between old ideas. Answers are emailed to me the evening before the lecture. Given the flavor and purpose of these questions, including solutions seems foolish.

Formulating interesting and effective exercises is as difficult, or more so, than building a narrative. But it is the place where a student really learns the material. As such, for the student’s benefit, complete solutions should be given. As the list of exercises expands, over time solutions will also be provided. Exercises and their solutions are referenced with a section name, followed by a dot, then a letter (C,M, or T) and a number. The letter ‘C’ indicates a problem that is mostly computational in nature, while the letter ‘T’ indicates a problem that is more theoretical in nature. A problem with a letter ‘M’ is somewhere in between (middle, mid-level, median, middling), probably a mix of computation and applications of theorems. So Solution MO.T34 is a solution to an exercise in Section MO that is theoretical in nature. The number ‘34’ has no intrinsic meaning.

More on Freedom This book is freely-distributable under the terms of the GFDL, along with the underlying TeX code from which the book is built. This arrangement provides many benefits unavailable with traditional texts.

- No cost, or low cost, to students. With no physical vessel (i.e. paper, binding), no transportation costs (Internet bandwidth being a negligible cost) and no marketing
costs (evaluation and desk copies are free to all), anyone with an Internet connection can obtain it, and a teacher could make available paper copies in sufficient quantities for a class. The cost to print a copy is not insignificant, but is just a fraction of the cost of a traditional textbook. Students will not feel the need to sell back their book, and in future years can even pick up a newer edition freely.

- The book will not go out of print. No matter what, a teacher can maintain their own copy and use the book for as many years as they desire. Further, the naming schemes for chapters, sections, theorems, etc. is designed so that the addition of new material will not break any course syllabi or assignment list.

- With many eyes reading the book and with frequent postings of updates, the reliability should become very high. Please report any errors you find that persist into the latest version.

- For those with a working installation of the popular typesetting program \TeX, the book has been designed so that it can be customized. Page layouts, presence of exercises, solutions, sections or chapters can all be easily controlled. Furthermore, many variants of mathematical notation are achieved via \TeX macros. So by changing a single macro, one’s favorite notation can be reflected throughout the text. For example, every transpose of a matrix is coded in the source as $\text{\textbackslash transpose}\{A\}$, which when printed will yield $A^t$. However by changing the definition of $\text{\textbackslash transpose}\{\}$, any desired alternative notation will then appear throughout the text instead.

- The book has also been designed to make it easy for others to contribute material. Would you like to see a section on symmetric bilinear forms? Consider writing one and contributing it to one of the Topics chapters. Does there need to be more exercises about the null space of a matrix? Send me some. Historical Notes? Contact me, and we will see about adding those in also.

- You have no legal obligation to pay for this book. It has been licensed with no expectation that you pay for it. You do not even have a moral obligation to pay for the book. Thomas Jefferson (1743 – 1826), the author of the United States Declaration of Independence, wrote,

> If nature has made any one thing less susceptible than all others of exclusive property, it is the action of the thinking power called an idea, which an individual may exclusively possess as long as he keeps it to himself; but the moment it is divulged, it forces itself into the possession of every one, and the receiver cannot dispossess himself of it. Its peculiar character, too, is that no one possesses the less, because every other possesses the whole of it. He who receives an idea from me, receives instruction himself without lessening mine; as he who lights his taper at mine, receives light without darkening me. That ideas should freely spread from one to another over the globe, for the moral and mutual instruction of man, and improvement of his condition, seems to have been peculiarly and benevolently designed by nature, when she made them, like fire, expansible over all space, without lessening their density in any point, and like the air in which we breathe, move, and have our physical being, incapable of confinement or exclusive appropriation.
Letter to Isaac McPherson  
August 13, 1813

However, if you feel a royalty is due the author, or if you would like to encourage the author, or if you wish to show others that this approach to textbook publishing can also bring financial gains, then donations are gratefully received. Moreover, non-financial forms of help can often be even more valuable. A simple note of encouragement, submitting a report of an error, or contributing some exercises or perhaps an entire section for the Topics or Applications chapters are all important ways you can acknowledge the freedoms accorded to this work by the copyright holder and other contributors.

Conclusion  Foremost, I hope that students find their time spent with this book profitable. I hope that instructors find it flexible enough to fit the needs of their course. And I hope that everyone will send me their comments and suggestions, and also consider the myriad ways they can help (as listed on the book’s website at linear.ups.edu).

Robert A. Beezer  
Tacoma, Washington  
December, 2004
## Contents

<table>
<thead>
<tr>
<th>Topic</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOL Solutions</td>
<td>27</td>
</tr>
<tr>
<td>RREF Reduced Row-Echelon Form</td>
<td>29</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>41</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>43</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>45</td>
</tr>
<tr>
<td>TSS Types of Solution Sets</td>
<td>49</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>58</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>59</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>61</td>
</tr>
<tr>
<td>HSE Homogeneous Systems of Equations</td>
<td>63</td>
</tr>
<tr>
<td>SHS Solutions of Homogeneous Systems</td>
<td>63</td>
</tr>
<tr>
<td>MVNSE Matrix and Vector Notation for Systems of Equations</td>
<td>66</td>
</tr>
<tr>
<td>NSM Null Space of a Matrix</td>
<td>68</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>70</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>71</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>73</td>
</tr>
<tr>
<td>NSM NonSingular Matrices</td>
<td>75</td>
</tr>
<tr>
<td>NSM NonSingular Matrices</td>
<td>75</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>82</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>83</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>85</td>
</tr>
<tr>
<td>Chapter V Vectors</td>
<td>87</td>
</tr>
<tr>
<td>VO Vector Operations</td>
<td>87</td>
</tr>
<tr>
<td>VEASM Vector equality, addition, scalar multiplication</td>
<td>88</td>
</tr>
<tr>
<td>VSP Vector Space Properties</td>
<td>92</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>94</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>95</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>97</td>
</tr>
<tr>
<td>LC Linear Combinations</td>
<td>99</td>
</tr>
<tr>
<td>LC Linear Combinations</td>
<td>99</td>
</tr>
<tr>
<td>VFSS Vector Form of Solution Sets</td>
<td>104</td>
</tr>
<tr>
<td>URREF Uniqueness of Reduced Row-Echelon Form</td>
<td>111</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>114</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>115</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>117</td>
</tr>
<tr>
<td>SS Spanning Sets</td>
<td>119</td>
</tr>
<tr>
<td>SSV Span of a Set of Vectors</td>
<td>119</td>
</tr>
<tr>
<td>SSNS Spanning Sets of Null Spaces</td>
<td>122</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>126</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>127</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>129</td>
</tr>
<tr>
<td>LI Linear Independence</td>
<td>133</td>
</tr>
<tr>
<td>LIV Linearly Independent Vectors</td>
<td>133</td>
</tr>
<tr>
<td>LINSM Linear Independence and NonSingular Matrices</td>
<td>139</td>
</tr>
<tr>
<td>NSSLI Null Spaces, Spans, Linear Independence</td>
<td>140</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>142</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>143</td>
</tr>
</tbody>
</table>

Version 0.52
## Contents

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Title</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOL Solutions</td>
<td>Linear Dependence and Spans</td>
<td>147</td>
</tr>
<tr>
<td>LDS</td>
<td>Linearly Dependent Sets and Spans</td>
<td>151</td>
</tr>
<tr>
<td>LDSS</td>
<td>Linearly Dependent Sets and Spans</td>
<td>151</td>
</tr>
<tr>
<td>COV</td>
<td>Casting Out Vectors</td>
<td>153</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>160</td>
</tr>
<tr>
<td>EXC</td>
<td>Exercises</td>
<td>161</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>Orthogonality</td>
<td>163</td>
</tr>
<tr>
<td>O</td>
<td>Orthogonality</td>
<td>165</td>
</tr>
<tr>
<td>CAV</td>
<td>Complex arithmetic and vectors</td>
<td>165</td>
</tr>
<tr>
<td>IP</td>
<td>Inner products</td>
<td>166</td>
</tr>
<tr>
<td>N</td>
<td>Norm</td>
<td>169</td>
</tr>
<tr>
<td>OV</td>
<td>Orthogonal Vectors</td>
<td>170</td>
</tr>
<tr>
<td>GSP</td>
<td>Gram-Schmidt Procedure</td>
<td>173</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>176</td>
</tr>
<tr>
<td>EXC</td>
<td>Exercises</td>
<td>177</td>
</tr>
<tr>
<td>Chapter M</td>
<td>Matrices</td>
<td>179</td>
</tr>
<tr>
<td>MO</td>
<td>Matrix Operations</td>
<td>179</td>
</tr>
<tr>
<td>MEASM</td>
<td>Matrix equality, addition, scalar multiplication</td>
<td>179</td>
</tr>
<tr>
<td>VSP</td>
<td>Vector Space Properties</td>
<td>181</td>
</tr>
<tr>
<td>TSM</td>
<td>Transposes and Symmetric Matrices</td>
<td>182</td>
</tr>
<tr>
<td>MCC</td>
<td>Matrices and Complex Conjugation</td>
<td>185</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>186</td>
</tr>
<tr>
<td>MM</td>
<td>Matrix Multiplication</td>
<td>187</td>
</tr>
<tr>
<td>MVP</td>
<td>Matrix-Vector Product</td>
<td>187</td>
</tr>
<tr>
<td>MM</td>
<td>Matrix Multiplication</td>
<td>191</td>
</tr>
<tr>
<td>MMEE</td>
<td>Matrix Multiplication, Entry-by-Entry</td>
<td>192</td>
</tr>
<tr>
<td>PMM</td>
<td>Properties of Matrix Multiplication</td>
<td>194</td>
</tr>
<tr>
<td>PSHS</td>
<td>Particular Solutions, Homogeneous Solutions</td>
<td>199</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>202</td>
</tr>
<tr>
<td>EXC</td>
<td>Exercises</td>
<td>203</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>Matrix Inverses and Systems of Linear Equations</td>
<td>205</td>
</tr>
<tr>
<td>MISLE</td>
<td>Matrix Inverses and Systems of Linear Equations</td>
<td>207</td>
</tr>
<tr>
<td>IM</td>
<td>Inverse of a Matrix</td>
<td>208</td>
</tr>
<tr>
<td>CIM</td>
<td>Computing the Inverse of a Matrix</td>
<td>210</td>
</tr>
<tr>
<td>PMI</td>
<td>Properties of Matrix Inverses</td>
<td>214</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>217</td>
</tr>
<tr>
<td>EXC</td>
<td>Exercises</td>
<td>219</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>Orthogonal Matrices</td>
<td>221</td>
</tr>
<tr>
<td>OM</td>
<td>Orthogonal Matrices</td>
<td>223</td>
</tr>
<tr>
<td>READ</td>
<td>Reading Questions</td>
<td>226</td>
</tr>
<tr>
<td>EXC</td>
<td>Exercises</td>
<td>229</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>Column and Row Spaces</td>
<td>231</td>
</tr>
<tr>
<td>CRS</td>
<td>Column and Row Spaces</td>
<td>233</td>
</tr>
<tr>
<td>CSSE</td>
<td>Column spaces and systems of equations</td>
<td>235</td>
</tr>
<tr>
<td>CSSOC</td>
<td>Column space spanned by original columns</td>
<td>237</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>CSNSM Column Space of a Nonsingular Matrix</td>
<td>240</td>
<td></td>
</tr>
<tr>
<td>RSM Row Space of a Matrix</td>
<td>242</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>248</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>249</td>
<td></td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>253</td>
<td></td>
</tr>
<tr>
<td>FS Four Subsets</td>
<td>255</td>
<td></td>
</tr>
<tr>
<td>LNS Left Null Space</td>
<td>255</td>
<td></td>
</tr>
<tr>
<td>CRS Computing Column Spaces</td>
<td>255</td>
<td></td>
</tr>
<tr>
<td>EEF Extended echelon form</td>
<td>259</td>
<td></td>
</tr>
<tr>
<td>FS Four Subsets</td>
<td>262</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>267</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>269</td>
<td></td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>271</td>
<td></td>
</tr>
<tr>
<td>Chapter VS Vector Spaces</td>
<td>275</td>
<td></td>
</tr>
<tr>
<td>VS Vector Spaces</td>
<td>275</td>
<td></td>
</tr>
<tr>
<td>EVS Examples of Vector Spaces</td>
<td>277</td>
<td></td>
</tr>
<tr>
<td>VSP Vector Space Properties</td>
<td>282</td>
<td></td>
</tr>
<tr>
<td>RD Recycling Definitions</td>
<td>286</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>287</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>289</td>
<td></td>
</tr>
<tr>
<td>S Subspaces</td>
<td>291</td>
<td></td>
</tr>
<tr>
<td>TS Testing Subspaces</td>
<td>292</td>
<td></td>
</tr>
<tr>
<td>TSS The Span of a Set</td>
<td>297</td>
<td></td>
</tr>
<tr>
<td>SC Subspace Constructions</td>
<td>302</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>303</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>305</td>
<td></td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>307</td>
<td></td>
</tr>
<tr>
<td>B Bases</td>
<td>309</td>
<td></td>
</tr>
<tr>
<td>LI Linear independence</td>
<td>309</td>
<td></td>
</tr>
<tr>
<td>SS Spanning Sets</td>
<td>313</td>
<td></td>
</tr>
<tr>
<td>B Bases</td>
<td>317</td>
<td></td>
</tr>
<tr>
<td>BRS Bases from Row Spaces</td>
<td>321</td>
<td></td>
</tr>
<tr>
<td>BNSM Bases and NonSingular Matrices</td>
<td>323</td>
<td></td>
</tr>
<tr>
<td>VR Vector Representation</td>
<td>324</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>325</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>327</td>
<td></td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>329</td>
<td></td>
</tr>
<tr>
<td>D Dimension</td>
<td>331</td>
<td></td>
</tr>
<tr>
<td>D Dimension</td>
<td>331</td>
<td></td>
</tr>
<tr>
<td>DVS Dimension of Vector Spaces</td>
<td>336</td>
<td></td>
</tr>
<tr>
<td>RNM Rank and Nullity of a Matrix</td>
<td>338</td>
<td></td>
</tr>
<tr>
<td>RNNSM Rank and Nullity of a NonSingular Matrix</td>
<td>339</td>
<td></td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>341</td>
<td></td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>343</td>
<td></td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>345</td>
<td></td>
</tr>
<tr>
<td>PD Properties of Dimension</td>
<td>347</td>
<td></td>
</tr>
</tbody>
</table>
## Contents

- **GT Goldilocks' Theorem** ........................................ 347
- **RT Ranks and Transposes** ...................................... 351
- **OBC Orthonormal Bases and Coordinates** .................. 353
- **READ Reading Questions** ....................................... 356
- **EXC Exercises** .................................................. 357
- **SOL Solutions** .................................................. 359

### Chapter D Determinants

- **DM Determinants of Matrices** ................................. 361
- **CD Computing Determinants** .................................. 363
- **PD Properties of Determinants** ............................... 365
- **READ Reading Questions** ....................................... 367
- **EXC Exercises** .................................................. 369
- **SOL Solutions** .................................................. 371

### Chapter E Eigenvalues

- **EE Eigenvalues and Eigenvectors** ............................ 373
- **EEM Eigenvalues and Eigenvectors of a Matrix** ......... 373
- **PM Polynomials and Matrices** ................................ 375
- **EEE Existence of Eigenvalues and Eigenvectors** ........ 377
- **CEE Computing Eigenvalues and Eigenvectors** .......... 380
- **ECEE Examples of Computing Eigenvalues and Eigenvectors** 384
- **READ Reading Questions** ....................................... 391
- **EXC Exercises** .................................................. 393
- **SOL Solutions** .................................................. 395
- **PEE Properties of Eigenvalues and Eigenvectors** ...... 399
- **ME Multiplicities of Eigenvalues** ............................ 405
- **EHM Eigenvalues of Hermitian Matrices** .................. 408
- **READ Reading Questions** ....................................... 410
- **SD Similarity and Diagonalization** .......................... 411
- **SM Similar Matrices** .......................................... 411
- **PSM Properties of Similar Matrices** ....................... 412
- **D Diagonalization** .............................................. 415
- **OD Orthonormal Diagonalization** ............................. 423
- **READ Reading Questions** ....................................... 423
- **EXC Exercises** .................................................. 425
- **SOL Solutions** .................................................. 427

### Chapter LT Linear Transformations

- **LT Linear Transformations** .................................... 429
- **MLT Matrices and Linear Transformations** ............... 434
- **LTLC Linear Transformations and Linear Combinations** 439
- **PI Pre-Images** .................................................. 441
- **NLTFO New Linear Transformations From Old** .......... 444
- **READ Reading Questions** ....................................... 448
- **EXC Exercises** .................................................. 449
- **SOL Solutions** .................................................. 451
- **ILT Injective Linear Transformations** ....................... 453
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>EILT Examples of Injective Linear Transformations</td>
<td>453</td>
</tr>
<tr>
<td>KLT Kernel of a Linear Transformation</td>
<td>456</td>
</tr>
<tr>
<td>ILTLI Injective Linear Transformations and Linear Independence</td>
<td>461</td>
</tr>
<tr>
<td>ILTD Injective Linear Transformations and Dimension</td>
<td>462</td>
</tr>
<tr>
<td>CILT Composition of Injective Linear Transformations</td>
<td>463</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>464</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>465</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>467</td>
</tr>
<tr>
<td>SLT Surjective Linear Transformations</td>
<td>469</td>
</tr>
<tr>
<td>ESLT Examples of Surjective Linear Transformations</td>
<td>469</td>
</tr>
<tr>
<td>RLT Range of a Linear Transformation</td>
<td>473</td>
</tr>
<tr>
<td>SSSLT Spanning Sets and Surjective Linear Transformations</td>
<td>478</td>
</tr>
<tr>
<td>SLTD Surjective Linear Transformations and Dimension</td>
<td>480</td>
</tr>
<tr>
<td>CSLT Composition of Surjective Linear Transformations</td>
<td>481</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>481</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>483</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>485</td>
</tr>
<tr>
<td>IVLT Invertible Linear Transformations</td>
<td>487</td>
</tr>
<tr>
<td>IVLT Invertible Linear Transformations</td>
<td>487</td>
</tr>
<tr>
<td>IV Invertibility</td>
<td>491</td>
</tr>
<tr>
<td>SI Structure and Isomorphism</td>
<td>493</td>
</tr>
<tr>
<td>RNLT Rank and Nullity of a Linear Transformation</td>
<td>495</td>
</tr>
<tr>
<td>SLELT Systems of Linear Equations and Linear Transformations</td>
<td>498</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>500</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>501</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>503</td>
</tr>
<tr>
<td><strong>Chapter R Representations</strong></td>
<td>505</td>
</tr>
<tr>
<td>VR Vector Representations</td>
<td>505</td>
</tr>
<tr>
<td>CVS Characterization of Vector Spaces</td>
<td>512</td>
</tr>
<tr>
<td>CP Coordinatization Principle</td>
<td>513</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>516</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>519</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>521</td>
</tr>
<tr>
<td>MR Matrix Representations</td>
<td>523</td>
</tr>
<tr>
<td>NRFO New Representations from Old</td>
<td>530</td>
</tr>
<tr>
<td>PMR Properties of Matrix Representations</td>
<td>535</td>
</tr>
<tr>
<td>IVLT Invertible Linear Transformations</td>
<td>540</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>543</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>545</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>547</td>
</tr>
<tr>
<td>CB Change of Basis</td>
<td>549</td>
</tr>
<tr>
<td>EELT Eigenvalues and Eigenvectors of Linear Transformations</td>
<td>549</td>
</tr>
<tr>
<td>CBM Change-of-Basis Matrix</td>
<td>549</td>
</tr>
<tr>
<td>MRS Matrix Representations and Similarity</td>
<td>550</td>
</tr>
<tr>
<td>READ Reading Questions</td>
<td>553</td>
</tr>
<tr>
<td>EXC Exercises</td>
<td>555</td>
</tr>
<tr>
<td>SOL Solutions</td>
<td>557</td>
</tr>
</tbody>
</table>
Chapter A Archetypes

A ................................................................. 563
B ................................................................. 568
C ................................................................. 573
D ................................................................. 577
E ................................................................. 581
F ................................................................. 585
G ................................................................. 590
H ................................................................. 594
I ................................................................. 599
J ................................................................. 604
K ................................................................. 609
L ................................................................. 613
M ................................................................. 617
N ................................................................. 620
O ................................................................. 622
P ................................................................. 625
Q ................................................................. 627
R ................................................................. 631
S ................................................................. 634
T ................................................................. 634
U ................................................................. 634
V ................................................................. 634
W ................................................................. 635

Part T Topics

Chapter P Preliminaries

CNO Complex Number Operations ....................................................... 639
CNA Arithmetic with complex numbers ............................................. 639
CCN Conjugates of Complex Numbers ........................................... 640
MCN Modulus of a Complex Number ............................................ 641

Part A Applications

645
Definitions

Section WILA
Section SSLE
SLE System of Linear Equations ........................................... 14
ES Equivalent Systems ......................................................... 16
EO Equation Operations ....................................................... 16

Section RREF
M Matrix ........................................................................... 29
MN Matrix Notation ............................................................ 29
AM Augmented Matrix .......................................................... 31
RO Row Operations ............................................................... 32
REM Row-Equivalent Matrices ................................................ 32
RREF Reduced Row-Echelon Form .......................................... 34
ZRM Zero Row of a Matrix ..................................................... 34
LO Leading Ones .................................................................. 34
PC Pivot Columns .................................................................. 34

Section TSS
CS Consistent System ............................................................ 49
IDV Independent and Dependent Variables ................................. 52

Section HSE
HS Homogeneous System ....................................................... 63
TSHSE Trivial Solution to Homogeneous Systems of Equations .... 64
CV Column Vector ................................................................ 66
ZV Zero Vector .................................................................... 66
CM Coefficient Matrix ............................................................ 66
VOC Vector of Constants ....................................................... 67
SV Solution Vector ................................................................ 67
NSM Null Space of a Matrix ................................................... 68

Section NSM
SQM Square Matrix ................................................................ 75
NM Nonsingular Matrix ........................................................ 75
IM Identity Matrix .................................................................. 76

Section VO
VSCV Vector Space of Column Vectors ................................. 87
CVE Column Vector Equality ............................................... 88
CVA Column Vector Addition ............................................... 89
CVSM Column Vector Scalar Multiplication .............................. 90

Section LC
LCCV Linear Combination of Column Vectors ....................... 99
Section SS
SSCV Span of a Set of Column Vectors

Section LI
RLDCV Relation of Linear Dependence for Column Vectors
LICV Linear Independence of Column Vectors

Section LDS

Section O
CCCV Complex Conjugate of a Column Vector
IP Inner Product
NV Norm of a Vector
OV Orthogonal Vectors
OSV Orthogonal Set of Vectors
ONS OrthoNormal Set

Section MO
VSM Vector Space of $m \times n$ Matrices
ME Matrix Equality
MA Matrix Addition
MSM Matrix Scalar Multiplication
ZM Zero Matrix
TM Transpose of a Matrix
SYM Symmetric Matrix
CCM Complex Conjugate of a Matrix

Section MM
MVP Matrix-Vector Product
MM Matrix Multiplication

Section MISLE
MI Matrix Inverse
SUV Standard Unit Vectors

Section MINSM
OM Orthogonal Matrices
A Adjoint
HM Hermitian Matrix

Section CRS
CSM Column Space of a Matrix
RSM Row Space of a Matrix

Section FS
LNS Left Null Space
EEF Extended Echelon Form

Version 0.52
Section VS

VS Vector Space ........................................... 275

Section S

S Subspace .................................................. 291
TS Trivial Subspaces ........................................ 295
LC Linear Combination ..................................... 297
SS Span of a Set ............................................ 298

Section B

RLD Relation of Linear Dependence ...................... 309
LI Linear Independence ..................................... 309
TSS To Span a Subspace .................................... 313
B Basis .......................................................... 317

Section D

D Dimension .................................................. 331
NOM Nullity Of a Matrix ................................... 338
ROM Rank Of a Matrix ....................................... 338

Section PD

Section DM

SM SubMatrix ................................................ 361
DM Determinant .............................................. 361
MIM Minor In a Matrix ....................................... 363
CIM Cofactor In a Matrix .................................... 363

Section EE

EEM Eigenvalues and Eigenvectors of a Matrix ........... 373
CP Characteristic Polynomial ............................... 381
EM Eigenspace of a Matrix .................................. 382
AME Algebraic Multiplicity of an Eigenvalue .......... 384
GME Geometric Multiplicity of an Eigenvalue .......... 384

Section PEE

Section SD

SIM Similar Matrices ....................................... 411
DIM Diagonal Matrix ......................................... 415
DZM Diagonalizable Matrix .................................. 415

Section LT

LT Linear Transformation .................................... 429
PI Pre-Image .................................................. 442
LTA Linear Transformation Addition ...................... 444
LTSM Linear Transformation Scalar Multiplication .... 445
LTC Linear Transformation Composition .................. 446

Version 0.52
## Definitions

### Section ILT
- **ILT** Injective Linear Transformation .................................................. 453
- **KLT** Kernel of a Linear Transformation ................................................... 457

### Section SLT
- **SLT** Surjective Linear Transformation ................................................... 469
- **RLT** Range of a Linear Transformation .................................................... 473

### Section IVLT
- **IDLT** Identity Linear Transformation ..................................................... 487
- **IVLT** Invertible Linear Transformations ................................................... 487
- **IVS** Isomorphic Vector Spaces ................................................................. 493
- **ROLT** Rank Of a Linear Transformation ................................................... 495
- **NOLT** Nullity Of a Linear Transformation ................................................ 495

### Section VR
- **VR** Vector Representation ........................................................................... 505

### Section MR
- **MR** Matrix Representation .......................................................................... 523

### Section CB
- **EELT** Eigenvalue and Eigenvector of a Linear Transformation .................. 549
- **CBM** Change-of-Basis Matrix ....................................................................... 549

### Section CNO
- **CCN** Conjugate of a Complex Number ....................................................... 640
- **MCN** Modulus of a Complex Number .......................................................... 641
Theorems

Section WILA
Section SSLE

**EOPSS** Equation Operations Preserve Solution Sets .................. 17

Section RREF

**REMES** Row-Equivalent Matrices represent Equivalent Systems .......... 32
**REMEF** Row-Equivalent Matrix in Echelon Form .......................... 35

Section TSS

**RCLS** Recognizing Consistency of a Linear System .................... 53
**ICRN** Inconsistent Systems, $r$ and $n$ .................................. 54
**CSRN** Consistent Systems, $r$ and $n$ .................................. 54
**FVCS** Free Variables for Consistent Systems ............................ 55
**PSSLS** Possible Solution Sets for Linear Systems ...................... 56
**CMVEI** Consistent, More Variables than Equations, Infinite solutions ... 56

Section HSE

**HSC** Homogeneous Systems are Consistent ............................... 64
**HMVEI** Homogeneous, More Variables than Equations, Infinite solutions ... 65

Section NSM

**NSRRI** NonSingular matrices Row Reduce to the Identity matrix ........ 77
**NSTNS** NonSingular matrices have Trivial Null Spaces ................. 78
**NSMUS** NonSingular Matrices and Unique Solutions ..................... 79
**NSME1** NonSingular Matrix Equivalences, Round 1 ....................... 82

Section VO

**VSPCV** Vector Space Properties of Column Vectors ..................... 92

Section LC

**SLSLC** Solutions to Linear Systems are Linear Combinations .......... 103
**VFSLS** Vector Form of Solutions to Linear Systems .................... 106
**RREFU** Reduced Row-Echelon Form is Unique ............................ 112

Section SS

**SSNS** Spanning Sets for Null Spaces .................................. 122

Section LI

**LIVHS** Linearly Independent Vectors and Homogeneous Systems .......... 135
**LIVRN** Linearly Independent Vectors, $r$ and $n$ ....................... 137
**MVSLD** More Vectors than Size implies Linear Dependence ............. 139
**NSLIC** NonSingular matrices have Linearly Independent Columns ...... 139
**NSME2** NonSingular Matrix Equivalences, Round 2 ..................... 140
**BNS** Basis for Null Spaces ............................................ 141
Section MINSM

- **PWSMS** Product With a Singular Matrix is Singular ............................................. 223
- **OSIS** One-Sided Inverse is Sufficient ...................................................................... 224
- **NSI** NonSingularity is Invertibility ......................................................................... 225
- **NSME3** NonSingular Matrix Equivalences, Round 3 ................................................. 225
- **SNSCM** Solution with NonSingular Coefficient Matrix ........................................... 225
- **OMI** Orthogonal Matrices are Invertible ................................................................... 227
- **COMOS** Columns of Orthogonal Matrices are Orthonormal Sets .............................. 227
- **OMPIP** Orthogonal Matrices Preserve Inner Products .............................................. 228

Section CRS

- **CSCS** Column Spaces and Consistent Systems ......................................................... 236
- **BCSOC** Basis of the Column Space with Original Columns ..................................... 238
- **CSNSM** Column Space of a NonSingular Matrix ...................................................... 241
- **NSME4** NonSingular Matrix Equivalences, Round 4 .............................................. 241
- **REMRS** Row-Equivalent Matrices have equal Row Spaces ..................................... 243
- **BRS** Basis for the Row Space .................................................................................. 245
- **CSRST** Column Space, Row Space, Transpose ......................................................... 246

Section FS

- **PEEF** Properties of Extended Echelon Form .......................................................... 260
- **FS** Four Subsets ........................................................................................................ 262

Section VS

- **ZVU** Zero Vector is Unique ..................................................................................... 282
- **AIU** Additive Inverses are Unique .......................................................................... 282
- **ZSSM** Zero Scalar in Scalar Multiplication .............................................................. 283
- **ZVSM** Zero Vector in Scalar Multiplication .............................................................. 283
- **AISM** Additive Inverses from Scalar Multiplication ................................................ 283
- **SMEZV** Scalar Multiplication Equals the Zero Vector ............................................ 284
- **VAC** Vector Addition Cancellation ........................................................................... 285
- **CSSM** Canceling Scalars in Scalar Multiplication ..................................................... 285
- **CVSM** Canceling Vectors in Scalar Multiplication ................................................... 286

Section S

- **TSS** Testing Subsets for Subspaces ........................................................................ 293
- **NSMS** Null Space of a Matrix is a Subspace ............................................................ 296
- **SSS** Span of a Set is a Subspace .............................................................................. 298
- **RMS** Range of a Matrix is a Subspace ..................................................................... 302
- **RSMS** Row Space of a Matrix is a Subspace ............................................................ 303

Section B

- **SUVB** Standard Unit Vectors are a Basis ............................................................... 318
- **CNSMB** Columns of NonSingular Matrix are a Basis ............................................. 323
- **NSME5** NonSingular Matrix Equivalences, Round 5 ............................................. 323
- **VRRB** Vector Representation Relative to a Basis .................................................... 324
### Section D

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSLD</td>
<td>Spanning Sets and Linear Dependence</td>
</tr>
<tr>
<td>BIS</td>
<td>Bases have Identical Sizes</td>
</tr>
<tr>
<td>DCM</td>
<td>Dimension of ( \mathbb{C}^m )</td>
</tr>
<tr>
<td>DP</td>
<td>Dimension of ( P_n )</td>
</tr>
<tr>
<td>DM</td>
<td>Dimension of ( M_{mn} )</td>
</tr>
<tr>
<td>CRN</td>
<td>Computing Rank and Nullity</td>
</tr>
<tr>
<td>RPNC</td>
<td>Rank Plus Nullity is Columns</td>
</tr>
<tr>
<td>RNNSM</td>
<td>Rank and Nullity of a NonSingular Matrix</td>
</tr>
<tr>
<td>NSME6</td>
<td>NonSingular Matrix Equivalences, Round 6</td>
</tr>
</tbody>
</table>

### Section PD

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELIS</td>
<td>Extending Linearly Independent Sets</td>
</tr>
<tr>
<td>G</td>
<td>Goldilocks</td>
</tr>
<tr>
<td>EDYES</td>
<td>Equal Dimensions Yields Equal Subspaces</td>
</tr>
<tr>
<td>RMRT</td>
<td>Rank of a Matrix is the Rank of the Transpose</td>
</tr>
<tr>
<td>COB</td>
<td>Coordinates and Orthonormal Bases</td>
</tr>
</tbody>
</table>

### Section DM

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DMST</td>
<td>Determinant of Matrices of Size Two</td>
</tr>
<tr>
<td>DERC</td>
<td>Determinant Expansion about Rows and Columns</td>
</tr>
<tr>
<td>DT</td>
<td>Determinant of the Transpose</td>
</tr>
<tr>
<td>DRMM</td>
<td>Determinant Respects Matrix Multiplication</td>
</tr>
<tr>
<td>SMZD</td>
<td>Singular Matrices have Zero Determinants</td>
</tr>
<tr>
<td>NSME7</td>
<td>NonSingular Matrix Equivalences, Round 7</td>
</tr>
</tbody>
</table>

### Section EE

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMHE</td>
<td>Every Matrix Has an Eigenvalue</td>
</tr>
<tr>
<td>EMRCP</td>
<td>Eigenvalues of a Matrix are Roots of Characteristic Polynomials</td>
</tr>
<tr>
<td>EMS</td>
<td>Eigenspace for a Matrix is a Subspace</td>
</tr>
<tr>
<td>EMNS</td>
<td>Eigenspace of a Matrix is a Null Space</td>
</tr>
</tbody>
</table>

### Section PEE

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDELI</td>
<td>Eigenvectors with Distinct Eigenvalues are Linearly Independent</td>
</tr>
<tr>
<td>SMZE</td>
<td>Singular Matrices have Zero Eigenvalues</td>
</tr>
<tr>
<td>NSME8</td>
<td>NonSingular Matrix Equivalences, Round 8</td>
</tr>
<tr>
<td>ESMM</td>
<td>Eigenvalues of a Scalar Multiple of a Matrix</td>
</tr>
<tr>
<td>EOMP</td>
<td>Eigenvalues Of Matrix Powers</td>
</tr>
<tr>
<td>EPM</td>
<td>Eigenvalues of the Polynomial of a Matrix</td>
</tr>
<tr>
<td>EIM</td>
<td>Eigenvalues of the Inverse of a Matrix</td>
</tr>
<tr>
<td>ETM</td>
<td>Eigenvalues of the Transpose of a Matrix</td>
</tr>
<tr>
<td>ERICP</td>
<td>Eigenvalues of Real Matrices come in Conjugate Pairs</td>
</tr>
<tr>
<td>DCP</td>
<td>Degree of the Characteristic Polynomial</td>
</tr>
<tr>
<td>NEM</td>
<td>Number of Eigenvalues of a Matrix</td>
</tr>
<tr>
<td>ME</td>
<td>Multiplicities of an Eigenvalue</td>
</tr>
<tr>
<td>MNEM</td>
<td>Maximum Number of Eigenvalues of a Matrix</td>
</tr>
<tr>
<td>HMRE</td>
<td>Hermitian Matrices have Real Eigenvalues</td>
</tr>
<tr>
<td>Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>HMOE</td>
<td>Hermitian Matrices have Orthogonal Eigenvectors</td>
</tr>
<tr>
<td>SER</td>
<td>Similarity is an Equivalence Relation</td>
</tr>
<tr>
<td>SMEE</td>
<td>Similar Matrices have Equal Eigenvalues</td>
</tr>
<tr>
<td>DC</td>
<td>Diagonalization Characterization</td>
</tr>
<tr>
<td>DMLE</td>
<td>Diagonalizable Matrices have Large Eigenspaces</td>
</tr>
<tr>
<td>DED</td>
<td>Distinct Eigenvalues implies Diagonalizable</td>
</tr>
<tr>
<td>LTTZZ</td>
<td>Linear Transformations Take Zero to Zero</td>
</tr>
<tr>
<td>MBLT</td>
<td>Matrices Build Linear Transformations</td>
</tr>
<tr>
<td>MLTCV</td>
<td>Matrix of a Linear Transformation, Column Vectors</td>
</tr>
<tr>
<td>LTLC</td>
<td>Linear Transformations and Linear Combinations</td>
</tr>
<tr>
<td>LTDB</td>
<td>Linear Transformation Defined on a Basis</td>
</tr>
<tr>
<td>SLTLT</td>
<td>Sum of Linear Transformations is a Linear Transformation</td>
</tr>
<tr>
<td>MLTLT</td>
<td>Multiple of a Linear Transformation is a Linear Transformation</td>
</tr>
<tr>
<td>VSLT</td>
<td>Vector Space of Linear Transformations</td>
</tr>
<tr>
<td>CLTLT</td>
<td>Composition of Linear Transformations is a Linear Transformation</td>
</tr>
<tr>
<td>KLTS</td>
<td>Kernel of a Linear Transformation is a Subspace</td>
</tr>
<tr>
<td>KPI</td>
<td>Kernel and Pre-Image</td>
</tr>
<tr>
<td>KILT</td>
<td>Kernel of an Injective Linear Transformation</td>
</tr>
<tr>
<td>ILTLI</td>
<td>Injective Linear Transformations and Linear Independence</td>
</tr>
<tr>
<td>ILTB</td>
<td>Injective Linear Transformations and Bases</td>
</tr>
<tr>
<td>ILTD</td>
<td>Injective Linear Transformations and Dimension</td>
</tr>
<tr>
<td>CILTI</td>
<td>Composition of Injective Linear Transformations is Injective</td>
</tr>
<tr>
<td>RLTS</td>
<td>Range of a Linear Transformation is a Subspace</td>
</tr>
<tr>
<td>RSLT</td>
<td>Range of a Surjective Linear Transformation</td>
</tr>
<tr>
<td>SSRLT</td>
<td>Spanning Set for Range of a Linear Transformation</td>
</tr>
<tr>
<td>RPI</td>
<td>Range and Pre-Image</td>
</tr>
<tr>
<td>SLTB</td>
<td>Surjective Linear Transformations and Bases</td>
</tr>
<tr>
<td>SLTD</td>
<td>Surjective Linear Transformations and Dimension</td>
</tr>
<tr>
<td>CSLTS</td>
<td>Composition of Surjective Linear Transformations is Surjective</td>
</tr>
<tr>
<td>ILTLT</td>
<td>Inverse of a Linear Transformation is a Linear Transformation</td>
</tr>
<tr>
<td>ILT</td>
<td>Inverse of an Invertible Linear Transformation</td>
</tr>
<tr>
<td>ILTIS</td>
<td>Invertible Linear Transformations are Injective and Surjective</td>
</tr>
<tr>
<td>CIVLT</td>
<td>Composition of Invertible Linear Transformations</td>
</tr>
<tr>
<td>ICLT</td>
<td>Inverse of a Composition of Linear Transformations</td>
</tr>
<tr>
<td>IVSED</td>
<td>Isomorphic Vector Spaces have Equal Dimension</td>
</tr>
<tr>
<td>ROSLT</td>
<td>Rank Of a Surjective Linear Transformation</td>
</tr>
<tr>
<td>NOILT</td>
<td>Nullity Of an Invertible Linear Transformation</td>
</tr>
<tr>
<td>RPNDD</td>
<td>Rank Plus Nullity is Domain Dimension</td>
</tr>
</tbody>
</table>
### Section VR

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>VRLT Vector Representation is a Linear Transformation</td>
<td>505</td>
</tr>
<tr>
<td>VRI Vector Representation is Injective</td>
<td>511</td>
</tr>
<tr>
<td>VRS Vector Representation is Surjective</td>
<td>511</td>
</tr>
<tr>
<td>VRILT Vector Representation is an Invertible Linear Transformation</td>
<td>512</td>
</tr>
<tr>
<td>CFDVS Characterization of Finite Dimensional Vector Spaces</td>
<td>512</td>
</tr>
<tr>
<td>IFDVS Isomorphism of Finite Dimensional Vector Spaces</td>
<td>513</td>
</tr>
<tr>
<td>CLI Coordinatization and Linear Independence</td>
<td>514</td>
</tr>
<tr>
<td>CSS Coordinatization and Spanning Sets</td>
<td>514</td>
</tr>
</tbody>
</table>

### Section MR

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTMR Fundamental Theorem of Matrix Representation</td>
<td>526</td>
</tr>
<tr>
<td>MRSLT Matrix Representation of a Sum of Linear Transformations</td>
<td>530</td>
</tr>
<tr>
<td>MRMLT Matrix Representation of a Multiple of a Linear Transformation</td>
<td>530</td>
</tr>
<tr>
<td>MRCLT Matrix Representation of a Composition of Linear Transformations</td>
<td>531</td>
</tr>
<tr>
<td>KNSI Kernel and Null Space Isomorphism</td>
<td>535</td>
</tr>
<tr>
<td>RCSI Range and Column Space Isomorphism</td>
<td>538</td>
</tr>
<tr>
<td>IMR Invertible Matrix Representations</td>
<td>540</td>
</tr>
</tbody>
</table>

### Section CB

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>CB Change-of-Basis</td>
<td>550</td>
</tr>
<tr>
<td>ICBM Inverse of Change-of-Basis Matrix</td>
<td>550</td>
</tr>
<tr>
<td>MRCB Matrix Representation and Change of Basis</td>
<td>551</td>
</tr>
<tr>
<td>SCB Similarity and Change of Basis</td>
<td>551</td>
</tr>
<tr>
<td>EER Eigenvalues, Eigenvectors, Representations</td>
<td>552</td>
</tr>
</tbody>
</table>

### Section CNO

<table>
<thead>
<tr>
<th>Theorem</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCRA Complex Conjugation Respects Addition</td>
<td>640</td>
</tr>
<tr>
<td>CCRM Complex Conjugation Respects Multiplication</td>
<td>640</td>
</tr>
<tr>
<td>CCT Complex Conjugation Twice</td>
<td>640</td>
</tr>
</tbody>
</table>
Notation

Section WILA
Section SSLE
Section RREF

**ME** Matrix Entries ([A]_{ij}) ........................................... 29

Section TSS

**RREFA** Reduced Row-Echelon Form Analysis .................................. 49

Section HSE

**VN** Vector (u) .......................................................... 66
**ZVN** Zero Vector (0) .................................................. 66
**LSN** Linear System (LS(A, b)) ........................................ 68
**AMN** Augmented Matrix ([A | b]) ...................................... 68

Section NSM
Section VO
Section LC
Section SS
Section LI
Section LDS
Section O
Section MO
Section MM
Section MISLE
Section MINSM
Section CRS
Section FS
Section VS
Section S
Section B
Section D
Section PD
Section DM
Section EE
Section PEE
Section SD
Section LT
Section ILT
Section SLT
Section IVLT
Section VR
Section MR
Section CB
Section CNO
## Examples

### Section WILA
- TMP Trail Mix Packaging ........................................ 4

### Section SSLE
- STNE Solving two (nonlinear) equations .......................... 13
- NSE Notation for a system of equations .......................... 14
- TTS Three typical systems ........................................ 15
- US Three equations, one solution ................................. 20
- IS Three equations, infinitely many solutions .................... 21

### Section RREF
- AM A matrix ......................................................... 29
- AMAA Augmented matrix for Archetype A ......................... 31
- TREM Two row-equivalent matrices ............................... 32
- USR Three equations, one solution, reprised ...................... 33
- RREF A matrix in reduced row-echelon form ...................... 34
- NRREF A matrix not in reduced row-echelon form ................ 35
- SAB Solutions for Archetype B ................................. 37
- SAA Solutions for Archetype A .................................. 38
- SAE Solutions for Archetype E ................................. 39

### Section TSS
- RREFN Reduced row-echelon form notation ..................... 49
- ISSI Describing infinite solution sets, Archetype I ............. 50
- CFV Counting free variables .................................... 55
- OSGMD One solution gives many, Archetype D .................. 57

### Section HSE
- AHSAC Archetype C as a homogeneous system .................... 63
- HUSAB Homogeneous, unique solution, Archetype B ............. 64
- HISAA Homogeneous, infinite solutions, Archetype A ........ 64
- HISAD Homogeneous, infinite solutions, Archetype D ........ 65
- NSLE Notation for systems of linear equations .................. 68
- NSEAI Null space elements of Archetype I ..................... 69
- CNS1 Computing a null space, #1 .......................... 69
- CNS2 Computing a null space, #2 .......................... 70

### Section NSM
- S A singular matrix, Archetype A ............................. 76
- NS A nonsingular matrix, Archetype A ........................ 76
- IM An identity matrix .......................................... 76
- SRR Singular matrix, row-reduced ............................ 77
- NSRR NonSingular matrix, row-reduced .................. 77
- NSS Null space of a singular matrix ........................ 78
- NSNS Null space of a nonsingular matrix ..................... 78
<table>
<thead>
<tr>
<th>Module</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA</td>
<td>Addition of two matrices in $M_{23}$</td>
</tr>
<tr>
<td>MSM</td>
<td>Scalar multiplication in $M_{32}$</td>
</tr>
<tr>
<td>TM</td>
<td>Transpose of a $3 \times 4$ matrix</td>
</tr>
<tr>
<td>SYM</td>
<td>A symmetric $5 \times 5$ matrix</td>
</tr>
<tr>
<td>CCM</td>
<td>Complex conjugate of a matrix</td>
</tr>
</tbody>
</table>

**Section MM**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTV</td>
</tr>
<tr>
<td>MNSLE</td>
</tr>
<tr>
<td>MBC</td>
</tr>
<tr>
<td>PTM</td>
</tr>
<tr>
<td>MMNC</td>
</tr>
<tr>
<td>PTMEE</td>
</tr>
<tr>
<td>PSNS</td>
</tr>
</tbody>
</table>

**Section MISLE**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>SABMI</td>
</tr>
<tr>
<td>MWIAA</td>
</tr>
<tr>
<td>MIAK</td>
</tr>
<tr>
<td>CMIAK</td>
</tr>
<tr>
<td>CMIAB</td>
</tr>
</tbody>
</table>

**Section MINSM**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>OM3</td>
</tr>
<tr>
<td>OPM</td>
</tr>
<tr>
<td>OSMC</td>
</tr>
</tbody>
</table>

**Section CRS**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSMCS</td>
</tr>
<tr>
<td>MCSM</td>
</tr>
<tr>
<td>CSTW</td>
</tr>
<tr>
<td>ROCD</td>
</tr>
<tr>
<td>CSAA</td>
</tr>
<tr>
<td>CSAB</td>
</tr>
<tr>
<td>RSAI</td>
</tr>
<tr>
<td>RSREM</td>
</tr>
<tr>
<td>IAS</td>
</tr>
<tr>
<td>CSROI</td>
</tr>
</tbody>
</table>

**Section FS**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSANS</td>
</tr>
<tr>
<td>SEEF</td>
</tr>
<tr>
<td>FS1</td>
</tr>
<tr>
<td>FS2</td>
</tr>
<tr>
<td>FSAG</td>
</tr>
</tbody>
</table>

**Section VS**

<table>
<thead>
<tr>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>VSCV</td>
</tr>
</tbody>
</table>
VSM The vector space of matrices, $M_{mn}$ ........................................... 277
VSP The vector space of polynomials, $P_n$ ........................................... 277
VSIS The vector space of infinite sequences .............................................. 278
VSF The vector space of functions ............................................................ 279
VSS The singleton vector space ................................................................. 279
CVS The crazy vector space ........................................................................... 280
PCVS Properties for the Crazy Vector Space ................................................. 284

Section S
SC3 A subspace of $C^3$ .................................................................................. 291
SP4 A subspace of $P_4$ .................................................................................. 294
NSC2Z A non-subspace in $C^2$, zero vector .................................................. 294
NSC2A A non-subspace in $C^2$, additive closure ........................................... 295
NSC2S A non-subspace in $C^2$, scalar multiplication closure ......................... 295
RSNS Recasting a subspace as a null space ..................................................... 296
LCM A linear combination of matrices ........................................................... 297
SSP Span of a set of polynomials .................................................................. 299
SM32 A subspace of $M_{32}$ ............................................................................ 300

Section B
LIP4 Linear independence in $P_4$ ................................................................... 309
LIM32 Linear Independence in $M_{32}$ ............................................................ 311
SSP4 Spanning set in $P_4$ .............................................................................. 313
SSM22 Spanning set in $M_{22}$ ....................................................................... 315
BP Bases for $P_n$ .......................................................................................... 318
BM A basis for the vector space of matrices .................................................. 319
BS4 A basis for a subspace of $P_4$ ................................................................. 319
BSM22 A basis for a subspace of $M_{32}$ .......................................................... 320
RSB Row space basis ..................................................................................... 321
RS Reducing a span ....................................................................................... 322
CABAK Columns as Basis, Archetype K ....................................................... 323
AVR A vector representation ......................................................................... 324

Section D
LDP4 Linearly dependent set in $P_4$ ............................................................... 335
dm22 Dimension of a subspace of $M_{32}$ ....................................................... 336
dsp4 Dimension of a subspace of $P_4$ ............................................................. 337
VSPUD Vector space of polynomials with unbounded degree ......................... 337
RNM Rank and nullity of a matrix ................................................................ 338
RNSM Rank and nullity of a square matrix .................................................... 339

Section PD
BPR Bases for $P_n$, reprised ........................................................................ 349
BDM22 Basis by dimension in $M_{32}$ ............................................................ 349
SVP4 Sets of vectors in $P_4$ ........................................................................... 350
RRTI Rank, rank of transpose, Archetype I .................................................... 352
CROB4 Coordinatization relative to an orthonormal basis, $C^n$ ................. 354
CROB3 Coordinatization relative to an orthonormal basis, $C^3$ ................. 355
## Examples xxxi

### Section DM
<table>
<thead>
<tr>
<th>SS</th>
<th>Some submatrices</th>
<th>361</th>
</tr>
</thead>
<tbody>
<tr>
<td>D33M</td>
<td>Determinant of a $3 \times 3$ matrix</td>
<td>362</td>
</tr>
<tr>
<td>MC</td>
<td>Minors and cofactors</td>
<td>363</td>
</tr>
<tr>
<td>TCSD</td>
<td>Two computations, same determinant</td>
<td>364</td>
</tr>
<tr>
<td>DUTM</td>
<td>Determinant of an upper-triangular matrix</td>
<td>365</td>
</tr>
<tr>
<td>ZNDAB</td>
<td>Zero and nonzero determinant, Archetypes A and B</td>
<td>366</td>
</tr>
</tbody>
</table>

### Section EE
| SEE      | Some eigenvalues and eigenvectors                               | 373 |
| PM       | Polynomial of a matrix                                          | 375 |
| CAEHW    | Computing an eigenvalue the hard way                           | 378 |
| CPMS3    | Characteristic polynomial of a matrix, size 3                  | 381 |
| EMS3     | Eigenvalues of a matrix, size 3                                 | 382 |
| ESMS3    | Eigenspaces of a matrix, size 3                                | 383 |
| EMMS4    | Eigenvalue multiplicities, matrix of size 4                    | 384 |
| ESMS4    | Eigenvalues, symmetric matrix of size 4                         | 385 |
| HMEM5    | High multiplicity eigenvalues, matrix of size 5                 | 386 |
| CEMS6    | Complex eigenvalues, matrix of size 6                           | 387 |
| DEMS5    | Distinct eigenvalues, matrix of size 5                          | 390 |

### Section PEE
| BDE      | Building desired eigenvalues                                    | 402 |

### Section SD
| SMS5     | Similar matrices of size 5                                      | 411 |
| SMS4     | Similar matrices of size 4                                      | 412 |
| EENS     | Equal eigenvalues, not similar                                  | 414 |
| DAB      | Diagonalization of Archetype B                                  | 415 |
| DMS3     | Diagonalizing a matrix of size 3                                | 417 |
| NDMS4    | A non-diagonalizable matrix of size 4                           | 420 |
| DEHD     | Distinct eigenvalues, hence diagonalizable                      | 420 |
| HPDM     | High power of a diagonalizable matrix                           | 421 |

### Section LT
| ALT      | A linear transformation                                         | 430 |
| NLT      | Not a linear transformation                                     | 431 |
| LTPM     | Linear transformation, polynomials to matrices                  | 432 |
| LTTP     | Linear transformation, polynomials to polynomials               | 433 |
| LTM      | Linear transformation from a matrix                            | 434 |
| MFLT     | Matrix from a linear transformation                             | 436 |
| MOLT     | Matrix of a linear transformation                               | 438 |
| LTDB1    | Linear transformation defined on a basis                        | 440 |
| LTDB2    | Linear transformation defined on a basis                        | 440 |
| LTDB3    | Linear transformation defined on a basis                        | 441 |
| SPIAS    | Sample pre-images, Archetype S                                  | 442 |
| STLT     | Sum of two linear transformations                                | 444 |

Version 0.52
Examples xxxiii

Section CB
Section CNO

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACN</td>
<td>Arithmetic of complex numbers</td>
<td>639</td>
</tr>
<tr>
<td>CSCN</td>
<td>Conjugate of some complex numbers</td>
<td>640</td>
</tr>
<tr>
<td>MSCN</td>
<td>Modulus of some complex numbers</td>
<td>641</td>
</tr>
</tbody>
</table>
Computation Notes

Section WILA
Section SSLE
Section RREF

ME.MMA Matrix Entry (Mathematica) ........................................ 30
ME.TI86 Matrix Entry (TI-86) .................................................. 30
ME.TI83 Matrix Entry (TI-83) .................................................. 30
RR.MMA Row Reduce (Mathematica) ........................................... 40
RR.TI86 Row Reduce (TI-86) .................................................... 40
RR.TI83 Row Reduce (TI-83) .................................................... 40

Section TSS

LS.MMA Linear Solve (Mathematica) ......................................... 57

Section HSE
Section NSM
Section VO

VLC.MMA Vector Linear Combinations (Mathematica) .................. 91
VLC.TI86 Vector Linear Combinations (TI-86) ............................. 91
VLC.TI83 Vector Linear Combinations (TI-83) ............................. 92

Section LC
Section SS
Section LI
Section LDS
Section O
Section MO

TM.MMA Transpose of a Matrix (Mathematica) ............................ 185
TM.TI86 Transpose of a Matrix (TI-86) ..................................... 185

Section MM

MM.MMA Matrix Multiplication (Mathematica) ............................ 192

Section MISLE

MI.MMA Matrix Inverses (Mathematica) .................................... 214

Section MINSM
Section CRS
Section FS
Section VS
Section S
Section B
Section D
Section PD
Section DM
Section EE

xxxvii
Section PEE
Section SD
Section LT
Section ILT
Section SLT
Section IVLT
Section VR
Section MR
Section CB
Section CNO
Contributors


Riegsecker, Joe.  Middlebury, Indiana. joepye(at)pobox(dot)com


xxxix
GNU Free Documentation License

Version 1.2, November 2002
59 Temple Place, Suite 330, Boston, MA 02111-1307 USA

Everyone is permitted to copy and distribute verbatim copies of this license document,
but changing it is not allowed.

Preamble

The purpose of this License is to make a manual, textbook, or other functional and
useful document “free” in the sense of freedom: to assure everyone the effective freedom
to copy and redistribute it, with or without modifying it, either commercially or non-
commercially. Secondarily, this License preserves for the author and publisher a way to
get credit for their work, while not being considered responsible for modifications made
by others.

This License is a kind of “copyleft”, which means that derivative works of the doc-
ument must themselves be free in the same sense. It complements the GNU General
Public License, which is a copyleft license designed for free software.

We have designed this License in order to use it for manuals for free software, be-
cause free software needs free documentation: a free program should come with manuals
providing the same freedoms that the software does. But this License is not limited to
software manuals; it can be used for any textual work, regardless of subject matter or
whether it is published as a printed book. We recommend this License principally for
works whose purpose is instruction or reference.

1. APPLICABILITY AND DEFINITIONS

This License applies to any manual or other work, in any medium, that contains a
notice placed by the copyright holder saying it can be distributed under the terms of this
License. Such a notice grants a world-wide, royalty-free license, unlimited in duration,
to use that work under the conditions stated herein. The “Document”, below, refers
to any such manual or work. Any member of the public is a licensee, and is addressed
as “you”. You accept the license if you copy, modify or distribute the work in a way
requiring permission under copyright law.

A “Modified Version” of the Document means any work containing the Document
or a portion of it, either copied verbatim, or with modifications and/or translated into
another language.

A “Secondary Section” is a named appendix or a front-matter section of the Doc-
ument that deals exclusively with the relationship of the publishers or authors of the
Document to the Document’s overall subject (or to related matters) and contains noth-
ing that could fall directly within that overall subject. (Thus, if the Document is in part
a textbook of mathematics, a Secondary Section may not explain any mathematics.) The
relationship could be a matter of historical connection with the subject or with related
matters, or of legal, commercial, philosophical, ethical or political position regarding
them.

The “Invariant Sections” are certain Secondary Sections whose titles are design-
nated, as being those of Invariant Sections, in the notice that says that the Document is
released under this License. If a section does not fit the above definition of Secondary then it is not allowed to be designated as Invariant. The Document may contain zero Invariant Sections. If the Document does not identify any Invariant Sections then there are none.

The “Cover Texts” are certain short passages of text that are listed, as Front-Cover Texts or Back-Cover Texts, in the notice that says that the Document is released under this License. A Front-Cover Text may be at most 5 words, and a Back-Cover Text may be at most 25 words.

A “Transparent” copy of the Document means a machine-readable copy, represented in a format whose specification is available to the general public, that is suitable for revising the document straightforwardly with generic text editors or (for images composed of pixels) generic paint programs or (for drawings) some widely available drawing editor, and that is suitable for input to text formatters or for automatic translation to a variety of formats suitable for input to text formatters. A copy made in an otherwise Transparent file format whose markup, or absence of markup, has been arranged to thwart or discourage subsequent modification by readers is not Transparent. An image format is not Transparent if used for any substantial amount of text. A copy that is not “Transparent” is called “Opaque”.

Examples of suitable formats for Transparent copies include plain ASCII without markup, Texinfo input format, LaTeX input format, SGML or XML using a publicly available DTD, and standard-conforming simple HTML, PostScript or PDF designed for human modification. Examples of transparent image formats include PNG, XCF and JPG. Opaque formats include proprietary formats that can be read and edited only by proprietary word processors, SGML or XML for which the DTD and/or processing tools are not generally available, and the machine-generated HTML, PostScript or PDF produced by some word processors for output purposes only.

The “Title Page” means, for a printed book, the title page itself, plus such following pages as are needed to hold, legibly, the material this License requires to appear in the title page. For works in formats which do not have any title page as such, “Title Page” means the text near the most prominent appearance of the work’s title, preceding the beginning of the body of the text.

A section “Entitled XYZ” means a named subunit of the Document whose title either is precisely XYZ or contains XYZ in parentheses following text that translates XYZ in another language. (Here XYZ stands for a specific section name mentioned below, such as “Acknowledgements”, “Dedications”, “Endorsements”, or “History”.) To “Preserve the Title” of such a section when you modify the Document means that it remains a section “Entitled XYZ” according to this definition.

The Document may include Warranty Disclaimers next to the notice which states that this License applies to the Document. These Warranty Disclaimers are considered to be included by reference in this License, but only as regards disclaiming warranties: any other implication that these Warranty Disclaimers may have is void and has no effect on the meaning of this License.

2. VERBATIM COPYING

You may copy and distribute the Document in any medium, either commercially or noncommercially, provided that this License, the copyright notices, and the license notice saying this License applies to the Document are reproduced in all copies, and that you add no other conditions whatsoever to those of this License. You may not use technical
measures to obstruct or control the reading or further copying of the copies you make
or distribute. However, you may accept compensation in exchange for copies. If you
distribute a large enough number of copies you must also follow the conditions in section
3.

You may also lend copies, under the same conditions stated above, and you may
publicly display copies.

3. COPYING IN QUANTITY

If you publish printed copies (or copies in media that commonly have printed covers)
of the Document, numbering more than 100, and the Document’s license notice requires
Cover Texts, you must enclose the copies in covers that carry, clearly and legibly, all
these Cover Texts: Front-Cover Texts on the front cover, and Back-Cover Texts on the
back cover. Both covers must also clearly and legibly identify you as the publisher of
these copies. The front cover must present the full title with all words of the title equally
prominent and visible. You may add other material on the covers in addition. Copying
with changes limited to the covers, as long as they preserve the title of the Document
and satisfy these conditions, can be treated as verbatim copying in other respects.

If the required texts for either cover are too voluminous to fit legibly, you should put
the first ones listed (as many as fit reasonably) on the actual cover, and continue the rest
onto adjacent pages.

If you publish or distribute Opaque copies of the Document numbering more than 100,
you must either include a machine-readable Transparent copy along with each Opaque
copy, or state in or with each Opaque copy a computer-network location from which
the general network-using public has access to download using public-standard network
protocols a complete Transparent copy of the Document, free of added material. If you use
the latter option, you must take reasonably prudent steps, when you begin distribution
of Opaque copies in quantity, to ensure that this Transparent copy will remain thus
accessible at the stated location until at least one year after the last time you distribute
an Opaque copy (directly or through your agents or retailers) of that edition to the public.

It is requested, but not required, that you contact the authors of the Document well
before redistributing any large number of copies, to give them a chance to provide you
with an updated version of the Document.

4. MODIFICATIONS

You may copy and distribute a Modified Version of the Document under the conditions
of sections 2 and 3 above, provided that you release the Modified Version under precisely
this License, with the Modified Version filling the role of the Document, thus licensing
distribution and modification of the Modified Version to whoever possesses a copy of it.
In addition, you must do these things in the Modified Version:

A. Use in the Title Page (and on the covers, if any) a title distinct from that of the
Document, and from those of previous versions (which should, if there were any,
be listed in the History section of the Document). You may use the same title as
a previous version if the original publisher of that version gives permission.

B. List on the Title Page, as authors, one or more persons or entities responsible for
authorship of the modifications in the Modified Version, together with at least five
of the principal authors of the Document (all of its principal authors, if it has fewer
than five), unless they release you from this requirement.
C. State on the Title page the name of the publisher of the Modified Version, as the publisher.

D. Preserve all the copyright notices of the Document.

E. Add an appropriate copyright notice for your modifications adjacent to the other copyright notices.

F. Include, immediately after the copyright notices, a license notice giving the public permission to use the Modified Version under the terms of this License, in the form shown in the Addendum below.

G. Preserve in that license notice the full lists of Invariant Sections and required Cover Texts given in the Document’s license notice.

H. Include an unaltered copy of this License.

I. Preserve the section Entitled “History”, Preserve its Title, and add to it an item stating at least the title, year, new authors, and publisher of the Modified Version as given on the Title Page. If there is no section Entitled “History” in the Document, create one stating the title, year, authors, and publisher of the Document as given on its Title Page, then add an item describing the Modified Version as stated in the previous sentence.

J. Preserve the network location, if any, given in the Document for public access to a Transparent copy of the Document, and likewise the network locations given in the Document for previous versions it was based on. These may be placed in the “History” section. You may omit a network location for a work that was published at least four years before the Document itself, or if the original publisher of the version it refers to gives permission.

K. For any section Entitled “Acknowledgements” or “Dedications”, Preserve the Title of the section, and preserve in the section all the substance and tone of each of the contributor acknowledgements and/or dedications given therein.

L. Preserve all the Invariant Sections of the Document, unaltered in their text and in their titles. Section numbers or the equivalent are not considered part of the section titles.

M. Delete any section Entitled “Endorsements”. Such a section may not be included in the Modified Version.

N. Do not retitle any existing section to be Entitled “Endorsements” or to conflict in title with any Invariant Section.

O. Preserve any Warranty Disclaimers.

If the Modified Version includes new front-matter sections or appendices that qualify as Secondary Sections and contain no material copied from the Document, you may at your option designate some or all of these sections as invariant. To do this, add their titles to the list of Invariant Sections in the Modified Version’s license notice. These titles must be distinct from any other section titles.
You may add a section Entitled “Endorsements”, provided it contains nothing but endorsements of your Modified Version by various parties—for example, statements of peer review or that the text has been approved by an organization as the authoritative definition of a standard.

You may add a passage of up to five words as a Front-Cover Text, and a passage of up to 25 words as a Back-Cover Text, to the end of the list of Cover Texts in the Modified Version. Only one passage of Front-Cover Text and one of Back-Cover Text may be added by (or through arrangements made by) any one entity. If the Document already includes a cover text for the same cover, previously added by you or by arrangement made by the same entity you are acting on behalf of, you may not add another; but you may replace the old one, on explicit permission from the previous publisher that added the old one.

The author(s) and publisher(s) of the Document do not by this License give permission to use their names for publicity for or to assert or imply endorsement of any Modified Version.

5. COMBINING DOCUMENTS

You may combine the Document with other documents released under this License, under the terms defined in section 4 above for modified versions, provided that you include in the combination all of the Invariant Sections of all of the original documents, unmodified, and list them all as Invariant Sections of your combined work in its license notice, and that you preserve all their Warranty Disclaimers.

The combined work need only contain one copy of this License, and multiple identical Invariant Sections may be replaced with a single copy. If there are multiple Invariant Sections with the same name but different contents, make the title of each such section unique by adding at the end of it, in parentheses, the name of the original author or publisher of that section if known, or else a unique number. Make the same adjustment to the section titles in the list of Invariant Sections in the license notice of the combined work.

In the combination, you must combine any sections Entitled “History” in the various original documents, forming one section Entitled “History”; likewise combine any sections Entitled “Acknowledgements”, and any sections Entitled “Dedications”. You must delete all sections Entitled “Endorsements”.

6. COLLECTIONS OF DOCUMENTS

You may make a collection consisting of the Document and other documents released under this License, and replace the individual copies of this License in the various documents with a single copy that is included in the collection, provided that you follow the rules of this License for verbatim copying of each of the documents in all other respects.

You may extract a single document from such a collection, and distribute it individually under this License, provided you insert a copy of this License into the extracted document, and follow this License in all other respects regarding verbatim copying of that document.

7. AGGREGATION WITH INDEPENDENT WORKS
A compilation of the Document or its derivatives with other separate and independent documents or works, in or on a volume of a storage or distribution medium, is called an “aggregate” if the copyright resulting from the compilation is not used to limit the legal rights of the compilation’s users beyond what the individual works permit. When the Document is included in an aggregate, this License does not apply to the other works in the aggregate which are not themselves derivative works of the Document.

If the Cover Text requirement of section 3 is applicable to these copies of the Document, then if the Document is less than one half of the entire aggregate, the Document’s Cover Texts may be placed on covers that bracket the Document within the aggregate, or the electronic equivalent of covers if the Document is in electronic form. Otherwise they must appear on printed covers that bracket the whole aggregate.

8. TRANSLATION

Translation is considered a kind of modification, so you may distribute translations of the Document under the terms of section 4. Replacing Invariant Sections with translations requires special permission from their copyright holders, but you may include translations of some or all Invariant Sections in addition to the original versions of these Invariant Sections. You may include a translation of this License, and all the license notices in the Document, and any Warranty Disclaimers, provided that you also include the original English version of this License and the original versions of those notices and disclaimers. In case of a disagreement between the translation and the original version of this License or a notice or disclaimer, the original version will prevail.

If a section in the Document is Entitled “Acknowledgements”, “Dedications”, or “History”, the requirement (section 4) to Preserve its Title (section 1) will typically require changing the actual title.

9. TERMINATION

You may not copy, modify, sublicense, or distribute the Document except as expressly provided for under this License. Any other attempt to copy, modify, sublicense or distribute the Document is void, and will automatically terminate your rights under this License. However, parties who have received copies, or rights, from you under this License will not have their licenses terminated so long as such parties remain in full compliance.

10. FUTURE REVISIONS OF THIS LICENSE

The Free Software Foundation may publish new, revised versions of the GNU Free Documentation License from time to time. Such new versions will be similar in spirit to the present version, but may differ in detail to address new problems or concerns. See http://www.gnu.org/copyleft/.

Each version of the License is given a distinguishing version number. If the Document specifies that a particular numbered version of this License “or any later version” applies to it, you have the option of following the terms and conditions either of that specified version or of any later version that has been published (not as a draft) by the Free Software Foundation. If the Document does not specify a version number of this License, you may choose any version ever published (not as a draft) by the Free Software Foundation.

ADDENDUM: How to use this License for your documents

Version 0.52
To use this License in a document you have written, include a copy of the License
in the document and put the following copyright and license notices just after the title
page:

Copyright ©YEAR YOUR NAME. Permission is granted to copy, distribute
and/or modify this document under the terms of the GNU Free Documenta-
tion License, Version 1.2 or any later version published by the Free Software
Foundation; with no Invariant Sections, no Front-Cover Texts, and no Back-
Cover Texts. A copy of the license is included in the section entitled “GNU
Free Documentation License”.

If you have Invariant Sections, Front-Cover Texts and Back-Cover Texts, replace the
“with...Texts.” line with this:

with the Invariant Sections being LIST THEIR TITLES, with the Front-
Cover Texts being LIST, and with the Back-Cover Texts being LIST.

If you have Invariant Sections without Cover Texts, or some other combination of the
three, merge those two alternatives to suit the situation.

If your document contains nontrivial examples of program code, we recommend re-
leasing these examples in parallel under your choice of free software license, such as the
GNU General Public License, to permit their use in free software.
Part C
Core
The subject of linear algebra can be partially explained by the meaning of the two terms comprising the title. “Linear” is a term you will appreciate better at the end of this course, and indeed, attaining this appreciation could be taken as one of the primary goals of this course. However for now, you can understand it to mean anything that is “straight” or “flat.” For example in the \( xy \)-plane you might be accustomed to describing straight lines (is there any other kind?) as the set of solutions to an equation of the form \( y = mx + b \), where the slope \( m \) and the \( y \)-intercept \( b \) are constants that together describe the line. In multivariate calculus, you may have discussed planes. Living in three dimensions, with coordinates described by triples \( (x, y, z) \), they can be described as the set of solutions to equations of the form \( ax + by + cz = d \), where \( a, b, c, d \) are constants that together determine the plane. While we might describe planes as “flat,” lines in three dimensions might be described as “straight.” From a multivariate calculus course you will recall that lines are sets of points described by equations such as \( x = 3t - 4 \), \( y = -7t + 2 \), \( z = 9t \), where \( t \) is a parameter that can take on any value.

Another view of this notion of “flatness” is to recognize that the sets of points just described are solutions to equations of a relatively simple form. These equations involve addition and multiplication only. We will have a need for subtraction, and occasionally we will divide, but mostly you can describe “linear” equations as involving only addition and multiplication. Here are some examples of typical equations we will see in the next few sections:

\[
2x + 3y - 4z = 13 \quad 4x_1 + 5x_2 - x_3 + x_4 + x_5 = 0 \quad 9a - 2b + 7c + 2d = -7
\]

What we will not see are equations like:

\[
xy + 5yz = 13 \quad x_1 + x_2^3/x_4 - x_3x_4x_5^2 = 0 \quad \tan(ab) + \log(c - d) = -7
\]
The exception will be that we will on occasion need to take a square root.

You have probably heard the word “algebra” frequently in your mathematical preparation for this course. Most likely, you have spent a good ten to fifteen years learning the algebra of the real numbers, along with some introduction to the very similar algebra of complex numbers (see Section CNO [639]). However, there are many new algebras to learn and use, and likely linear algebra will be your second algebra. Like learning a second language, the necessary adjustments can be challenging at times, but the rewards are many. And it will make learning your third and fourth algebras even easier. Perhaps you have heard of “groups” and “rings” (or maybe you have studied them already), which are excellent examples of other algebras with very interesting properties and applications. In any event, prepare yourself to learn a new algebra and realize that some of the old rules you used for the real numbers may no longer apply to this new algebra you will be learning!

The brief discussion above about lines and planes suggests that linear algebra has an inherently geometric nature, and this is true. Examples in two and three dimensions can be used to provide valuable insight into important concepts of this course. However, much of the power of linear algebra will be the ability to work with “flat” or “straight” objects in higher dimensions, without concerning ourselves with visualizing the situation. While much of our intuition will come from examples in two and three dimensions, we will maintain an algebraic approach to the subject, with the geometry being secondary. Others may wish to switch this emphasis around, and that can lead to a very fruitful and beneficial course, but here and now we are laying our bias bare.

Subsection A

An application: packaging trail mix

We conclude this section with a rather involved example that will highlight some of the power and techniques of linear algebra. Work through all of the details with pencil and paper, until you believe all the assertions made. However, in this introductory example, do not concern yourself with how some of the results are obtained or how you might be expected to solve a similar problem. We will come back to this example later and expose some of the techniques used and properties exploited. For now, use your background in mathematics to convince yourself that everything said here really is correct.

Example TMP
Trail Mix Packaging

Suppose you are the production manager at a food-packaging plant and one of your product lines is trail mix, a healthy snack popular with hikers and backpackers, containing raisins, peanuts and hard-shelled chocolate pieces. By adjusting the mix of these three ingredients, you are able to sell three varieties of this item. The fancy version is sold in half-kilogram packages at outdoor supply stores and has more chocolate and fewer raisins, thus commanding a higher price. The standard version is sold in one kilogram packages in grocery stores and gas station mini-markets. Since the standard version has roughly equal amounts of each ingredient, it is not as expensive as the fancy version. Finally, a bulk version is sold in bins at grocery stores for consumers to load into plastic bags in amounts of their choosing. To appeal to the shoppers that like bulk items for their
economy and healthfulness, this mix has many more raisins (at the expense of chocolate) and therefore sells for less.

Your production facilities have limited storage space and early each morning you are able to receive and store 380 kilograms of raisins, 500 kilograms of peanuts and 620 kilograms of chocolate pieces. As production manager, one of your most important duties is to decide how much of each version of trail mix to make every day. Clearly, you can have up to 1500 kilograms of raw ingredients available each day, so to be the most productive you will likely produce 1500 kilograms of trail mix each day. Also, you would prefer not to have any ingredients leftover each day, so that your final product is as fresh as possible and so that you can receive a maximum delivery the next morning. But how should these ingredients be allocated to the mixing of the bulk, standard and fancy versions?

First, we need a little more information about the mixes. Workers mix the ingredients in 15 kilogram batches, and each row of the table below gives a recipe for a 15 kilogram batch. There is some additional information on the costs of the ingredients and the price the manufacturer can charge for the different versions of the trail mix.

<table>
<thead>
<tr>
<th></th>
<th>Raisins (kg/batch)</th>
<th>Peanuts (kg/batch)</th>
<th>Chocolate (kg/batch)</th>
<th>Cost ($/kg)</th>
<th>Sale Price ($/kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>7</td>
<td>6</td>
<td>2</td>
<td>3.69</td>
<td>4.99</td>
</tr>
<tr>
<td>Standard</td>
<td>6</td>
<td>4</td>
<td>5</td>
<td>3.86</td>
<td>5.50</td>
</tr>
<tr>
<td>Fancy</td>
<td>2</td>
<td>5</td>
<td>8</td>
<td>4.45</td>
<td>6.50</td>
</tr>
<tr>
<td>Storage (kg)</td>
<td>380</td>
<td>500</td>
<td>620</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost ($/kg)</td>
<td>2.55</td>
<td>4.65</td>
<td>4.80</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As production manager, it is important to realize that you only have three decisions to make — the amount of bulk mix to make, the amount of standard mix to make and the amount of fancy mix to make. Everything else is beyond your control or is handled by another department within the company. Principally, you are also limited by the amount of raw ingredients you can store each day. Let us denote the amount of each mix to produce each day, measured in kilograms, by the variable quantities $b, s$ and $f$. Your production schedule can be described as values of $b, s$ and $f$ that do several things. First, we cannot make negative quantities of each mix, so

$$b \geq 0 \quad s \geq 0 \quad f \geq 0.$$  

Second, if we want to consume all of our ingredients each day, the storage capacities lead to three (linear) equations, one for each ingredient,

$$\frac{7}{15}b + \frac{6}{15}s + \frac{2}{15}f = 380 \quad \text{(raisins)}$$
$$\frac{6}{15}b + \frac{4}{15}s + \frac{5}{15}f = 500 \quad \text{(peanuts)}$$
$$\frac{2}{15}b + \frac{5}{15}s + \frac{8}{15}f = 620 \quad \text{(chocolate)}$$

It happens that this system of three equations has just one solution. In other words, as production manager, your job is easy, since there is but one way to use up all of your raw ingredients making trail mix. This single solution is

$$b = 300 \text{ kg} \quad s = 300 \text{ kg} \quad f = 900 \text{ kg}.$$
We do not yet have the tools to explain why this solution is the only one, but it should be simple for you to verify that this is indeed a solution. (Go ahead, we will wait.) Determining solutions such as this, and establishing that they are unique, will be the main motivation for our initial study of linear algebra.

So we have solved the problem of making sure that we make the best use of our limited storage space, and each day use up all of the raw ingredients that are shipped to us. Additionally, as production manager, you must report weekly to the CEO of the company, and you know he will be more interested in the profit derived from your decisions than in the actual production levels. So you compute,

\[
300(4.99 - 3.69) + 300(5.50 - 3.86) + 900(6.50 - 4.45) = 2727
\]

for a daily profit of $2,727 from this production schedule. The computation of the daily profit is also beyond our control, though it is definitely of interest, and it too looks like a “linear” computation.

As often happens, things do not stay the same for long, and now the marketing department has suggested that your company’s trail mix products standardize on every mix being one-third peanuts. Adjusting the peanut portion of each recipe by also adjusting the chocolate portion, leads to revised recipes, and slightly different costs for the bulk and standard mixes, as given in the following table.

<table>
<thead>
<tr>
<th></th>
<th>Raisins (kg/batch)</th>
<th>Peanuts (kg/batch)</th>
<th>Chocolate (kg/batch)</th>
<th>Cost ($/kg)</th>
<th>Sale Price ($/kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>7</td>
<td>5</td>
<td>3</td>
<td>3.70</td>
<td>4.99</td>
</tr>
<tr>
<td>Standard</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>3.85</td>
<td>5.50</td>
</tr>
<tr>
<td>Fancy</td>
<td>2</td>
<td>5</td>
<td>8</td>
<td>4.45</td>
<td>6.50</td>
</tr>
<tr>
<td>Storage (kg)</td>
<td>380</td>
<td>500</td>
<td>620</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost ($/kg)</td>
<td>2.55</td>
<td>4.65</td>
<td>4.80</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In a similar fashion as before, we desire values of \( b \), \( s \) and \( f \) so that

\[
b \geq 0, \quad s \geq 0, \quad f \geq 0
\]

and

\[
\begin{align*}
\frac{7}{15}b + \frac{6}{15}s + \frac{2}{15}f & = 380 \quad \text{(raisins)} \\
\frac{5}{15}b + \frac{5}{15}s + \frac{5}{15}f & = 500 \quad \text{(peanuts)} \\
\frac{3}{15}b + \frac{4}{15}s + \frac{8}{15}f & = 620 \quad \text{(chocolate)}
\end{align*}
\]

It now happens that this system of equations has \textit{infinitely} many solutions, as we will now demonstrate. Let \( f \) remain a variable quantity. Then if we make \( f \) kilograms of the fancy mix, we will make \( 4f - 3300 \) kilograms of the bulk mix and \(-5f + 4800\) kilograms of the standard mix. Let us now verify that, for any choice of \( f \), the values of \( b = 4f - 3300 \) and \( s = -5f + 4800 \) will yield a production schedule that exhausts all of the day’s supply of raw ingredients (right now, do not be concerned about how you might derive expressions
Subsection WILA.A  An application: packaging trail mix

like these for $b$ and $s$). Grab your pencil and paper and play along.

$$\frac{7}{15}(4f - 3300) + \frac{6}{15}(-5f + 4800) + \frac{2}{15}f = 0 + \frac{5700}{15} = 380$$

$$\frac{5}{15}(4f - 3300) + \frac{5}{15}(-5f + 4800) + \frac{5}{15}f = 0 + \frac{7500}{15} = 500$$

$$\frac{3}{15}(4f - 3300) + \frac{4}{15}(-5f + 4800) + \frac{8}{15}f = 0 + \frac{9300}{15} = 620$$

Convince yourself that these expressions for $b$ and $s$ allow us to vary $f$ and obtain an infinite number of possibilities for solutions to the three equations that describe our storage capacities. As a practical matter, there really are not an infinite number of solutions, since we are unlikely to want to end the day with a fractional number of bags of fancy mix, so our allowable values of $f$ should probably be integers. More importantly, we need to remember that we cannot make negative amounts of each mix! Where does this lead us? Positive quantities of the bulk mix requires that

$$b \geq 0 \quad \Rightarrow \quad 4f - 3300 \geq 0 \quad \Rightarrow \quad f \geq 825.$$ 

Similarly for the standard mix,

$$s \geq 0 \quad \Rightarrow \quad -5f + 4800 \geq 0 \quad \Rightarrow \quad f \leq 960.$$ 

So, as production manager, you really have to choose a value of $f$ from the finite set

$$\{825, 826, \ldots, 960\}$$

leaving you with 136 choices, each of which will exhaust the day’s supply of raw ingredients. Pause now and think about which you would choose.

Recalling your weekly meeting with the CEO suggests that you might want to choose a production schedule that yields the biggest possible profit for the company. So you compute an expression for the profit based on your as yet undetermined decision for the value of $f$,


Since $f$ has a negative coefficient it would appear that mixing fancy mix is detrimental to your profit and should be avoided. So you will make the decision to set daily fancy mix production at $f = 825$. This has the effect of setting $b = 4(825) - 3300 = 0$ and we stop producing bulk mix entirely. So the remainder of your daily production is standard mix at the level of $s = -5(825) + 4800 = 675$ kilograms and the resulting daily profit is $(-1.04)(825) + 3663 = 2805$. It is a pleasant surprise that daily profit has risen to $2,805$, but this is not the most important part of the story. What is important here is that there are a large number of ways to produce trail mix that use all of the day’s worth of raw ingredients and you were able to easily choose the one that netted the largest profit. Notice too how all of the above computations look “linear.”

In the food industry, things do not stay the same for long, and now the sales department says that increased competition has lead to the decision to stay competitive and charge just $5.25 for a kilogram of the standard mix, rather than the previous $5.50 per kilogram. This decision has no effect on the possibilities for the production schedule,
but will affect the decision based on profit considerations. So you revisit just the profit computation, suitably adjusted for the new selling price of standard mix,

\[(4f - 3300)(4.99 - 3.70) + (-5f + 4800)(5.25 - 3.85) + (f)(6.50 - 4.45) = 0.21f + 2463.\]

Now it would appear that fancy mix is beneficial to the company’s profit since the value of \(f\) has a positive coefficient. So you take the decision to make as much fancy mix as possible, setting \(f = 960\). This leads to \(s = -5(960) + 4800 = 0\) and the increased competition has driven you out of the standard mix market all together. The remainder of production is therefore bulk mix at a daily level of \(b = 4(960) - 3300 = 540\) kilograms and the resulting daily profit is \(0.21(960) + 2463 = 2664.6\). A daily profit of \$2,664.60\) is less than it used to be, but as production manager, you have made the best of a difficult situation and shown the sales department that the best course is to pull out of the highly competitive standard mix market completely.

This example is taken from a field of mathematics variously known by names such as operations research, system science or management science. More specifically, this is an perfect example of problems that are solved by the techniques of “linear programming.”

There is a lot going on under the hood in this example. The heart of the matter is the solution to systems of linear equations, which is the topic of the next few sections, and a recurrent theme throughout this course. We will return to this example on several occasions to reveal some of the reasons for its behavior.

**Subsection READ**

**Reading Questions**

1. Is the equation \(x^2 + xy + \tan(y^3) = 0\) linear or not? Why or why not?
2. Find all solutions to the system of two linear equations \(2x + 3y = -8, \ x - y = 6\).
3. Explain the importance of the procedures described in the trail mix application (Subsection WILA.A [4]) from the point-of-view of the production manager.
Subsection EXC
Exercises

C10  In Example TMP [4] the first table lists the cost (per kilogram) to manufacture each of the three varieties of trail mix (bulk, standard, fancy). For example, it costs $3.70 to make one kilogram of the bulk variety. Re-compute each of these three costs and notice that the computations are linear in character.
Contributed by Robert Beezer

M70  In Example TMP [4] two different prices were considered for marketing standard mix with the revised recipes (one-third peanuts in each recipe). Selling standard mix at $5.50 resulted in selling the minimum amount of the fancy mix and no bulk mix. At $5.25 it was best for profits to sell the maximum amount of fancy mix and then sell no standard mix. Determine a selling price for standard mix that allows for maximum profits while still selling some of each type of mix.
Contributed by Robert Beezer  Solution 11
If the price of standard mix is set at $5.292, then the profit function has a zero coefficient on the variable quantity $f$. So, we can set $f$ to be any integer quantity in \{825, 826, \ldots, 960\}. All but the extreme values ($f = 825$, $f = 960$) will result in production levels where some of every mix is manufactured. No matter what value of $f$ is chosen, the resulting profit will be the same, at $2,664.60$. 
Section SSLE
Solving Systems of Linear Equations

We will motivate our study of linear algebra by considering the problem of solving several linear equations simultaneously. The word “solve” tends to get abused somewhat, as in “solve this problem.” When talking about equations we understand a more precise meaning: find all of the values of some variable quantities that make an equation, or several equations, true.

Example STNE
Solving two (nonlinear) equations
Suppose we desire the simultaneous solutions of the two equations,

\[ x^2 + y^2 = 1 \]
\[ -x + \sqrt{3}y = 0 \]

You can easily check by substitution that \( x = \frac{\sqrt{3}}{2}, y = \frac{1}{2} \) and \( x = -\frac{\sqrt{3}}{2}, y = -\frac{1}{2} \) are both solutions. We need to also convince ourselves that these are the only solutions. To see this, plot each equation on the \( xy \)-plane, which means to plot \((x, y)\) pairs that make an individual equation true. In this case we get a circle centered at the origin with radius 1 and a straight line through the origin with slope \( \frac{1}{\sqrt{3}} \). The intersections of these two curves are our desired simultaneous solutions, and so we believe from our plot that the two solutions we know already are the only ones. We like to write solutions as sets, so in this case we write the set of solutions as

\[ S = \{ (\frac{\sqrt{3}}{2}, \frac{1}{2}), (-\frac{\sqrt{3}}{2}, -\frac{1}{2}) \} \]

In order to discuss systems of linear equations carefully, we need a precise definition. And before we do that, we will introduce our periodic discussions about “proof techniques.” Linear algebra is an excellent setting for learning how to read, understand and formulate proofs. To help you in this process, we will expound, at irregular intervals, about some important aspect of working with proofs.

Proof Technique D
Definitions
A definition is a made-up term, used as a kind of shortcut for some typically more complicated idea. For example, we say a whole number is even as a shortcut for saying that when we divide the number by two we get a remainder of zero. With a precise definition, we can answer certain questions unambiguously. For example, did you ever wonder if zero was an even number? Now the answer should be clear since we have a precise definition of what we mean by the term even.

A single term might have several possible definitions. For example, we could say that the whole number \( n \) is even if there is another whole number \( k \) such that \( n = 2k \). We say this is an equivalent definition since it categorizes even numbers the same way our first definition does.
Definitions are like two-way streets — we can use a definition to replace something rather complicated by its definition (if it fits) and we can replace a definition by its more complicated description. A definition is usually written as some form of an implication, such as “If something-nice-happens, then blatzo.” However, this also means that “If blatzo, then something-nice-happens,” even though this may not be formally stated. This is what we mean when we say a definition is a two-way street — it is really two implications, going in opposite “directions.”

Anybody (including you) can make up a definition, so long as it is unambiguous, but the real test of a definition’s utility is whether or not it is useful for describing interesting or frequent situations.

We will talk about theorems later (and especially equivalences). For now, be sure not to confuse the notion of a definition with that of a theorem.

In this book, we will display every new definition carefully set-off from the text, and the term being defined will be written thus: definition. Additionally, there is a full list of all the definitions, in order of their appearance located at the front of the book (Definitions). Finally, the acronym for each definition can be found in the index (Index). Definitions are critical to doing mathematics and proving theorems, so we’ve given you lots of ways to locate a definition should you forget its... uh, uh, well, ... definition.

Can you formulate a precise definition for what it means for a number to be odd? (Don’t just say it is the opposite of even. Act as if you don’t have a definition for even yet.) Can you formulate your definition a second, equivalent, way? Can you employ your definition to test an odd and an even number for “odd-ness”? ♦

Definition SLE
System of Linear Equations
A system of linear equations is a collection of \( m \) equations in the variable quantities \( x_1, x_2, x_3, \ldots, x_n \) of the form,

\[
\begin{align*}
    a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
    a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
    a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
    \vdots \\
    a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= b_m
\end{align*}
\]

where the values of \( a_{ij}, b_i \) and \( x_j \) are from the set of complex numbers, \( \mathbb{C} \). △

Don’t let the mention of the complex numbers, \( \mathbb{C} \), rattle you. We will stick with real numbers exclusively for many more sections, and it will sometimes seem like we only work with integers! However, we want to leave the possibility of complex numbers open, and there will be occasions in subsequent sections where they are necessary. You can review the basic properties of complex numbers in Section CNO [639], but these facts will not be critical until we reach Section O [165]. For now, here is an example to illustrate using the notation introduced in Definition SLE [14].

Example NSE
Notation for a system of equations
Given the system of linear equations,
\begin{align*}
x_1 + 2x_2 + x_4 &= 7 \\
x_1 + x_2 + x_3 - x_4 &= 3 \\
3x_1 + x_2 + 5x_3 - 7x_4 &= 1
\end{align*}
we have \( n = 4 \) variables and \( m = 3 \) equations. Also,
\begin{align*}
a_{11} &= 1 & a_{12} &= 2 & a_{13} &= 0 & a_{14} &= 1 & b_1 &= 7 \\
a_{21} &= 1 & a_{22} &= 1 & a_{23} &= 1 & a_{24} &= -1 & b_2 &= 3 \\
a_{31} &= 3 & a_{32} &= 1 & a_{33} &= 5 & a_{34} &= -7 & b_3 &= 1
\end{align*}
Additionally, convince yourself that \( x_1 = -2, \ x_2 = 4, \ x_3 = 2, \ x_4 = 1 \) is one solution (but it is not the only one!). ⊙

We will often shorten the term “system of linear equations” to “system of equations” leaving the linear aspect implied.

Subsection PSS
Possibilities for solution sets

The next example illustrates the possibilities for the solution set of a system of linear equations. We will not be too formal here, and the necessary theorems to back up our claims will come in subsequent sections. So read for feeling and come back later to revisit this example.

Example TTS
Three typical systems
Consider the system of two equations with two variables,
\begin{align*}
2x_1 + 3x_2 &= 3 \\
x_1 - x_2 &= 4
\end{align*}
If we plot the solutions to each of these equations separately on the \( x_1x_2 \)-plane, we get two lines, one with negative slope, the other with positive slope. They have exactly one point in common, \((x_1, x_2) = (3, -1)\), which is the solution \( x_1 = 3, \ x_2 = -1 \). From the geometry, we believe that this is the only solution to the system of equations, and so we say it is unique.

Now adjust the system with a different second equation,
\begin{align*}
2x_1 + 3x_2 &= 3 \\
4x_1 + 6x_2 &= 6
\end{align*}
A plot of the solutions to these equations individually results in two lines, one on top of the other! There are infinitely many pairs of points that make both equations true. We will learn shortly how to describe this infinite solution set precisely (see Example SAA 38, Theorem VFSLS 106). Notice now how the second equation is just a multiple of the first.
One more minor adjustment provides a third system of linear equations,

\[
2x_1 + 3x_2 = 3 \\
4x_1 + 6x_2 = 10.
\]

A plot now reveals two lines with identical slopes, i.e., parallel lines. They have no points in common, and so the system has a solution set that is empty, \( S = \emptyset \).

This example exhibits all of the typical behaviors of a system of equations. A subsequent theorem will tell us that every system of linear equations has a solution set that is empty, contains a single solution or contains infinitely many solutions (Theorem PSSLS \[56\]). Example STNE \[13\] yielded exactly two solutions, but this does not contradict the forthcoming theorem. The equations in Example STNE \[13\] are not linear because they do not match the form of Definition SLE \[14\], and so we cannot apply Theorem PSSLS \[56\] in this case.

Subsection ESEO
Equivalent systems and equation operations

With all this talk about finding solution sets for systems of linear equations, you might be ready to begin learning how to find these solution sets yourself. We begin with our first definition that takes a common word and gives it a very precise meaning in the context of systems of linear equations.

**Definition ES**
Equivalent Systems

Two systems of linear equations are equivalent if their solution sets are equal.  

Notice here that the two systems of equations could look very different (i.e. not be equal), but still have equal solution sets, and we would then call the systems equivalent. Two linear equations in two variables might be plotted as two lines that intersect in a single point. A different system, with three equations in two variables might have a plot that is three lines, all intersecting at a common point, with this common point identical to the intersection point for the first system. By our definition, we could then say these two very different looking systems of equations are equivalent, since they have identical solution sets. It is really like a weaker form of equality, where we allow the systems to be different in some respects, but we use the term equivalent to highlight the situation when their solution sets are equal.

With this definition, we can begin to describe our strategy for solving linear systems. Given a system of linear equations that looks difficult to solve, we would like to have an equivalent system that is easy to solve. Since the systems will have equal solution sets, we can solve the “easy” system and get the solution set to the “difficult” system. Here come the tools for making this strategy viable.

**Definition EO**
Equation Operations

Given a system of linear equations, the following three operations will transform the system into a different one, and each is known as an equation operation.
1. Swap the locations of two equations in the list.

2. Multiply each term of an equation by a nonzero quantity.

3. Multiply each term of one equation by some quantity, and add these terms to a second equation, on both sides of the equality. Leave the first equation the same after this operation, but replace the second equation by the new one. △

These descriptions might seem a bit vague, but the proof or the examples that follow should make it clear what is meant by each. We will shortly prove a key theorem about equation operations and solutions to linear systems of equations. But first, a discussion about exactly what a theorem is.

Proof Technique T
Theorems
Higher mathematics is about understanding theorems. Reading them, understanding them, applying them, proving them. We are ready to prove our first momentarily. Every theorem is a shortcut — we prove something in general, and then whenever we find a specific instance covered by the theorem we can immediately say that we know something else about the situation by applying the theorem. In many cases, this new information can be gained with much less effort than if we did not know the theorem.

The first step in understanding a theorem is to realize that the statement of every theorem can be rewritten using statements of the form “If something-happens, then something-else-happens.” The “something-happens” part is the hypothesis and the “something-else-happens” is the conclusion. To understand a theorem, it helps to rewrite its statement using this construction. To apply a theorem, we verify that “something-happens” in a particular instance and immediately conclude that “something-else-happens.” To prove a theorem, we must argue based on the assumption that the hypothesis is true, and arrive through the process of logic that the conclusion must then also be true. ◊

Theorem EOPSS
Equation Operations Preserve Solution Sets
If we apply one of the three equation operations of Definition EO [16] to the system of linear equations

\[
\begin{align*}
  a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
  a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
  a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
  &\vdots \\
  a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= b_m
\end{align*}
\]

then the original system and the transformed system are equivalent. □

Proof Technique SE
Set Equality
In the theorem we are about to prove, the conclusion is that two systems are equivalent. By Definition ES [16] this translates to requiring that solution sets be equal for the two systems. So we are being asked to show that two sets are equal. How do we do this? Well,
there is a very standard technique, and we will use it repeatedly through the course. So let’s add it to our toolbox now.

A set is just a collection of items, which we refer to generically as elements. If $A$ is a set, and $a$ is one of its elements, we write that piece of information as $a \in A$. Similarly, if $b$ is not in $A$, we write $b \notin A$. Given two sets, $A$ and $B$, we say that $A$ is a subset of $B$ if all the elements of $A$ are also in $B$. More formally (and much easier to work with) we describe this situation as follows: $A$ is a subset of $B$ if whenever $x \in A$, then $x \in B$. Notice the use of the “if-then” construction here. The notation for this is $A \subseteq B$. (If we want to disallow the possibility that $A$ is the same as $B$, we use $A \subset B$.)

But what does it mean for two sets to be equal? They must be the same. Well, that explanation is not really too helpful, is it? How about: If $A \subseteq B$ and $B \subseteq A$, then $A$ equals $B$. This gives us something to work with, if $A$ is a subset of $B$, and vice versa, then they must really be the same set. We will now make the symbol “$=$” do double-duty and extend its use to statements like $A = B$, where $A$ and $B$ are sets.

Proof We take each equation operation in turn and show that the solution sets of the two systems are equal, using the technique just outlined (Technique SE [17]).

1. It will not be our habit in proofs to resort to saying statements are “obvious,” but in this case, it should be. There is nothing about the order in which we write linear equations that affects their solutions, so the solution set will be equal if the systems only differ by a rearrangement of the order of the equations.

2. Suppose $\alpha \neq 0$ is a number. Let’s choose to multiply the terms of equation $i$ by $\alpha$ to build the new system of equations,

$$
\begin{align*}
 a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
 a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
 a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
 &\vdots \\
 \alpha a_{i1}x_1 + \alpha a_{i2}x_2 + \alpha a_{i3}x_3 + \cdots + \alpha a_{in}x_n &= \alpha b_i \\
 &\vdots \\
 a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= b_m.
\end{align*}
$$

Let $S$ denote the solutions to the system in the statement of the theorem, and let $T$ denote the solutions to the transformed system.

(a) Show $S \subseteq T$. Suppose $(x_1, x_2, x_3, \ldots, x_n) = (\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in S$ is a solution to the original system. Ignoring the $i$-th equation for a moment, we know it makes all the other equations of the transformed system true. We also know that

$$
a_{i1}\beta_1 + a_{i2}\beta_2 + a_{i3}\beta_3 + \cdots + a_{in}\beta_n = b_i
$$

which we can multiply by $\alpha$ to get

$$
\alpha a_{i1}\beta_1 + \alpha a_{i2}\beta_2 + \alpha a_{i3}\beta_3 + \cdots + \alpha a_{in}\beta_n = \alpha b_i.
$$

This says that the $i$-th equation of the transformed system is also true, so we have established that $(\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in T$, and therefore $S \subseteq T$. 

Version 0.52
3. Suppose $\alpha$ is a number. Let’s choose to multiply the terms of equation $i$ by $\alpha$ and add them to equation $j$ in order to build the new system of equations,

\[
\begin{align*}
  a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\
  a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\
  a_{31}x_1 + a_{32}x_2 + \cdots + a_{3n}x_n &= b_3 \\
  \vdots \\
  (\alpha a_{i1} + a_{j1})x_1 + (\alpha a_{i2} + a_{j2})x_2 + \cdots + (\alpha a_{in} + a_{jn})x_n &= \alpha b_i + b_j \\
  \vdots \\
  a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= b_m.
\end{align*}
\]

Let $S$ denote the solutions to the system in the statement of the theorem, and let $T$ denote the solutions to the transformed system.

(a) Show $S \subseteq T$. Suppose $(x_1, x_2, x_3, \ldots, x_n) = (\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in S$ is a solution to the original system. Ignoring the $j$-th equation for a moment, we know this solution makes all the other equations of the transformed system true. Using the fact that the solution makes the $i$-th equation for a moment, we find

\[
\begin{align*}
(\alpha a_{i1} + a_{j1})\beta_1 + (\alpha a_{i2} + a_{j2})\beta_2 + \cdots + (\alpha a_{in} + a_{jn})\beta_n &= \alpha b_i + b_j.
\end{align*}
\]

This says that the $j$-th equation of the original system is also true, so we have established that $(\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in S$, and therefore $T \subseteq S$. Locate the key point where we required that $\alpha \neq 0$, and consider what would happen if $\alpha = 0$.

(b) Now show $T \subseteq S$. Suppose $(x_1, x_2, x_3, \ldots, x_n) = (\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in T$ is a solution to the transformed system. Ignoring the $j$-th equation for a
moment, we know it makes all the other equations of the original system true. We then find

\[a_j \beta_1 + a_j \beta_2 + \cdots + a_j \beta_n =\]

\[a_j \beta_1 + a_j \beta_2 + \cdots + a_j \beta_n + ab_i - \alpha b_i =\]

\[a_j \beta_1 + a_j \beta_2 + \cdots + a_j \beta_n + (\alpha a_{i1} \beta_1 + \alpha a_{i2} \beta_2 + \cdots + \alpha a_{in} \beta_n) - \alpha b_i =\]

\[a_j \beta_1 + a_j \beta_2 + \cdots + a_j \beta_n + (\alpha a_{i1} \beta_1 + \alpha a_{i2} \beta_2 + \cdots + \alpha a_{jn} \beta_n) - \alpha b_i =\]

\[(\alpha a_{i1} + a_{j1}) \beta_1 + (\alpha a_{i2} + a_{j2}) \beta_2 + \cdots + (\alpha a_{in} + a_{jn}) \beta_n - \alpha b_i =\]

\[\alpha b_i + b_j - \alpha b_i = b_j\]

This says that the \(j\)-th equation of the original system is also true, so we have established that \((\beta_1, \beta_2, \beta_3, \ldots, \beta_n) \in S\), and therefore \(T \subseteq S\).

Why didn’t we need to require that \(\alpha \neq 0\) for this row operation? In other words, how does the third statement of the theorem read when \(\alpha = 0\)? Does our proof require some extra care when \(\alpha = 0\)? Compare your answers with the similar situation for the second row operation.

\[\textbf{Theorem EOPSS \[17\]}\]

is the necessary tool to complete our strategy for solving systems of equations. We will use equation operations to move from one system to another, all the while keeping the solution set the same. With the right sequence of operations, we will arrive at a simpler equation to solve. The next two examples illustrate this idea, while saving some of the details for later.

\[\textbf{Example US}\]

\[\textbf{Three equations, one solution}\]

We solve the following system by a sequence of equation operations.

\[
\begin{align*}
x_1 + 2x_2 + 2x_3 &= 4 \\
x_1 + 3x_2 + 3x_3 &= 5 \\
2x_1 + 6x_2 + 5x_3 &= 6
\end{align*}
\]

\(\alpha = -1\) times equation 1, add to equation 2:

\[
\begin{align*}
x_1 + 2x_2 + 2x_3 &= 4 \\
0x_1 + 1x_2 + 1x_3 &= 1 \\
2x_1 + 6x_2 + 5x_3 &= 6
\end{align*}
\]

\(\alpha = -2\) times equation 1, add to equation 3:

\[
\begin{align*}
x_1 + 2x_2 + 2x_3 &= 4 \\
0x_1 + 1x_2 + 1x_3 &= 1 \\
0x_1 + 2x_2 + 1x_3 &= -2
\end{align*}
\]

\(\alpha = -2\) times equation 2, add to equation 3:

\[
\begin{align*}
x_1 + 2x_2 + 2x_3 &= 4 \\
0x_1 + 1x_2 + 1x_3 &= 1 \\
0x_1 + 0x_2 + 1x_3 &= -4
\end{align*}
\]
\( \alpha = -1 \) times equation 3:
\[
\begin{align*}
    x_1 + 2x_2 + 2x_3 &= 4 \\
    0x_1 + 1x_2 + 1x_3 &= 1 \\
    0x_1 + 0x_2 + 1x_3 &= 4
\end{align*}
\]
which can be written more clearly as
\[
\begin{align*}
    x_1 + 2x_2 + 2x_3 &= 4 \\
    x_2 + x_3 &= 1 \\
    x_3 &= 4
\end{align*}
\]
This is now a very easy system of equations to solve. The third equation requires that \( x_3 = 4 \) to be true. Making this substitution into equation 2 we arrive at \( x_2 = -3 \), and finally, substituting these values of \( x_2 \) and \( x_3 \) into the first equation, we find that \( x_1 = 2 \).

Note too that this is the only solution to this final system of equations, since we were forced to choose these values to make the equations true. Since we performed equation operations on each system to obtain the next one in the list, all of the systems listed here are all equivalent to each other by Theorem EOPSS [17]. Thus \((x_1, x_2, x_3) = (2, -3, 4)\) is the unique solution to the original system of equations (and all of the other systems of equations).

\( \square \)

**Example IS**

Three equations, infinitely many solutions

The following system of equations made an appearance earlier in this section (Example NSE [14]), where we listed one of its solutions. Now, we will try to find all of the solutions to this system.
\[
\begin{align*}
    x_1 + 2x_2 + 0x_3 + x_4 &= 7 \\
    x_1 + x_2 + x_3 - x_4 &= 3 \\
    3x_1 + x_2 + 5x_3 - 7x_4 &= 1
\end{align*}
\]
\( \alpha = -1 \) times equation 1, add to equation 2:
\[
\begin{align*}
    x_1 + 2x_2 + 0x_3 + x_4 &= 7 \\
    0x_1 - x_2 + x_3 - 2x_4 &= -4 \\
    3x_1 + x_2 + 5x_3 - 7x_4 &= 1
\end{align*}
\]
\( \alpha = -3 \) times equation 1, add to equation 3:
\[
\begin{align*}
    x_1 + 2x_2 + 0x_3 + x_4 &= 7 \\
    0x_1 - x_2 + x_3 - 2x_4 &= -4 \\
    0x_1 - 5x_2 + 5x_3 - 10x_4 &= -20
\end{align*}
\]
\( \alpha = -5 \) times equation 2, add to equation 3:
\[
\begin{align*}
    x_1 + 2x_2 + 0x_3 + x_4 &= 7 \\
    0x_1 - x_2 + x_3 - 2x_4 &= -4 \\
    0x_1 + 0x_2 + 0x_3 + 0x_4 &= 0
\end{align*}
\]
\[ \alpha = -1 \times \text{equation 2:} \]

\[
\begin{align*}
    x_1 + 2x_2 + 0x_3 + x_4 &= 7 \\
    0x_1 + x_2 - x_3 + 2x_4 &= 4 \\
    0x_1 + 0x_2 + 0x_3 + 0x_4 &= 0
\end{align*}
\]

which can be written more clearly as

\[
\begin{align*}
    x_1 + 2x_2 + x_4 &= 7 \\
    x_2 - x_3 + 2x_4 &= 4 \\
    0 &= 0
\end{align*}
\]

What does the equation 0 = 0 mean? We can choose \textit{any} values for \(x_1, x_2, x_3, x_4\) and this equation will be true, so we only need to consider further the first two equations, since the third is true no matter what. We can analyze the second equation without consideration of the variable \(x_1\). It would appear that there is considerable latitude in how we can choose \(x_2, x_3, x_4\) and make this equation true. Let’s choose \(x_3 = \beta_3\) and \(x_4 = \beta_4\). Then equation 2 becomes

\[
x_2 - \beta_3 + 2\beta_4 = 4 \quad \text{rearranges to} \quad x_2 = 4 + \beta_3 - 2\beta_4
\]

Now we can take these arbitrary values for \(x_3\) and \(x_4\), and this expression for \(x_2\) and employ them in equation 1,

\[
x_1 + 2(4 + \beta_3 - 2\beta_4) + \beta_4 = 7 \quad \text{rearranges to} \quad x_1 = -1 - 2\beta_3 + 3\beta_4
\]

So our arbitrary choices of values for \(x_3\) and \(x_4\) (\(\beta_3\) and \(\beta_4\)) translate into specific values of \(x_1\) and \(x_2\). The lone solution given in Example NSE 14 was obtained by choosing \(\beta_3 = 2\) and \(\beta_4 = 1\). Now we can easily and quickly find many more (infinitely more). Suppose we choose \(\beta_3 = 5\) and \(\beta_4 = -2\), then we compute

\[
x_1 = -1 - 2(5) + 3(-2) = -17 \\
x_2 = 4 + 5 - 2(-2) = 13
\]

and you can verify that \((x_1, x_2, x_3, x_4) = (-17, 13, 5, -2)\) makes all three equations true. The entire solution set is written as

\[
S = \{(-1 - 2\beta_3 + 3\beta_4, 4 + \beta_3 - 2\beta_4, \beta_3, \beta_4) \mid \beta_3 \in \mathbb{C}, \beta_4 \in \mathbb{C}\}
\]

It would be instructive to finish off your study of this example by taking the general form of the solutions given in this set and substituting them into each of the three equations and verify that they are true in each case.

In the next section we will describe how to use equation operations to systematically solve any system of linear equations. But first, one of our more important pieces of advice about doing mathematics.

\textbf{Proof Technique L}

\textbf{Language}
Like any science, the language of math must be understood before further study can continue.

Erin Wilson, Student
September, 2004

Mathematics is a language. It is a way to express complicated ideas clearly, precisely, and unambiguously. Because of this, it can be difficult to read. Read slowly, and have pencil and paper at hand. It will usually be necessary to read something several times. While reading can be difficult, it is even hard to speak mathematics, and so that is the topic of this technique.

I am going to suggest a simple modification to the way you use language that will make it much, much easier to become proficient at speaking mathematics and eventually it will become second nature. Think of it as a training aid or practice drill you might use when learning to become skilled at a sport.

First, eliminate pronouns from your vocabulary when discussing linear algebra, in class or with your colleagues. Do not use: it, that, those, their or similar sources of confusion. This is the single easiest step you can take to make your oral expression of mathematics clearer to others, and in turn, it will greatly help your own understanding.

Now rid yourself of the word “thing” (or variants like “something”). When you are tempted to use this word realize that there is some object you want to discuss, and we likely have a definition for that object (see the discussion at Technique D [13]). Always “think about your objects” and many aspects of the study of mathematics will get easier. Ask yourself: “Am I working with a set, a number, a function, an operation, or what?” Knowing what an object is will allow you to narrow down the procedures you may apply to it. If you have studied an object-oriented computer programming language, then perhaps this advice will be even clearer, since you know that a compiler will often complain with an error message if you confuse your objects.

Third, eliminate the verb “works” (as in “the equation works”) from your vocabulary. This term is used as a substitute when we are not sure just what we are trying to accomplish. Usually we are trying to say that some object fulfills some condition. The condition might even have a definition associated with it, making it even easier to describe.

Last, speak slooooowly and thoughtfully as you try to get by without all these lazy words. It is hard at first, but you will get better with practice. Especially in class, when the pressure is on and all eyes are on you, don’t succumb to the temptation to use these weak words. Slow down, we’d all rather wait for a slow, well-formed question or answer than a fast, sloppy, incomprehensible one.

You will find the improvement in your ability to speak clearly about complicated ideas will greatly improve your ability to think clearly about complicated ideas. And I believe that you cannot think clearly about complicated ideas if you cannot formulate questions or answers clearly in the correct language. This is as applicable to the study of law, economics or philosophy as it is to the study of science or mathematics.

So when you come to class, check your pronouns at the door, along with other weak words. And when studying with friends, you might make a game of catching one another using pronouns, “thing,” or “works.” I know I’ll be calling you on it!

Proof Technique GS
Getting Started
“I don’t know how to get started!” is often the lament of the novice proof-builder. Here
are a few pieces of advice.

1. As mentioned in Technique T [17], rewrite the statement of the theorem in an “if-then” form. This will simplify identifying the hypothesis and conclusion, which are referenced in the next few items.

2. Ask yourself what kind of statement you are trying to prove. This is always part of your conclusion. Are you being asked to conclude that two numbers are equal, that a function is differentiable or a set is a subset of another? You cannot bring other techniques to bear if you do not know what type of conclusion you have.

3. Write down reformulations of your hypotheses. Interpret and translate each definition properly.

4. Write your hypothesis at the top of a sheet of paper and your conclusion at the bottom. See if you can formulate a statement that precedes the conclusion and also implies it. Work down from your hypothesis, and up from your conclusion, and see if you can meet in the middle. When you are finished, rewrite the proof nicely, from hypothesis to conclusion, with verifiable implications giving each subsequent statement.

5. As you work through your proof, think about what kinds of objects your symbols represent. For example, suppose $A$ is a set and $f(x)$ is a real-valued function. Then the expression $A + f$ might make no sense if we have not defined what it means to “add” a set to a function, so we can stop at that point and adjust accordingly. On the other hand we might understand $2f$ to be the function whose rule is described by $(2f)(x) = 2f(x)$. “Think about your objects” means to always verify that your objects and operations are compatible.

Subsection READ

Reading Questions

1. How many solutions does the system of equations $3x + 2y = 4$, $6x + 4y = 8$ have? Explain your answer.

2. How many solutions does the system of equations $3x + 2y = 4$, $6x + 4y = -2$ have? Explain your answer.

3. What do we mean when we say mathematics is a language?
Subsection EXC
Exercises

C10 Find a solution to the system in Example IS 21 where $\beta_3 = 6$ and $\beta_4 = 2$. Find two other solutions to the system. Find a solution where $\beta_1 = -17$ and $\beta_2 = 14$. How many possible answers are there to each of these questions? Contributed by Robert Beezer

C20 Each archetype (Chapter A 559) that is a system of equations begins by listing some specific solutions. Verify the specific solutions listed in the following archetypes by evaluating the system of equations with the solutions listed.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577
Archetype E 581
Archetype F 585
Archetype G 590
Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer


M40 Solutions to the system in Example IS 21 are given as

$$(x_1, x_2, x_3, x_4) = (-1 - 2\beta_3 + 3\beta_4, 4 + \beta_3 - 2\beta_4, \beta_3, \beta_4)$$

Evaluate the three equations of the original system with these expressions in $\beta_3$ and $\beta_4$ and verify that each equation is true, no matter what values are chosen for $\beta_3$ and $\beta_4$. Contributed by Robert Beezer

M70 We have seen in this section that systems of linear equations have limited possibilities for solution sets, and we will shortly prove Theorem PSSLS 50 that describes these possibilities exactly. This exercise will show that if we relax the requirement that our equations be linear, then the possibilities expand greatly. Consider a system of two equations in the two variables $x$ and $y$, where the departure from linearity involves simply squaring the variables.

$$x^2 - y^2 = 1$$
$$x^2 + y^2 = 4$$

After solving this system of non-linear equations, replace the second equation in turn by $x^2 + 2x + y^2 = 3$, $x^2 + y^2 = 1$, $x^2 - x + y^2 = 0$, $4x^2 + 4y^2 = 1$ and solve each resulting
system of two equations in two variables.

Contributed by Robert Beezer Solution 27

**T20** Explain why the second equation operation in Definition EO 16 requires that the scalar be nonzero, while in the third equation operation this prohibition on the scalar is not present.

Contributed by Robert Beezer Solution 27

**T10** Technique D 13 asks you to formulate a definition of what it means for an integer to be odd. What is your definition? (Don’t say “the opposite of even.”) Is 6 odd? Is 11 odd? Justify your answers by using your definition.

Contributed by Robert Beezer Solution 27
M30  Contributed by Robert Beezer  Statement 25
If \( x, y \) and \( z \) represent the money held by Dan, Diane and Donna, then \( y = 15 - z \) and \( x = 20 - y = 20 - (15 - z) = 5 + z \). We can let \( z \) take on any value from 0 to 15 without any of the three amounts being negative, since presumably middle-schoolers are too young to assume debt.

Then the total capital held by the three is \( x + y + z = (5 + z) + (15 - z) + z = 20 + z \). So their combined holdings can range anywhere from $20 (Donna is broke) to $35 (Donna is flush).

We will have more to say about this situation in Section TSS 49, and specifically Theorem CMVEI 56.

M70  Contributed by Robert Beezer  Statement 25
The equation \( x^2 - y^2 = 1 \) has a solution set by itself that has the shape of a hyperbola when plotted. The five different second equations have solution sets that are circles when plotted individually. Where the hyperbola and circle intersect are the solutions to the system of two equations. As the size and location of the circle varies, the number of intersections varies from four to none (in the order given). Sketching the relevant equations would be instructive, as was discussed in Example STNE 13.

The exact solution sets are (according to the choice of the second equation),
\[
\begin{align*}
x^2 + y^2 &= 4 : \left\{ \left( \frac{\sqrt{5}}{2}, \frac{\sqrt{3}}{2} \right), \left( -\frac{\sqrt{5}}{2}, -\frac{\sqrt{3}}{2} \right), \left( -\frac{\sqrt{5}}{2}, \frac{\sqrt{3}}{2} \right) \right\} \\
x^2 + 2x + y^2 &= 3 : \left\{ (1, 0), (-2, \sqrt{3}), (-2, -\sqrt{3}) \right\} \\
x^2 + y^2 &= 1 : \left\{ (1, 0), (-1, 0) \right\} \\
x^2 - x + y^2 &= 0 : \left\{ (1, 0) \right\} \\
4x^2 + 4y^2 &= 1 : \{ \}
\end{align*}
\]

T10  Contributed by Robert Beezer  Statement 26
We can say that an integer is odd if when it is divided by 2 there is a remainder of 1. So 6 is not odd since \( 6 = 3 \times 2 \), while 11 is odd since \( 11 = 5 \times 2 + 1 \).

T20  Contributed by Robert Beezer  Statement 26
Definition EO 16 is engineered to make Theorem EOPSS 17 true. If we were to allow a zero scalar to multiply an equation then that equation would be transformed to the equation \( 0 = 0 \), which is true for any possible values of the variables. Any restrictions on the solution set imposed by the original equation would be lost.

However, in the third operation, it is allowed to choose a zero scalar, multiply an equation by this scalar and add the transformed equation to a second equation (leaving the first unchanged). The result? Nothing. The second equation is the same as it was before. So the theorem is true in this case, the two systems are equivalent. But in practice, this would be a silly thing to actually ever do! We still allow it though, in order to keep our theorem as general as possible.

Notice the location in the proof of Theorem EOPSS 17 where the expression \( \frac{1}{\alpha} \) appears — this explains the prohibition on \( \alpha = 0 \) in the second equation operation.
Section RREF
Reduced Row-Echelon Form

After solving a few systems of equations, you will recognize that it doesn’t matter so much what we call our variables, as opposed to what numbers act as their coefficients. A system in the variables \(x_1, x_2, x_3\) would behave the same if we changed the names of the variables to \(a, b, c\) and kept all the constants the same and in the same places. In this section, we will isolate the key bits of information about a system of equations into something called a matrix, and then use this matrix to systematically solve the equations. Along the way we will obtain one of our most important and useful computational tools.

Definition M
Matrix
An \(m \times n\) matrix is a rectangular layout of numbers from \(\mathbb{C}\) having \(m\) rows and \(n\) columns.

Notation MN
Matrix Notation
We will use upper-case Latin letters from the start of the alphabet (\(A, B, C, \ldots\)) to denote matrices and squared-off brackets to delimit the layout. Many use large parentheses instead of brackets — the distinction is not important. Rows of a matrix will be referenced starting at the top and working down (i.e. row 1 is at the top) and columns will be referenced starting from the left (i.e. column 1 is at the left).

Notation ME
Matrix Entries ([\(A\)]\(_{ij}\))
For a matrix \(A\), the notation \([A]_{ij}\) will refer to the complex number in row \(i\) and column \(j\) of \(A\).

Be careful with this notation for individual entries, since it is easy to think that \([A]_{ij}\) refers to the whole matrix. It does not. It is just a number, but is a convenient way to talk about all the entries at once. This notation will get a heavy workout once we get to Chapter M [179].

Example AM
A matrix

\[
B = \begin{bmatrix}
-1 & 2 & 5 & 3 \\
1 & 0 & -6 & 1 \\
-4 & 2 & 2 & -2
\end{bmatrix}
\]

is a matrix with \(m = 3\) rows and \(n = 4\) columns. We can say that \([B]_{2,3} = -6\) while \([B]_{3,4} = -2\).

A calculator or computer language can be a convenient way to perform calculations with matrices. But first you have to enter the matrix. Here’s how it is done on various computing platforms.
Computation Note ME.MMA
Matrix Entry (Mathematica)
Matrices are input as lists of lists, since a list is a basic data structure in Mathematica. A matrix is a list of rows, with each row entered as a list. Mathematica uses braces (\{ , \}) to delimit lists. So the input
\[ a = \{\{1,2,3,4\},\{5,6,7,8\},\{9,10,11,12\}\} \]
would create a 3 \times 4 matrix named a that is equal to
\[
\begin{bmatrix}
1 & 2 & 3 & 4 \\
5 & 6 & 7 & 8 \\
9 & 10 & 11 & 12
\end{bmatrix}
\]
To display a matrix named a “nicely” in Mathematica, type \texttt{MatrixForm[a]} , and the output will be displayed with rows and columns. If you just type a , then you will get a list of lists, like how you input the matrix in the first place.

Computation Note ME.TI86
Matrix Entry (TI-86)
On the TI-86, press the MATRX key (Yellow-7) . Press the second menu key over, F2 , to bring up the EDIT screen. Give your matrix a name, one letter or many, then press ENTER . You can then change the size of the matrix (rows, then columns) and begin editing individual entries (which are initially zero). ENTER will move you from entry to entry, or the down arrow key will move you to the next row. A menu gives you extra options for editing.

Matrices may also be entered on the home screen as follows. Use brackets ([ , ]) to enclose rows with elements separated by commas. Group rows, in order, into a final set of brackets (with no commas between rows). This can then be stored in a name with the STO key. So, for example,
\[
[[1,2,3,4] [5,6,7,8] [9,10,11,12]] \rightarrow A
\]
will create a matrix named A that is equal to
\[
\begin{bmatrix}
1 & 2 & 3 & 4 \\
5 & 6 & 7 & 8 \\
9 & 10 & 11 & 12
\end{bmatrix}
\]

Computation Note ME.TI83
Matrix Entry (TI-83)
Contributed by Douglas Phelps
On the TI-83, press the MATRX key. Press the right arrow key twice so that EDIT is highlighted. Move the cursor down so that it is over the desired letter of the matrix and press ENTER . For example, let’s call our matrix B , so press the down arrow once and press ENTER . To enter a 2 \times 3 matrix, press 2 ENTER 3 ENTER . To create the matrix
\[
\begin{bmatrix}
1 & 2 & 3 \\
4 & 5 & 6
\end{bmatrix}
\]
press 1 ENTER 2 ENTER 3 ENTER 4 ENTER 5 ENTER 6 ENTER .
Definition AM  
Augmented Matrix  
Suppose we have a system of \( m \) equations in the \( n \) variables \( x_1, x_2, x_3, \ldots, x_n \) written as
\[
\begin{align*}
  a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
  a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
  a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
  \vdots \\
  a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= b_m
\end{align*}
\]
then the **augmented matrix** of the system of equations is the \( m \times (n + 1) \) matrix
\[
\begin{bmatrix}
  a_{11} & a_{12} & a_{13} & \cdots & a_{1n} & b_1 \\
  a_{21} & a_{22} & a_{23} & \cdots & a_{2n} & b_2 \\
  a_{31} & a_{32} & a_{33} & \cdots & a_{3n} & b_3 \\
  \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\
  a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} & b_m
\end{bmatrix}
\]

The augmented matrix *represents* all the important information in the system of equations, since the names of the variables have been ignored, and the only connection with the variables is the location of their coefficients in the matrix. It is important to realize that the augmented matrix is just that, a matrix, and *not* a system of equations. In particular, the augmented matrix does not have any "solutions," though it will be useful for finding solutions to the system of equations that it is associated with. (Think about your objects, and review Technique L \[22\].) However, notice that an augmented matrix always belongs to some system of equations, and vice versa, so it is tempting to try and blur the distinction between the two. Here’s a quick example.

Example AMAA  
Augmented matrix for Archetype A  
Archetype A \[563\] is the following system of 3 equations in 3 variables.
\[
\begin{align*}
  x_1 - x_2 + 2x_3 &= 1 \\
  2x_1 + x_2 + x_3 &= 8 \\
  x_1 + x_2 &= 5
\end{align*}
\]
Here is its augmented matrix.
\[
\begin{bmatrix}
  1 & -1 & 2 & 1 \\
  2 & 1 & 1 & 8 \\
  1 & 1 & 0 & 5
\end{bmatrix}
\]

An augmented matrix for a system of equations will save us the tedium of continually writing down the names of the variables as we solve the system. It will also release us from any dependence on the actual names of the variables. We have seen how certain operations we can perform on equations (Definition EO \[16\]) will preserve their solutions (Theorem EOPSS \[17\]). The next two definitions and the following theorem carry over these ideas to augmented matrices.
Definition RO
Row Operations
The following three operations will transform an \( m \times n \) matrix into a different matrix of the same size, and each is known as a row operation.

1. Swap the locations of two rows.
2. Multiply each entry of a single row by a nonzero quantity.
3. Multiply each entry of one row by some quantity, and add these values to the entry in the same column of a second row. Leave the first row the same after this operation, but replace the second row by the new values.

We will use a kind of shorthand to describe these operations:

1. \( R_i \leftrightarrow R_j \): Swap the location of rows \( i \) and \( j \).
2. \( \alpha R_i \): Multiply row \( i \) by the nonzero scalar \( \alpha \).
3. \( \alpha R_i + R_j \): Multiply row \( i \) by the scalar \( \alpha \) and add to row \( j \).

Definition REM
Row-Equivalent Matrices
Two matrices, \( A \) and \( B \), are row-equivalent if one can be obtained from the other by a sequence of row operations.

Example TREM
Two row-equivalent matrices
The matrices
\[
A = \begin{bmatrix}
2 & -1 & 3 & 4 \\
5 & 2 & -2 & 3 \\
1 & 1 & 0 & 6
\end{bmatrix}
\quad B = \begin{bmatrix}
1 & 1 & 0 & 6 \\
3 & 0 & -2 & -9 \\
2 & -1 & 3 & 4
\end{bmatrix}
\]
are row-equivalent as can be seen from
\[
\begin{bmatrix}
2 & -1 & 3 & 4 \\
5 & 2 & -2 & 3 \\
1 & 1 & 0 & 6
\end{bmatrix}
\stackrel{R_1 \leftrightarrow R_3}{\longrightarrow}
\begin{bmatrix}
1 & 1 & 0 & 6 \\
5 & 2 & -2 & 3 \\
2 & -1 & 3 & 4
\end{bmatrix}
\stackrel{-2R_1 + R_2}{\longrightarrow}
\begin{bmatrix}
1 & 1 & 0 & 6 \\
3 & 0 & -2 & -9 \\
2 & -1 & 3 & 4
\end{bmatrix}
\]
We can also say that any pair of these three matrices are row-equivalent.

Notice that each of the three row operations is reversible [Exercise RREF.T10], so we do not have to be careful about the distinction between “\( A \) is row-equivalent to \( B \)” and “\( B \) is row-equivalent to \( A \)” [Exercise RREF.T11]. The preceding definitions are designed to make the following theorem possible. It says that row-equivalent matrices represent systems of linear equations that have identical solution sets.

Theorem REMES
Row-Equivalent Matrices represent Equivalent Systems
Suppose that \( A \) and \( B \) are row-equivalent augmented matrices. Then the systems of linear equations that they represent are equivalent systems.
Proof If we perform a single row operation on an augmented matrix, it will have the same effect as if we did the analogous equation operation on the corresponding system of equations. By exactly the same methods as we used in the proof of Theorem EOPSS \[17\] we can see that each of these row operations will preserve the set of solutions for the corresponding system of equations.

So at this point, our strategy is to begin with a system of equations, represent it by an augmented matrix, perform row operations (which will preserve solutions for the corresponding systems) to get a “simpler” augmented matrix, convert back to a “simpler” system of equations and then solve that system, knowing that its solutions are those of the original system. Here’s a rehash of Example US \[20\] as an exercise in using our new tools.

Example USR
Three equations, one solution, reprised
We solve the following system using augmented matrices and row operations. This is the same system of equations solved in Example US \[20\] using equation operations.

\[
\begin{align*}
  x_1 + 2x_2 + 2x_3 &= 4 \\
  x_1 + 3x_2 + 3x_3 &= 5 \\
  2x_1 + 6x_2 + 5x_3 &= 6
\end{align*}
\]

Form the augmented matrix,

\[
A = \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  1 & 3 & 3 & 5 \\
  2 & 6 & 5 & 6 \\
\end{bmatrix}
\]

and apply row operations,

\[
\begin{align*}
  -1R_1+R_2 & \rightarrow \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  0 & 1 & 1 & 1 \\
  2 & 6 & 5 & 6 \\
\end{bmatrix} \\
  -2R_1+R_3 & \rightarrow \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  0 & 1 & 1 & 1 \\
  0 & 2 & 1 & -2 \\
\end{bmatrix} \\
  -2R_2+R_3 & \rightarrow \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  0 & 1 & 1 & 1 \\
  0 & 0 & -1 & -4 \\
\end{bmatrix} \\
  -1R_3 & \rightarrow \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  0 & 1 & 1 & 1 \\
  0 & 0 & 1 & 4 \\
\end{bmatrix}
\end{align*}
\]

So the matrix

\[
B = \begin{bmatrix}
  1 & 2 & 2 & 4 \\
  0 & 1 & 1 & 1 \\
  0 & 0 & 1 & 4 \\
\end{bmatrix}
\]
is row equivalent to \( A \) and by Theorem REMES[32] the system of equations below has the same solution set as the original system of equations.

\[
\begin{align*}
    x_1 + 2x_2 + 2x_3 &= 4 \\
    x_2 + x_3 &= 1 \\
    x_3 &= 4
\end{align*}
\]

Solving this “simpler” system is straightforward and is identical to the process in Example US[20].

The preceding example amply illustrates the definitions and theorems we have seen so far. But it still leaves two questions unanswered. Exactly what is this “simpler” form for a matrix, and just how do we get it? Here’s the answer to the first question, a definition of reduced row-echelon form.

**Definition RREF**  
Reduced Row-Echelon Form

A matrix is in **reduced row-echelon form** if it meets all of the following conditions:

1. A row where every entry is zero lies below any row that contains a nonzero entry.
2. The leftmost nonzero entry of a row is equal to 1.
3. The leftmost nonzero entry of a row is the only nonzero entry in its column.
4. Consider any two different leftmost nonzero entries, one located in row \( i \), column \( j \) and the other located in row \( s \), column \( t \). If \( s > i \), then \( t > j \).

The principal feature of reduced row-echelon form is the pattern of leading 1’s guaranteed by conditions (2) and (4), reminiscent of a flight of geese, or steps in a staircase, or water cascading down a mountain stream. Because we will make frequent reference to reduced row-echelon form, we make precise definitions of three terms.

**Definition ZRM**  
Zero Row of a Matrix

A row of a matrix where every entry is zero is called a **zero row**.

**Definition LO**  
Leading Ones

For a matrix in reduced row-echelon form, the leftmost nonzero entry of any row that is not a zero row will be called a **leading 1**.

**Definition PC**  
Pivot Columns

For a matrix in reduced row-echelon form, a column containing a leading 1 will be called a **pivot column**.

**Example RREF**

A matrix in **reduced row-echelon form**

The matrix \( C \) is in reduced row-echelon form.

\[
\begin{bmatrix}
1 & -3 & 0 & 6 & 0 & 0 & -5 & 9 \\
0 & 0 & 0 & 0 & 1 & 0 & 3 & -7 \\
0 & 0 & 0 & 0 & 0 & 1 & 7 & 3 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]
This matrix has two zero rows and three leading 1’s. Columns 1, 5, and 6 are pivot columns.

Example NRREF
A matrix not in reduced row-echelon form
The matrix $D$ is not in reduced row-echelon form, as it fails each of the four requirements once.

\[
\begin{bmatrix}
1 & 0 & -3 & 0 & 6 & 0 & 7 & -5 & 9 \\
0 & 0 & 0 & 5 & 0 & 1 & 0 & 3 & -7 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 7 & 3 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & -4 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

Proof Technique C
Constructive Proofs
Conclusions of proofs come in a variety of types. Often a theorem will simply assert that something exists. The best way, but not the only way, to show something exists is to actually build it. Such a proof is called constructive. The thing to realize about constructive proofs is that the proof itself will contain a procedure that might be used computationally to construct the desired object. If the procedure is not too cumbersome, then the proof itself is as useful as the statement of the theorem. Such is the case with our next theorem.

Theorem REMEF
Row-Equivalent Matrix in Echelon Form
Suppose $A$ is a matrix. Then there is a (unique!) matrix $B$ so that

1. $A$ and $B$ are row-equivalent.
2. $B$ is in reduced row-echelon form.

Proof Suppose that $A$ has $m$ rows. We will describe a process for converting $A$ into $B$ via row operations.

Set $k = 1$.

1. If $k = m + 1$, then stop converting the matrix.
2. Among all of the entries in rows $k$ through $m$ locate the leftmost nonzero entry (there may be several entries that tie for being leftmost). Denote the column of this entry by $\ell$. If this is not possible because all the entries are zero, then stop converting the matrix.
3. If the nonzero entry found in the preceding step is not in row $k$, swap rows so that row $k$ has a nonzero entry in column $\ell$.
4. Use the second row operation to multiply row $k$ by the reciprocal of the value in column $\ell$, thereby creating a leading 1 in row $k$ at column $\ell$. 

Version 0.52
5. Use row \( k \) and the third row operation to convert all the other entries in column \( \ell \) into zeros.

6. Increase \( k \) by one and return to step 1.

The result of this procedure is the matrix \( B \). We need to establish that it has the requisite properties. First, the steps of the process only use row operations to convert the matrix, so \( A \) and \( B \) are row-equivalent.

It is a bit more work to be certain that \( B \) is in reduced row-echelon form. Suppose we have completed the stage of the algorithm for \( k = i \) and during this pass we used \( \ell = j \). At the conclusion of this \( i \)-th trip through the steps, we claim the first \( i \) rows form a matrix in reduced row-echelon form, and the entries in rows \( i + 1 \) through \( m \) in columns 1 through \( j \) are all zero. To see this, notice that

1. The definition of \( j \) insures that the entries of rows \( i + 1 \) through \( m \), in columns 1 through \( j - 1 \) are all zero.
2. Row \( i \) has a leading nonzero entry equal to 1 by the result of step 4.
3. The employment of the leading 1 of row \( i \) in step 5 will make every element of column \( j \) zero in rows 1 through \( i - 1 \), as well as in rows \( i + 1 \) through \( m \).
4. Rows 1 through \( i - 1 \) are only affected by step 5. The zeros in columns 1 through \( j - 1 \) of row \( i \) mean that none of the entries in columns 1 through \( j - 1 \) for rows 1 through \( i - 1 \) will change by the row operations employed in step 5.
5. Since columns 1 through \( j \) are all zero for rows \( i + 1 \) through \( m \), any nonzero entry found on the next pass will be in a column to the right of column \( j \), ensuring that the fourth condition of reduced row-echelon form is met.

6. If the procedure halts with \( i = m + 1 \), then every row of \( B \) has a leading 1, and hence has no zero rows. If the procedure halts because step 2 fails to find a nonzero entry, then rows \( i \) through \( m \) are all zero rows, and they are all at the bottom of the matrix.

So now we can put it all together. Begin with a system of linear equations (Definition SLE [14]), and represent it by its augmented matrix (Definition AM [31]). Use row operations (Definition RO [32]) to convert this matrix into reduced row-echelon form (Definition RREF [34]), using the procedure outlined in the proof of Theorem REMEF [35]. Theorem REMEF [35] also tells us we can always accomplish this, and that the result is row-equivalent (Definition REM [32]) to the original augmented matrix. Since the matrix in reduced-row echelon form has the same solution set, we can analyze it instead of the original matrix, viewing it as the augmented matrix of a different system of equations. The beauty of augmented matrices in reduced row-echelon form is that the solution sets to their corresponding systems can be easily determined, as we will see in the next few examples and in the next section.

We will see through the course that almost every interesting property of a matrix can be discerned by looking at a row-equivalent matrix in reduced row-echelon form. For this reason it is important to know that the matrix \( B \) guaranteed to exist by Theorem REMEF [35] is unique. We could prove this result right now, but the proof will be much
easier to state and understand a few sections from now when we have a few more definitions. However, the proof we will provide does not explicitly require any more theorems than we have right now, so we can, and will, make use of the uniqueness of $B$ between now and then by citing [Theorem RREFU] [112]. You might want to jump forward now to read the statement of this important theorem and save studying its proof for later, once the rest of us get there.

We will now run through some examples of using these definitions and theorems to solve some systems of equations. From now on, when we have a matrix in reduced row-echelon form, we will mark the leading 1’s with a small box. In your work, you can box ’em, circle ’em or write ’em in a different color — just identify ’em somehow. This device will prove very useful later and is a very good habit to start developing right now.

**Example SAB**

**Solutions for Archetype B**

Let’s find the solutions to the following system of equations,

\[
\begin{align*}
-7x_1 - 6x_2 - 12x_3 &= -33 \\
5x_1 + 5x_2 + 7x_3 &= 24 \\
x_1 + 4x_3 &= 5
\end{align*}
\]

First, form the augmented matrix,

\[
\begin{bmatrix}
-7 & -6 & -12 & -33 \\
5 & 5 & 7 & 24 \\
1 & 0 & 4 & 5
\end{bmatrix}
\]

and work to reduced row-echelon form, first with $i = 1$,

\[
\begin{align*}
R_1 &\leftrightarrow R_3 \quad \begin{bmatrix}
1 & 0 & 4 & 5 \\
5 & 5 & 7 & 24 \\
-7 & -6 & -12 & -33
\end{bmatrix} \\
-5R_3 + R_2 &\rightarrow \begin{bmatrix}
1 & 0 & 4 & 5 \\
0 & 5 & -13 & -1 \\
0 & 0 & 1 & 2
\end{bmatrix}
\end{align*}
\]

Now, with $i = 2$,

\[
\begin{align*}
\frac{1}{5}R_2 &\rightarrow \begin{bmatrix}
1 & 0 & 4 & 5 \\
0 & 1 & -13 & -1 \\
0 & -6 & 16 & 2
\end{bmatrix} \\
6R_2 + R_3 &\rightarrow \begin{bmatrix}
1 & 0 & 4 & 5 \\
0 & 1 & -13 & -1 \\
0 & 0 & 1 & 2
\end{bmatrix}
\end{align*}
\]

And finally, with $i = 3$,

\[
\begin{align*}
\frac{5}{2}R_3 &\rightarrow \begin{bmatrix}
1 & 0 & 4 & 5 \\
0 & 1 & -13 & -1 \\
0 & 0 & 1 & 2
\end{bmatrix} \\
\frac{12}{5}R_3 + R_2 &\rightarrow \begin{bmatrix}
1 & 0 & 4 & 5 \\
0 & 1 & 0 & 5 \\
0 & 0 & 1 & 2
\end{bmatrix} \\
-4R_3 + R_1 &\rightarrow \begin{bmatrix}
1 & 0 & 0 & -3 \\
0 & 1 & 0 & 5 \\
0 & 0 & 1 & 2
\end{bmatrix}
\end{align*}
\]

This is now the augmented matrix of a very simple system of equations, namely $x_1 = -3, x_2 = 5, x_3 = 2$, which has an obvious solution. Furthermore, we can see that this is the only solution to this system, so we have determined the entire solution set. You might compare this example with the procedure we used in [Example US] [20].
Archetypes A and B are meant to contrast each other in many respects. So let’s solve Archetype A now.

**Example SAA**

**Solutions for Archetype A**

Let’s find the solutions to the following system of equations,

\[
\begin{align*}
x_1 - x_2 + 2x_3 &= 1 \\
2x_1 + x_2 + x_3 &= 8 \\
x_1 + x_2 &= 5
\end{align*}
\]

First, form the augmented matrix,

\[
\begin{bmatrix}
1 & -1 & 2 & 1 \\
2 & 1 & 1 & 8 \\
1 & 1 & 0 & 5
\end{bmatrix}
\]

and work to reduced row-echelon form, first with \( i = 1 \),

\[
-2R_1 + R_2 \rightarrow \begin{bmatrix}
1 & -1 & 2 & 1 \\
0 & 3 & -3 & 6 \\
1 & 1 & 0 & 5
\end{bmatrix} -1R_1 + R_3 \rightarrow \begin{bmatrix}
1 & -1 & 2 & 1 \\
0 & 3 & -3 & 6 \\
0 & 2 & -2 & 4
\end{bmatrix}
\]

Now, with \( i = 2 \),

\[
\frac{1}{3}R_2 \rightarrow \begin{bmatrix}
1 & -1 & 2 & 1 \\
0 & 1 & -1 & 2 \\
0 & 2 & -2 & 4
\end{bmatrix} 1R_2 + R_1 \rightarrow \begin{bmatrix}
1 & 0 & 1 & 3 \\
0 & 1 & -1 & 2 \\
0 & 2 & -2 & 4
\end{bmatrix} -2R_2 + R_3 \rightarrow \begin{bmatrix}
1 & 0 & 1 & 3 \\
0 & 1 & -1 & 2 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

The system of equations represented by this augmented matrix needs to be considered a bit differently than that for Archetype B. First, the last row of the matrix is the equation \( 0 = 0 \), which is always true, so we can safely ignore it as we analyze the other two equations. These equations are,

\[
\begin{align*}
x_1 + x_3 &= 3 \\
x_2 - x_3 &= 2
\end{align*}
\]

While this system is fairly easy to solve, it also appears to have a multitude of solutions. For example, choose \( x_3 = 1 \) and see that then \( x_1 = 2 \) and \( x_2 = 3 \) will together form a solution. Or choose \( x_3 = 0 \), and then discover that \( x_1 = 3 \) and \( x_2 = 2 \) lead to a solution. Try it yourself: pick any value of \( x_3 \) you please, and figure out what \( x_1 \) and \( x_2 \) should be to make the first and second equations (respectively) true. We’ll wait while you do that. Because of this behavior, we say that \( x_3 \) is a “free” or “independent” variable. But why do we vary \( x_3 \) and not some other variable? For now, notice that the third column of the augmented matrix does not have any leading 1’s in its column. With this idea, we can rearrange the two equations, solving each for the variable that corresponds to the leading 1 in that row.

\[
\begin{align*}
x_1 &= 3 - x_3 \\
x_2 &= 2 + x_3
\end{align*}
\]
To write the solutions in set notation, we have

\[ S = \{(3 - x_3, 2 + x_3, x_3) \mid x_3 \in \mathbb{C}\} \]

We’ll learn more in the next section about systems with infinitely many solutions and how to express their solution sets. Right now, you might look back at Example IS [21].

**Example SAE**

**Solutions for Archetype E**

Let’s find the solutions to the following system of equations,

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 2 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= 3 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 2
\end{align*}
\]

First, form the augmented matrix,

\[
\begin{bmatrix}
2 & 1 & 7 & -7 & 2 \\
-3 & 4 & -5 & -6 & 3 \\
1 & 1 & 4 & -5 & 2
\end{bmatrix}
\]

and work to reduced row-echelon form, first with \(i = 1\),

\[
R_1 \leftrightarrow R_3 \\
\begin{bmatrix}
1 & 1 & 4 & -5 & 2 \\
-3 & 4 & -5 & -6 & 3 \\
2 & 1 & 7 & -7 & 2
\end{bmatrix}
\]

\[
3R_1 + R_2 \\
\begin{bmatrix}
1 & 1 & 4 & -5 & 2 \\
0 & 7 & 7 & -21 & 9 \\
2 & 1 & 7 & -7 & 2
\end{bmatrix}
\]

\[
-2R_1 + R_3 \\
\begin{bmatrix}
1 & 1 & 4 & -5 & 2 \\
0 & 7 & 7 & -21 & 9 \\
0 & -1 & -1 & 3 & -2
\end{bmatrix}
\]

Now, with \(i = 2\),

\[
R_2 \leftrightarrow R_3 \\
\begin{bmatrix}
1 & 1 & 4 & -5 & 2 \\
0 & -1 & -1 & 3 & -2 \\
0 & 7 & 7 & -21 & 9
\end{bmatrix}
\]

\[
-1R_2 \\
\begin{bmatrix}
1 & 1 & 4 & -5 & 2 \\
0 & 1 & 1 & -3 & 2 \\
0 & 7 & 7 & -21 & 9
\end{bmatrix}
\]

\[
-1R_2 + R_1 \\
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 2 \\
0 & 7 & 7 & -21 & 9
\end{bmatrix}
\]

\[
-7R_2 + R_3 \\
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 2 \\
0 & 0 & 0 & 0 & -5
\end{bmatrix}
\]
And finally, with \( i = 3 \),

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 2 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

Let’s analyze the equations in the system represented by this augmented matrix. The third equation will read \( 0 = 1 \). This is patently false, all the time. No choice of values for our variables will ever make it true. We’re done. Since we cannot even make the last equation true, we have no hope of making all of the equations simultaneously true. So this system has no solutions, and its solution set is the empty set, \( \emptyset = \{ \} \).

Notice that we could have reached this conclusion sooner. After performing the row operation \(-7R_2 + R_3\), we can see that the third equation reads \(-5\), a false statement. Since the system represented by this matrix has no solutions, none of the systems represented has any solutions. However, for this example, we have chosen to bring the matrix fully to reduced row-echelon form for the practice.

These three examples (Example SAB [37], Example SAA [38], Example SAE [39]) illustrate the full range of possibilities for a system of linear equations — no solutions, one solution, or infinitely many solutions. In the next section we’ll examine these three scenarios more closely.

We will frequently use the term row-reduce as a verb. To row-reduce a matrix \( A \) will mean to apply row operations to \( A \) in order to find another matrix, \( B \), that is in reduced row-echelon form and is row-equivalent to \( A \). Theorem REMEEF [35] tells us that this process will always be successful and Theorem RREFU [112] tells us that the result will be unambiguous. Typically, the analysis of \( A \) will proceed by analyzing \( B \) and applying theorems whose hypotheses include the row-equivalence of \( A \) and \( B \).

After some practice by hand, you will want to use your favorite computing device to do the computations required to bring a matrix to reduced row-echelon form (Exercise RREF.C30 [44]).

**Computation Note RR.MMA**

**Row Reduce (Mathematica)**

If \( a \) is the name of a matrix in Mathematica, then the command \( \text{RowReduce}[a] \) will output the reduced row-echelon form of the matrix.

**Computation Note RR.TI86**

**Row Reduce (TI-86)**

If \( A \) is the name of a matrix stored in the TI-86, then the command \( \text{rref } A \) will return the reduced row-echelon form of the matrix. This command can also be found by pressing the \( \text{MATRX} \) key, then \( F4 \) for OPS, and finally, \( F5 \) for \( \text{rref} \).

**Computation Note RR.TI83**

**Row Reduce (TI-83)**

Contributed by Douglas Phelps

Suppose \( B \) is the name of a matrix stored in the TI-83. Press the \( \text{MATRX} \) key. Press the
right arrow key once so that **MATH** is highlighted. Press the down arrow eleven times so that **rref** is highlighted, then press **ENTER**, to choose the matrix **B**, press **MATRX**, then the down arrow once followed by **ENTER**. Supply a right parenthesis ( ) and press **ENTER**.

**Subsection READ**

**Reading Questions**

1. Is the matrix below in reduced row-echelon form? Why or why not?

\[
\begin{bmatrix}
1 & 5 & 0 & 6 & 8 \\
0 & 0 & 1 & 2 & 0 \\
0 & 0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

2. Use row operations to convert the matrix below to reduced row-echelon form and report the final matrix.

\[
\begin{bmatrix}
2 & 1 & 8 \\
-1 & 1 & -1 \\
-2 & 5 & 4 \\
\end{bmatrix}
\]

3. Find all the solutions to the system below by using an augmented matrix and row operations. Report your final matrix and the set of solutions.

\[
\begin{align*}
2x_1 + 3x_2 - x_3 &= 0 \\
x_1 + 2x_2 + x_3 &= 3 \\
x_1 + 3x_2 + 3x_3 &= 7 \\
\end{align*}
\]
Subsection EXC
Exercises

C05  Each archetype below is a system of equations. Form the augmented matrix of the
system of equations, convert the matrix to reduced row-echelon form by using equation
operations and then describe the solution set of the original system of equations.

Archetype A  563
Archetype B  568
Archetype C  573
Archetype D  577
Archetype E  581
Archetype F  585
Archetype G  590
Archetype H  594
Archetype I  599
Archetype J  604

Contributed by Robert Beezer

For problems C10–C14, find all solutions to the system of linear equations. Write the
solutions as a set, using correct set notation.

C10

\[
\begin{align*}
2x_1 - 3x_2 + x_3 + 7x_4 &= 14 \\
2x_1 + 8x_2 - 4x_3 + 5x_4 &= -1 \\
-x_1 + 3x_2 - 3x_3 &= 4 \\
-5x_1 + 2x_2 + 3x_3 + 4x_4 &= -19
\end{align*}
\]

Contributed by Robert Beezer  Solution 45

C11

\[
\begin{align*}
3x_1 + 4x_2 - x_3 + 2x_4 &= 6 \\
x_1 - 2x_2 + 3x_3 + x_4 &= 2 \\
10x_2 - 10x_3 - x_4 &= 1
\end{align*}
\]

Contributed by Robert Beezer  Solution 45

C12

\[
\begin{align*}
2x_1 + 4x_2 + 5x_3 + 7x_4 &= -26 \\
x_1 + 2x_2 + x_3 - x_4 &= -4 \\
-2x_1 - 4x_2 + x_3 + 11x_4 &= -10
\end{align*}
\]

Contributed by Robert Beezer  Solution 45
C13

\[ x_1 + 2x_2 + 8x_3 - 7x_4 = -2 \]
\[ 3x_1 + 2x_2 + 12x_3 - 5x_4 = 6 \]
\[ -x_1 + x_2 + x_3 - 5x_4 = -10 \]

Contributed by Robert Beezer  Solution 45

C14

\[ 2x_1 + x_2 + 7x_3 - 2x_4 = 4 \]
\[ 3x_1 - 2x_2 + 11x_4 = 13 \]
\[ x_1 + x_2 + 5x_3 - 3x_4 = 1 \]

Contributed by Robert Beezer  Solution 46

C30  Row-reduce the matrix below without the aid of a calculator, indicating the row operations you are using at each step.

\[
\begin{bmatrix}
2 & 1 & 5 & 10 \\
1 & -3 & -1 & -2 \\
4 & -2 & 6 & 12 \\
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution 46

M50  A parking lot has 66 vehicles (cars, trucks, motorcycles and bicycles) in it. There are four times as many cars as trucks. The total number of tires (4 per car or truck, 2 per motorcycle or bicycle) is 252. How many cars are there? How many bicycles?

Contributed by Robert Beezer  Solution 46

T10  Prove that each of the three row operations (Definition RO 32) is reversible. More precisely, if the matrix \( B \) is obtained from \( A \) by application of a single row operation, show that there is a single row operation that will transform \( B \) back into \( A \).

Contributed by Robert Beezer  Solution 47

T11  Suppose that \( A, B \) and \( C \) are \( m \times n \) matrices. Use the definition of row-equivalence (Definition REM 32) to prove the following three facts.

1. \( A \) is row-equivalent to \( A \).
2. If \( A \) is row-equivalent to \( B \), then \( B \) is row-equivalent to \( A \).
3. If \( A \) is row-equivalent to \( B \), and \( B \) is row-equivalent to \( C \), then \( A \) is row-equivalent to \( C \).

A relationship that satisfies these three properties is known as an equivalence relation, an important idea in the study of various algebras. This is a formal way of saying that a relationship behaves like equality, without requiring the relationship to be as strict as equality itself. We’ll see it again in Theorem SER 413.

Contributed by Robert Beezer
C10 Contributed by Robert Beezer Statement [43]
The augmented matrix row-reduces to
\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & -3 \\
0 & 0 & 1 & 0 & -4 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
\]
and we see from the locations of the leading 1’s that the system is consistent (Theo-
rem RCLS [53]) and that \( n - r = 4 - 4 = 0 \) and so the system has no free vari-
bles (Theo-
rem CSRN [54]) and hence has a unique solution. This solution is \( \{(1, -3, -4, 1)\} \).

C11 Contributed by Robert Beezer Statement [43]
The augmented matrix row-reduces to
\[
\begin{bmatrix}
1 & 0 & 1 & 4/5 & 0 \\
0 & 1 & -1 & -1/10 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]
and a leading 1 in the last column tells us that the system is inconsistent (Theo-
rem RCLS [53]). So the solution set is \( \emptyset = \{\} \).

C12 Contributed by Robert Beezer Statement [43]
The augmented matrix row-reduces to
\[
\begin{bmatrix}
1 & 2 & 0 & -4 & 2 \\
0 & 0 & 1 & 3 & -6 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]
(Theorem RCLS [53]) and (Theorem CSRN [54]) tells us the system is consistent and
the solution set can be described with \( n - r = 4 - 2 = 2 \) free variables, namely \( x_2 \) and
\( x_4 \). Solving for the dependent variables \( (D = \{x_1, x_3\}) \) the first and second equations
represented in the row-reduced matrix yields,

\[
x_1 = 2 - 2x_2 + 4x_4 \\
x_3 = -6 - 3x_4
\]

As a set, we write this as

\[
\{(2 - 2x_2 + 4x_4, x_2, -6 - 3x_4, x_4) \mid x_2, x_4 \in \mathbb{C}\}
\]

C13 Contributed by Robert Beezer Statement [44]
The augmented matrix of the system of equations is
\[
\begin{bmatrix}
1 & 2 & 8 & -7 & -2 \\
3 & 2 & 12 & -5 & 6 \\
-1 & 1 & 1 & -5 & -10
\end{bmatrix}
\]
which row-reduces to
\[
\begin{bmatrix}
1 & 0 & 2 & 1 & 0 \\
0 & 1 & 3 & -4 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

With a leading one in the last column, Theorem RCLS tells us the system of equations is inconsistent, so the solution set is the empty set, \(\emptyset\).

C14 Contributed by Robert Beezer Statement 44
The augmented matrix of the system of equations is
\[
\begin{bmatrix}
2 & 1 & 7 & -2 & 4 \\
3 & -2 & 0 & 11 & 13 \\
1 & 1 & 5 & -3 & 1
\end{bmatrix}
\]
which row-reduces to
\[
\begin{bmatrix}
1 & 0 & 2 & 1 & 3 \\
0 & 1 & 3 & -4 & -2 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Then \(D = 1, 2\) and \(F = 3, 4, 5\), so the system is consistent (5 \(\not\in\) D) and can be described by the two free variables \(x_3\) and \(x_4\). Rearranging the equations represented by the two nonzero rows to gain expressions for the dependent variables \(x_1\) and \(x_2\), yields the solution set,
\[
\begin{align*}
S = \{ & \begin{bmatrix} 3 - 2x_3 - x_4 \\ -2 - 3x_3 + 4x_4 \\ x_3 \\ x_4 \end{bmatrix} | x_3, x_4 \in \mathbb{C} \} \\
& \end{align*}
\]

C30 Contributed by Robert Beezer Statement 44

\[
\begin{bmatrix}
2 & 1 & 5 & 10 \\
1 & -3 & -1 & -2 \\
4 & -2 & 6 & 12
\end{bmatrix}
\]
\(R_1 \rightarrow R_2\)
\[
\begin{bmatrix}
1 & -3 & -1 & -2 \\
0 & 7 & 7 & 14 \\
4 & -2 & 6 & 12
\end{bmatrix}
\]
\(-2R_1 + R_3\)
\[
\begin{bmatrix}
1 & -3 & -1 & -2 \\
0 & 7 & 7 & 14 \\
4 & -2 & 6 & 12
\end{bmatrix}
\]
\(-4R_1 + R_3\)
\[
\begin{bmatrix}
1 & -3 & -1 & -2 \\
0 & 7 & 7 & 14 \\
0 & 10 & 10 & 20
\end{bmatrix}
\]
\(-R_2\)
\[
\begin{bmatrix}
1 & -3 & -1 & -2 \\
0 & 1 & 1 & 2 \\
0 & 10 & 10 & 20
\end{bmatrix}
\]
\(3R_2 + R_1\)
\[
\begin{bmatrix}
1 & 0 & 2 & 4 \\
0 & 1 & 1 & 2 \\
0 & 10 & 10 & 20
\end{bmatrix}
\]
\(-10R_2 + R_3\)
\[
\begin{bmatrix}
1 & 0 & 2 & 4 \\
0 & 1 & 1 & 2 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

M50 Contributed by Robert Beezer Statement 44
Let \(c, t, m, b\) denote the number of cars, trucks, motorcycles, and bicycles. Then the statements from the problem yield the equations:
\[
\begin{align*}
c + t + m + b &= 66 \\
c - 4t &= 0 \\
4c + 4t + 2m + 2b &= 252
\end{align*}
\]
The augmented matrix for this system is

\[
\begin{bmatrix}
1 & 1 & 1 & 1 & 66 \\
1 & -4 & 0 & 0 & 0 \\
4 & 4 & 2 & 2 & 252
\end{bmatrix}
\]

which row-reduces to

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 48 \\
0 & 1 & 0 & 0 & 12 \\
0 & 0 & 1 & 1 & 6
\end{bmatrix}
\]

$c = 48$ is the first equation represented in the row-reduced matrix so there are 48 cars. $m + b = 6$ is the third equation represented in the row-reduced matrix so there are anywhere from 0 to 6 bicycles. We can also say that $b$ is a free variable, but the context of the problem limits it to 7 integer values since cannot have a negative number of motorcycles.

T10 Contributed by Robert Beezer Statement 44

If we can reverse each row operation individually, then we can reverse a sequence of row operations. The operations that reverse each operation are listed below, using our shorthand notation,

\[
\begin{align*}
R_i \leftrightarrow R_j & \quad R_i \leftrightarrow R_j \\
\alpha R_i, \alpha \neq 0 & \quad \frac{1}{\alpha} R_i \\
\alpha R_i + R_j & \quad - \alpha R_i + R_j
\end{align*}
\]
Section TSS
Types of Solution Sets

We will now be more careful about analyzing the reduced row-echelon form derived from the augmented matrix of a system of linear equations. In particular, we will see how to systematically handle the situation when we have infinitely many solutions to a system, and we will prove that every system of linear equations has either zero, one or infinitely many solutions. With these tools, we will be able to solve any system by a well-described method.

The computer scientist Donald Knuth said, “Science is what we understand well enough to explain to a computer. Art is everything else.” In this section we’ll remove solving systems of equations from the realm of art, and into the realm of science. We begin with a definition.

Definition CS
Consistent System
A system of linear equations is consistent if it has at least one solution. Otherwise, the system is called inconsistent.

We will want to first recognize when a system is inconsistent or consistent, and in the case of consistent systems we will be able to further refine the types of solutions possible. We will do this by analyzing the reduced row-echelon form of a matrix, so we now describe some useful notation that will help us talk about this form of a matrix.

Notation RREFA
Reduced Row-Echelon Form Analysis
Suppose that $B$ is an $m \times n$ matrix that is in reduced row-echelon form. Let $r$ equal the number of rows of $B$ that are not zero rows. Each of these $r$ rows then contains a leading 1, so let $d_i$ equal the column number where row $i$’s leading 1 is located. In other words, $d_i$ is the location of the $i$-th pivot column. For columns without a leading 1, let $f_i$ be the column number of the $i$-th column (reading from left to right) that does not contain a leading 1. Define

$$D = \{d_1, d_2, d_3, \ldots, d_r\} \quad F = \{f_1, f_2, f_3, \ldots, f_{n-r}\}$$

This notation can be a bit confusing, since we have subscripted variables that are in turn equal to subscripts used to index the matrix. However, many questions about matrices and systems of equations can be answered once we know $r$, $D$ and $F$. The choice of the letters $D$ and $F$ refer to our upcoming definition of dependent and free variables (Definition IDV [52]). An example may help.

Example RREFN
Reduced row-echelon form notation
For the $5 \times 9$ matrix

$$
B = \begin{bmatrix}
1 & 5 & 0 & 0 & 2 & 8 & 0 & 5 & -1 \\
0 & 0 & 1 & 0 & 4 & 7 & 0 & 2 & 0 \\
0 & 0 & 0 & 1 & 3 & 9 & 0 & 3 & -6 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 4 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

in reduced row-echelon form we have

$$
r = 4 \\
d_1 = 1 \\
f_1 = 2 \\
d_2 = 3 \\
f_2 = 5 \\
d_3 = 4 \\
f_3 = 6 \\
d_4 = 7 \\
f_4 = 8 \\
F = \{f_5\} = \{9\}.
$$

Notice that the sets $D = \{d_1, d_2, d_3, d_4\} = \{1, 3, 4, 7\}$ and $F = \{f_1, f_2, f_3, f_4, f_5\} = \{2, 5, 6, 8, 9\}$ have nothing in common and together account for all of the columns of $B$ (we say it is a partition of the set of column indices).

Before proving some theorems about the possibilities for solution sets to systems of equations, let’s analyze one particular system with an infinite solution set very carefully as an example. We’ll use this technique frequently, and shortly we’ll refine it slightly.

Archetypes I and J are both fairly large for doing computations by hand (though not impossibly large). Their properties are very similar, so we will frequently analyze the situation in Archetype I, and leave you the joy of analyzing Archetype J yourself. So work through Archetype I with the text, by hand and/or with a computer, and then tackle Archetype J yourself (and check your results with those listed). Notice too that the archetypes describing systems of equations each lists the values of $r$, $D$ and $F$. Here we go...

Example ISSI

**Describing infinite solution sets, Archetype I**

[Archetype I 599] is the system of $m = 4$ equations in $n = 7$ variables

\[
\begin{align*}
x_1 + 4x_2 - x_4 + 7x_6 - 9x_7 &= 3 \\
2x_1 + 8x_2 - x_3 + 3x_4 + 9x_5 - 13x_6 + 7x_7 &= 9 \\
2x_3 - 3x_4 - 4x_5 + 12x_6 - 8x_7 &= 1 \\
x_1 - 4x_2 + 2x_3 + 4x_4 + 8x_5 - 31x_6 + 37x_7 &= 4
\end{align*}
\]

has a $4 \times 8$ augmented matrix that is row-equivalent to the following matrix (check this!), and which is in reduced row-echelon form (the existence of this matrix is guaranteed by [Theorem REMEF 35]),

\[
\begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 & 4 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 & 2 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

So we find that $r = 3$ and

\[
D = \{d_1, d_2, d_3\} = \{1, 3, 4\} \quad \text{and} \quad F = \{f_1, f_2, f_3, f_4, f_5\} = \{2, 5, 6, 7, 8\}.
\]
Let \( i \) denote one of the \( r = 3 \) non-zero rows, and then we see that we can solve the corresponding equation represented by this row for the variable \( x_d_i \) and write it as a linear function of the variables \( x_{f_1}, x_{f_2}, x_{f_3}, x_{f_4} \) (notice that \( f_5 = 8 \) does not reference a variable). We’ll do this now, but you can already see how the subscripts upon subscripts takes some getting used to.

\[
\begin{align*}
(i = 1) & \quad x_{d_1} = x_1 = 4 - 4x_2 - 2x_5 - x_6 + 3x_7 \\
(i = 2) & \quad x_{d_2} = x_3 = 2 - x_5 + 3x_6 - 5x_7 \\
(i = 3) & \quad x_{d_3} = x_4 = 1 - 2x_5 + 6x_6 - 6x_7
\end{align*}
\]

Each element of the set \( F = \{f_1, f_2, f_3, f_4, f_5\} = \{2, 5, 6, 7, 8\} \) is the index of a variable, except for \( f_5 = 8 \). We refer to \( x_{f_1} = x_2, x_{f_2} = x_5, x_{f_3} = x_6 \) and \( x_{f_4} = x_7 \) as “free” (or “independent”) variables since they are allowed to assume any possible combination of values that we can imagine and we can continue on to build a solution to the system by solving individual equations for the values of the other (“dependent”) variables.

Each element of the set \( D = \{d_1, d_2, d_3\} = \{1, 3, 4\} \) is the index of a variable. We refer to the variables \( x_{d_1} = x_1, x_{d_2} = x_3 \) and \( x_{d_3} = x_4 \) as “dependent” variables since they depend on the independent variables. More precisely, for each possible choice of values for the independent variables we get exactly one set of values for the dependent variables that combine to form a solution of the system.

To express the solutions as a set, we write

\[
\{ (4 - 4x_2 - 2x_5 - x_6 + 3x_7, x_2, 2 - x_5 + 3x_6 - 5x_7, 1 - 2x_5 + 6x_6 - 6x_7, x_5, x_6, x_7) \mid x_2, x_5, x_6, x_7 \in \mathbb{C} \}
\]

The condition that \( x_2, x_5, x_6, x_7 \in \mathbb{C} \) is how we specify that the variables \( x_2, x_5, x_6, x_7 \) are “free” to assume any possible values.

This systematic approach to solving a system of equations will allow us to create a precise description of the solution set for any consistent system once we have found the reduced row-echelon form of the augmented matrix. It will work just as well when the set of free variables is empty and we get just a single solution. And we could program a computer to do it! Now have a whack at Archetype J (Exercise TSS.T10 [59]), mimicking the discussion in this example. We’ll still be here when you get back. ☀

Sets are an important part of algebra, and we’ve seen a few already. Being comfortable with sets is important for understanding and writing proofs. So here’s another proof technique.

**Proof Technique SN**

**Set Notation**

Sets are typically written inside of braces, as \{ \}, and have two components. The first is a description of the type of objects contained in a set, while the second is some sort of restriction on the properties the objects have. Every object in the set must be of the type described in the first part and it must satisfy the restrictions in the second part. Conversely, any object of the proper type for the first part, that also meets the conditions of the second part, will be in the set. These two parts are set off from each other somehow, often with a vertical bar (\|) or a colon (:). Membership of an element in a set is denoted with the symbol \( \in \).

I like to think of sets as clubs. The first part is some description of the type of people who might belong to the club, the basic objects. For example, a bicycle club would
describe its members as being people who like to ride bicycles. The second part is like a membership committee; it restricts the people who are allowed in the club. Continuing with our bicycle club, we might decide to limit ourselves to “serious” riders and only have members who can document having ridden 100 kilometers or more in a single day at least one time.

The restrictions on membership can migrate around some between the first and second part, and there may be several ways to describe the same set of objects. Here’s a more mathematical example, employing the set of all integers, \( \mathbb{Z} \), to describe the set of even integers.

\[
E = \{ x \in \mathbb{Z} \mid x \text{ is an even number} \} = \{ x \in \mathbb{Z} \mid 2 \text{ divides } x \text{ evenly} \} = \{ 2k \mid k \in \mathbb{Z} \}.
\]

Notice how this set tells us that its objects are integer numbers (not, say, matrices or functions, for example) and just those that are even. So we can write that \( 10 \in E \), while \( 17 \notin E \) once we check the membership criteria. We also recognize the question

\[
\begin{bmatrix}
1 & -3 & 5 \\
2 & 0 & 3
\end{bmatrix} \in E?
\]

as being ridiculous.

We mix our metaphors a bit when we call variables free versus dependent. Maybe we should call dependent variables “enslaved”? Here’s the definition.

**Definition IDV**

**Independent and Dependent Variables**

Suppose \( A \) is the augmented matrix of a system of linear equations and \( B \) is a row-equivalent matrix in reduced row-echelon form. Suppose \( j \) is the index of a column of \( B \) that contains the leading 1 for some row (i.e. column \( j \) is a pivot column), and this column is not the last column. Then the variable \( x_j \) is dependent. A variable that is not dependent is called independent or free.

We can now use the values of \( m, n, r \), and the independent and dependent variables to categorize the solutions sets to linear systems through a sequence of theorems. First the distinction between consistent and inconsistent systems, after two explanations of some proof techniques we will be using.

**Proof Technique E**

**Equivalences**

When a theorem uses the phrase “if and only if” (or the abbreviation “iff”) it is a shorthand way of saying that two if-then statements are true. So if a theorem says “P if and only if Q,” then it is true that “if P, then Q” while it is also true that “if Q, then P.” For example, it may be a theorem that “I wear bright yellow knee-high plastic boots if and only if it is raining.” This means that I never forget to wear my super-duper yellow boots when it is raining and I wouldn’t be seen in such silly boots unless it was raining. You never have one without the other. I’ve got my boots on and it is raining or I don’t have my boots on and it is dry.

The upshot for proving such theorems is that it is like a 2-for-1 sale, we get to do two proofs. Assume \( P \) and conclude \( Q \), then start over and assume \( Q \) and conclude \( P \). For this reason, “if and only if” is sometimes abbreviated by \( \iff \), while proofs indicate which of the two implications is being proved by prefacing each with \( \Rightarrow \) or \( \Leftarrow \). A carefully
written proof will remind the reader which statement is being used as the hypothesis, a quicker version will let the reader deduce it from the direction of the arrow. Tradition dictates we do the “easy” half first, but that’s hard for a student to know until you’ve finished doing both halves! Oh well, if you rewrite your proofs (a good habit), you can then choose to put the easy half first.

Theorems of this type are called equivalences or characterizations, and they are some of the most pleasing results in mathematics. They say that two objects, or two situations, are really the same. You don’t have one without the other, like rain and my yellow boots. The more different \( P \) and \( Q \) seem to be, the more pleasing it is to discover they are really equivalent. And if \( P \) describes a very mysterious solution or involves a tough computation, while \( Q \) is transparent or involves easy computations, then we’ve found a great shortcut for better understanding or faster computation. Remember that every theorem really is a shortcut in some form. You will also discover that if proving \( P \Rightarrow Q \) is very easy, then proving \( Q \Rightarrow P \) is likely to be proportionately harder. Sometimes the two halves are about equally hard. And in rare cases, you can string together a whole sequence of other equivalences to form the one you’re after and you don’t even need to do two halves. In this case, the argument of one half is just the argument of the other half, but in reverse.

One last thing about equivalences. If you see a statement of a theorem that says two things are “equivalent,” translate it first into an “if and only if” statement.

Proof Technique CP

Contrapositives

The contrapositive of an implication \( P \Rightarrow Q \) is the implication \( \text{not}(Q) \Rightarrow \text{not}(P) \), where “not” means the logical negation, or opposite. An implication is true if and only if its contrapositive is true. In symbols, \( (P \Rightarrow Q) \iff (\text{not}(Q) \Rightarrow \text{not}(P)) \) is a theorem. Such statements about logic, that are always true, are known as tautologies.

For example, it is a theorem that “if a vehicle is a fire truck, then it has big tires and has a siren.” (Yes, I’m sure you can conjure up a counterexample, but play along with me anyway.) The contrapositive is “if a vehicle does not have big tires or does not have a siren, then it is not a fire truck.” Notice how the “and” became an “or” when we negated the conclusion of the original theorem.

It will frequently happen that it is easier to construct a proof of the contrapositive than of the original implication. If you are having difficulty formulating a proof of some implication, see if the contrapositive is easier for you. The trick is to construct the negation of complicated statements accurately. More on that later.

Theorem RCLS

Recognizing Consistency of a Linear System

Suppose \( A \) is the augmented matrix of a system of linear equations with \( m \) equations in \( n \) variables. Suppose also that \( B \) is a row-equivalent matrix in reduced row-echelon form with \( r \) rows that are not zero rows. Then the system of equations is inconsistent if and only if the leading 1 of row \( r \) is located in column \( n + 1 \) of \( B \).

Proof \((\Leftarrow\Rightarrow)\) The first half of the proof begins with the assumption that the leading 1 of row \( r \) is located in column \( n + 1 \) of \( B \). Then row \( r \) of \( B \) begins with \( n \) consecutive zeros, finishing with the leading 1. This is a representation of the equation \( 0 = 1 \), which is false. Since this equation is false for any collection of values we might choose for the variables, there are no solutions for the system of equations, and it is inconsistent.
(⇒) For the second half of the proof, we wish to show that if we assume the system is inconsistent, then the final leading 1 is located in the last column. But instead of proving this directly, we’ll form the logically equivalent statement that is the contrapositive, and prove that instead (see [Technique CP][53]). Turning the implication around, and negating each portion, we arrive at the logically equivalent statement: If the leading 1 of row \( r \) is not in column \( n + 1 \), then the system of equations is consistent.

If the leading 1 for row \( i \) is located somewhere in columns 1 through \( n \), then every preceding row’s leading 1 is also located in columns 1 through \( n \). In other words, since the last leading 1 is not in the last column, no leading 1 for any row is in the last column, due to the echelon layout of the leading 1’s. Let \( b_{i,n+1}, 1 \leq i \leq r \), denote the entries of the last column of \( B \) for the first \( r \) rows. Employ our notation for columns of the reduced row-echelon form of a matrix (see [Notation RREFA][49]) to \( B \) and set \( x_{f_i} = 0, 1 \leq i \leq n - r \) and then set \( x_{d_i} = b_{i,n+1}, 1 \leq i \leq r \). In other words, set the dependent variables equal to the corresponding values in the final column and set all the free variables to zero. These values for the variables make the equations represented by the first \( r \) rows all true (convince yourself of this). Rows \( r + 1 \) through \( m \) (if any) are all zero rows, hence represent the equation \( 0 = 0 \) and are also all true. We have now identified one solution to the system, so we can say it is consistent.

The beauty of this theorem being an equivalence is that we can unequivocally test to see if a system is consistent or inconsistent by looking at just a single entry of the reduced row-echelon form matrix. We could program a computer to do it!

Notice that for a consistent system the row-reduced augmented matrix has \( n + 1 \in F \), so the largest element of \( F \) does not refer to a variable. Also, for an inconsistent system, \( n + 1 \in D \), and it then does not make much sense to discuss whether or not variables are free or dependent since there is no solution. With the characterization of [Theorem RCLS][53], we can explore the relationships between \( r \) and \( n \) in light of the consistency of a system of equations. First, a situation where we can quickly conclude the inconsistency of a system.

**Theorem ICRN**

**Inconsistent Systems, \( r \) and \( n \)**

Suppose \( A \) is the augmented matrix of a system of linear equations with \( m \) equations in \( n \) variables. Suppose also that \( B \) is a row-equivalent matrix in reduced row-echelon form with \( r \) rows that are not completely zeros. If \( r = n + 1 \), then the system of equations is inconsistent.

**Proof** If \( r = n + 1 \), then \( D = \{ 1, 2, 3, \ldots, n, n + 1 \} \) and every column of \( B \) contains a leading 1 and is a pivot column. In particular, the entry of column \( n + 1 \) for row \( r = n + 1 \) is a leading 1. [Theorem RCLS][53] then says that the system is inconsistent.

Next, if a system is consistent, we can distinguish between a unique solution and infinitely many solutions, and furthermore, we recognize that these are the only two possibilities.

**Theorem CSRN**

**Consistent Systems, \( r \) and \( n \)**

Suppose \( A \) is the augmented matrix of a *consistent* system of linear equations with \( m \) equations in \( n \) variables. Suppose also that \( B \) is a row-equivalent matrix in reduced row-echelon form with \( r \) rows that are not zero rows. Then \( r \leq n \). If \( r = n \), then the system has a unique solution, and if \( r < n \), then the system has infinitely many solutions.

Version 0.52
**Proof** This theorem contains three implications that we must establish. Notice first that $B$ has $n + 1$ columns, so there can be at most $n + 1$ pivot columns, i.e. $r \leq n + 1$. If $r = n + 1$, then Theorem ICRN tells us that the system is inconsistent, contrary to our hypothesis. We are left with $r \leq n$.

When $r = n$, we find $n - r = 0$ free variables (i.e. $F = \{n + 1\}$) and any solution must equal the unique solution given by the first $n$ entries of column $n + 1$ of $B$.

When $r < n$, we have $n - r > 0$ free variables, corresponding to columns of $B$ without a leading 1, excepting the final column, which also does not contain a leading 1 by Theorem RCLS. By varying the values of the free variables suitably, we can demonstrate infinitely many solutions. ■

The next theorem simply states a conclusion form the final paragraph of the previous proof, allowing us to state explicitly the number of free variables for a consistent system.

**Theorem FVCS**

**Free Variables for Consistent Systems**
Suppose $A$ is the augmented matrix of a consistent system of linear equations with $m$ equations in $n$ variables. Suppose also that $B$ is a row-equivalent matrix in reduced row-echelon form with $r$ rows that are not completely zeroes. Then the solution set can be described with $n - r$ free variables. □

**Proof Technique CV**

**Converses**
The converse of the implication $P \Rightarrow Q$ is the implication $Q \Rightarrow P$. There is no guarantee that the truth of these two statements are related. In particular, if an implication has been proven to be a theorem, then do not try to use its converse too, as if it were a theorem. Sometimes the converse is true (and we have an equivalence, see Technique E). But more likely the converse is false, especially if it wasn’t included in the statement of the original theorem.

For example, we have the theorem, “if a vehicle is a fire truck, then it is has big tires and has a siren.” The converse is false. The statement that “if a vehicle has big tires and a siren, then it is a fire truck” is false. A police vehicle for use on a sandy public beach would have big tires and a siren, yet is not equipped to fight fires.

We bring this up now, because Theorem CSRN has a tempting converse. Does this theorem say that if $r < n$, then the system is consistent? Definitely not, as Archetype E has $r = 3 < 4 = n$, yet is inconsistent. This example is then said to be a counterexample to the converse. Whenever you think a theorem that is an implication might actually be an equivalence, it is good to hunt around for a counterexample that shows the converse to be false (the archetypes, Chapter A, can be a good hunting ground). ◊

**Example CFV**

**Counting free variables**
For each archetype that is a system of equations, the values of $n$ and $r$ are listed. Many also contain a few sample solutions. We can use this information profitably, as illustrated by four examples.

1. Archetype A has $n = 3$ and $r = 2$. It can be seen to be consistent by the sample solutions given. Its solution set then has $n - r = 1$ free variables, and therefore will be infinite.
2. Archetype B \[568\] has \( n = 3 \) and \( r = 3 \). It can be seen to be consistent by the single sample solution given. Its solution set can then be described with \( n - r = 0 \) free variables, and therefore will have just the single solution.

3. Archetype H \[594\] has \( n = 2 \) and \( r = 3 \). In this case, \( r = n + 1 \), so Theorem ICRN \[54\] says the system is inconsistent. We should not try to apply Theorem FVCS \[55\] to count free variables, since the theorem only applies to consistent systems. (What would happen if you did?)

4. Archetype E \[581\] has \( n = 4 \) and \( r = 3 \). However, by looking at the reduced row-echelon form of the augmented matrix, we find a leading 1 in row 3, column 4. By Theorem RCLS \[53\] we recognize the system is then inconsistent. (Why doesn’t this example contradict Theorem ICRN \[54\]?)

We have accomplished a lot so far, but our main goal has been the following theorem, which is now very simple to prove. The proof is so simple that we ought to call it a corollary, but the result is important enough that it deserves to be called a theorem. Notice that this theorem was presaged first by Example TTS \[15\] and further foreshadowed by other examples.

**Theorem PSSLS**

**Possible Solution Sets for Linear Systems**

A system of linear equations has no solutions, a unique solution or infinitely many solutions. □

**Proof** By definition, a system is either inconsistent or consistent. The first case describes systems with no solutions. For consistent systems, we have the remaining two possibilities as guaranteed by, and described in, Theorem CSRN \[54\]. ■

We have one more theorem to round out our set of tools for determining solution sets to systems of linear equations.

**Theorem CMVEI**

**Consistent, More Variables than Equations, Infinite solutions**

Suppose a consistent system of linear equations has \( m \) equations in \( n \) variables. If \( n > m \), then the system has infinitely many solutions. □

**Proof** Suppose that the augmented matrix of the system of equations is row-equivalent to \( B \), a matrix in reduced row-echelon form with \( r \) nonzero rows. Because \( B \) has \( m \) rows in total, the number that are nonzero rows is less. In other words, \( r \leq m \). Follow this with the hypothesis that \( n > m \) and we find that the system has a solution set described by at least one free variable because

\[
 n - r \geq n - m > 0.
\]

A consistent system with free variables will have an infinite number of solutions, as given by Theorem CSRN \[54\]. ■

Notice that to use this theorem we need only know that the system is consistent, together with the values of \( m \) and \( n \). We do not necessarily have to compute a row-equivalent reduced row-echelon form matrix, even though we discussed such a matrix in the proof. This is the substance of the following example.
Example OSGMD
One solution gives many, Archetype D
Archetype D is the system of \( m = 3 \) equations in \( n = 4 \) variables,

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 8 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= -12 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 4
\end{align*}
\]

and the solution \( x_1 = 0, \ x_2 = 1, \ x_3 = 2, \ x_4 = 1 \) can be checked easily by substitution. Having been handed this solution, we know the system is consistent. This, together with \( n > m \), allows us to apply \textbf{Theorem CMVEI} \[56\] and conclude that the system has infinitely many solutions.

These theorems give us the procedures and implications that allow us to completely solve any system of linear equations. The main computational tool is using row operations to convert an augmented matrix into reduced row-echelon form. Here’s a broad outline of how we would instruct a computer to solve a system of linear equations.

1. Represent a system of linear equations by an augmented matrix (an array is the appropriate data structure in most computer languages).
2. Convert the matrix to a row-equivalent matrix in reduced row-echelon form using the procedure from the proof of \textbf{Theorem REMEF} \[35\].
3. Determine \( r \) and locate the leading 1 of row \( r \). If it is in column \( n + 1 \), output the statement that the system is inconsistent and halt.
4. With the leading 1 of row \( r \) not in column \( n + 1 \), there are two possibilities:
   (a) \( r = n \) and the solution is unique. It can be read off directly from the entries in rows 1 through \( n \) of column \( n + 1 \).
   (b) \( r < n \) and there are infinitely many solutions. If only a single solution is needed, set all the free variables to zero and read off the dependent variable values from column \( n + 1 \), as in the second half of the proof of \textbf{Theorem RCLS} \[53\]. If the entire solution set is required, figure out some nice compact way to describe it, since your finite computer is not big enough to hold all the solutions (we’ll have such a way soon).

The above makes it all sound a bit simpler than it really is. In practice, row operations employ division (usually to get a leading entry of a row to convert to a leading 1) and that will introduce round-off errors. Entries that should be zero sometimes end up being very, very small nonzero entries, or small entries lead to overflow errors when used as divisors. A variety of strategies can be employed to minimize these sorts of errors, and this is one of the main topics in the important subject known as numerical linear algebra.

Computation Note LS.MMA
Linear Solve  (Mathematica)
Mathematica will solve a linear system of equations using the \texttt{LinearSolve[]} command. The inputs are a matrix with the coefficients of the variables (but not the column of constants), and a list containing the constant terms of each equation. This will look a bit odd, since the lists in the matrix are rows, but the column of constants is also input
as a list and so looks like a row rather than a column. The result will be a single solution (even if there are infinitely many), reported as a list, or the statement that there is no solution. When there are infinitely many, the single solution reported is exactly that solution used in the proof of Theorem RCLS [53], where the free variables are all set to zero, and the dependent variables come along with values from the final column of the row-reduced matrix.

As an example, Archetype A [563] is

\[
\begin{align*}
    x_1 - x_2 + 2x_3 &= 1 \\ 
    2x_1 + x_2 + x_3 &= 8 \\ 
    x_1 + x_2 &= 5 
\end{align*}
\]

To ask Mathematica for a solution, enter

\[
\text{LinearSolve} \left[ \begin{array}{ccc}
    1 & -1 & 2 \\
    2 & 1 & 1 \\
    1 & 1 & 0
\end{array} \right], \begin{array}{c}
    1 \\
    8 \\
    5
\end{array} \right] 
\]

and you will get back the single solution

\[
\{3, 2, 0\}
\]

We will see later how to coax Mathematica into giving us infinitely many solutions for this system.

In this section we’ve gained a foolproof procedure for solving any system of linear equations, no matter how many equations or variables. We also have a handful of theorems that allow us to determine partial information about a solution set without actually constructing the whole set itself. Donald Knuth would be proud.

**Subsection READ**

**Reading Questions**

1. How do we recognize when a system of linear equations is inconsistent?

2. Suppose we have converted the augmented matrix of a system of equations into reduced row-echelon form. How do we then identify the dependent and independent (free) variables?

3. What are the possible solution sets for a system of linear equations?
C10 In the spirit of Example ISSI 50, describe the infinite solution set for Archetype J 604.

Contributed by Robert Beezer

M45 Prove that Archetype J 604 has infinitely many solutions *without* row-reducing the augmented matrix.

Contributed by Robert Beezer Solution 61

For Exercises M51–M54 say *as much as possible* about each system’s solution set. Be sure to make it clear which theorems you are using to reach your conclusions.

M51 A consistent system of 8 equations in 6 variables.

Contributed by Robert Beezer Solution 61

M52 A consistent system of 6 equations in 8 variables.

Contributed by Robert Beezer Solution 61

M54 A system with 12 equations in 35 variables.

Contributed by Robert Beezer Solution 61

M60 Without doing any computations, and without examining any solutions, say as much as possible about the form of the solution set for each archetype that is a system of equations.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577
Archetype E 581
Archetype F 585
Archetype G 590
Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer

T10 An inconsistent system may have \( r > n \). If we try (incorrectly!) to apply Theorem FVCS 55 to such a system, how many free variables would we discover?

Contributed by Robert Beezer Solution 61
Subsection SOL
Solutions

M45 Contributed by Robert Beezer Statement 59
Demonstrate that the system is consistent by verifying any one of the four sample solutions provided. Then because \( n = 9 > 6 = m \), Theorem CMVEI 56 gives us the conclusion that the system has infinitely many solutions.

Notice that we only know the system will have at least \( 9 - 6 = 3 \) free variables, but very well could have more. We do not know know that \( r = 6 \), only that \( r \leq 6 \).

M51 Contributed by Robert Beezer Statement 59
Consistent means there is at least one solution (Definition CS 49). It will have either a unique solution or infinitely many solutions (Theorem PSSLS 56).

M52 Contributed by Robert Beezer Statement 59
With 6 rows in the augmented matrix, the row-reduced version will have \( r \leq 6 \). Since the system is consistent, apply Theorem CSRN 54 to see that \( n - r \geq 2 \) implies infinitely many solutions.

M54 Contributed by Robert Beezer Statement 59
The system could be inconsistent. If it is consistent, then Theorem CMVEI 56 tells us the solution set will be infinite. So we can be certain that there is not a unique solution.

T10 Contributed by Robert Beezer Statement 59
Theorem FVCS 55 will indicate a negative number of free variables, but we can say even more. If \( r > n \), then the only possibility is that \( r = n + 1 \), and then we compute \( n - r = n - (n + 1) = -1 \) free variables.
Section HSE
Homogeneous Systems of Equations

In this section we specialize to systems of linear equations where every equation has a zero as its constant term. Along the way, we will begin to express more and more ideas in the language of matrices and begin a move away from writing out whole systems of equations. The ideas initiated in this section will carry through the remainder of the course.

Subsection SHS
Solutions of Homogeneous Systems

As usual, we begin with a definition.

Definition HS
Homogeneous System
A system of linear equations is \textit{homogeneous} if each equation has a 0 for its constant term. Such a system then has the form

\[
\begin{align*}
a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= 0 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= 0 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= 0 \\
\vdots \\
a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= 0
\end{align*}
\]

Example AHSAC
Archetype C as a homogeneous system
For each archetype that is a system of equations, we have formulated a similar, yet different, homogeneous system of equations by replacing each equation’s constant term with a zero. To wit, for \textbf{Archetype C} \[573\], we can convert the original system of equations into the homogeneous system,

\[
\begin{align*}
2x_1 - 3x_2 + x_3 - 6x_4 &= 0 \\
4x_1 + x_2 + 2x_3 + 9x_4 &= 0 \\
3x_1 + x_2 + x_3 + 8x_4 &= 0
\end{align*}
\]

Can you quickly find a solution to this system without row-reducing the augmented matrix? \(\oplus\)

As you might have discovered by studying \textbf{Example AHSAC} \[63\], setting each variable to zero will \textit{always} be a solution of a homogeneous system. This is the substance of the following theorem.
Theorem HSC
Homogeneous Systems are Consistent
Suppose that a system of linear equations is homogeneous. Then the system is consistent.

Proof Set each variable of the system to zero. When substituting these values into each equation, the left-hand side evaluates to zero, no matter what the coefficients are. Since a homogeneous system has zero on the right-hand side of each equation as the constant term, each equation is true. With one demonstrated solution, we can call the system consistent.

Since this solution is so obvious, we now define it as the trivial solution.

Definition TSHSE
Trivial Solution to Homogeneous Systems of Equations
Suppose a homogeneous system of linear equations has $n$ variables. The solution $x_1 = 0$, $x_2 = 0, \ldots, x_n = 0$ is called the trivial solution.

Here are three typical examples, which we will reference throughout this section. Work through the row operations as we bring each to reduced row-echelon form. Also notice what is similar in each example, and what differs.

Example HUSAB
Homogeneous, unique solution, Archetype B
Archetype B can be converted to the homogeneous system,

\[
-11x_1 + 2x_2 - 14x_3 = 0 \\
23x_1 - 6x_2 + 33x_3 = 0 \\
14x_1 - 2x_2 + 17x_3 = 0
\]

whose augmented matrix row-reduces to

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{bmatrix}
\]

By Theorem HSC, the system is consistent, and so the computation $n - r = 3 - 3 = 0$ means the solution set contains just a single solution. Then, this lone solution must be the trivial solution.

Example HISAA
Homogeneous, infinite solutions, Archetype A
Archetype A can be converted to the homogeneous system,

\[
x_1 - x_2 + 2x_3 = 0 \\
2x_1 + x_2 + x_3 = 0 \\
x_1 + x_2 = 0
\]

whose augmented matrix row-reduces to

\[
\begin{bmatrix}
1 & 0 & 1 & 0 \\
0 & 1 & -1 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]
By Theorem HSC [64], the system is consistent, and so the computation \( n - r = 3 - 2 = 1 \) means the solution set contains one free variable by Theorem FVCS [55], and hence has infinitely many solutions. We can describe this solution set using the free variable \( x_3 \),

\[
S = \{(x_1, x_2, x_3) | x_1 = -x_3, x_2 = x_3\} = \{(-x_3, x_3, x_3) | x_3 \in \mathbb{C}\}
\]

Geometrically, these are points in three dimensions that lie on a line through the origin. ⊙

**Example HISAD**

**Homogeneous, infinite solutions, Archetype D**

Archetype D [577] (and identically, Archetype E [581]) can be converted to the homogeneous system,

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 0 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= 0 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 0
\end{align*}
\]

whose augmented matrix row-reduces to

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

By Theorem HSC [64], the system is consistent, and so the computation \( n - r = 4 - 2 = 2 \) means the solution set contains two free variables by Theorem FVCS [55], and hence has infinitely many solutions. We can describe this solution set using the free variables \( x_3 \) and \( x_4 \),

\[
S = \{(x_1, x_2, x_3, x_4) | x_1 = -3x_3 + 2x_4, x_2 = -x_3 + 3x_4\} = \{(-3x_3 + 2x_4, -x_3 + 3x_4, x_3, x_4) | x_3, x_4 \in \mathbb{C}\}
\]

After working through these examples, you might perform the same computations for the slightly larger example, Archetype J [604].

Example HISAD [65] suggests the following theorem.

**Theorem HMVEI**

**Homogeneous, More Variables than Equations, Infinite solutions**

Suppose that a homogeneous system of linear equations has \( m \) equations and \( n \) variables with \( n > m \). Then the system has infinitely many solutions. □

**Proof** We are assuming the system is homogeneous, so Theorem HSC [64] says it is consistent. Then the hypothesis that \( n > m \), together with Theorem CMVEI [56], gives infinitely many solutions. ■

Example HUSAB [64] and Example HISAA [64] are concerned with homogeneous systems where \( n = m \) and expose a fundamental distinction between the two examples. One has a unique solution, while the other has infinitely many. These are exactly the only two possibilities for a homogeneous system and illustrate that each is possible (unlike the case when \( n > m \) where Theorem HMVEI [65] tells us that there is only one possibility for a homogeneous system).
Subsection MVNSE
Matrix and Vector Notation for Systems of Equations

Notice that when we do row operations on the augmented matrix of a homogeneous system of linear equations the last column of the matrix is all zeros. Any one of the three allowable row operations will convert zeros to zeros and thus, the final column of the matrix in reduced row-echelon form will also be all zeros. This observation might suffice as a first explanation of the reason for some of the following definitions.

Definition CV
Column Vector
A column vector of size $m$ is an ordered list of $m$ numbers, which is written vertically, in order starting at the top and proceeding to the bottom. At times, we will refer to a column vector as simply a vector.

Notation VN
Vector (u)
Column vectors will be written in bold, usually with lower case letters $u, v, w, x, y, z$. Some books like to write vectors with arrows, such as $\vec{u}$. Writing by hand, some like to put arrows on top of the symbol, or a tilde underneath the symbol, as in $\vec{u}$. To refer to entry $i$ of the vector $v$ we write $[v]_i$.

Definition ZV
Zero Vector
The zero vector of size $m$ is the column vector of size $m$ where each entry is the number zero,

$$0 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Notation ZVN
Zero Vector (0)
The zero vector will be written as $0$.

Definition CM
Coefficient Matrix
For a system of linear equations,

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n = b_1$$
$$a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n = b_2$$
$$a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n = b_3$$
$$\vdots$$
$$a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n = b_m$$
the **coefficient matrix** is the $m \times n$ matrix

$$A = \begin{bmatrix}
a_{11} & a_{12} & a_{13} & \ldots & a_{1n} \\
a_{21} & a_{22} & a_{23} & \ldots & a_{2n} \\
a_{31} & a_{32} & a_{33} & \ldots & a_{3n} \\
\vdots \\
a_{m1} & a_{m2} & a_{m3} & \ldots & a_{mn}
\end{bmatrix}$$

---

**Definition VOC**

**Vector of Constants**

For a system of linear equations,

\[
a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n = b_1 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n = b_2 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n = b_3 \\
\vdots \\
a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n = b_m
\]

the **vector of constants** is the column vector of size $m$

$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_m \end{bmatrix}$$

---

**Definition SV**

**Solution Vector**

For a system of linear equations,

\[
a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n = b_1 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n = b_2 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n = b_3 \\
\vdots \\
a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n = b_m
\]

the **solution vector** is the column vector of size $m$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_m \end{bmatrix}$$

The solution vector may do double-duty on occasion. It might refer to a list of variable quantities at one point, and subsequently refer to values of those variables that actually form a particular solution to that system.
**Notation LSN**
Linear System ($\mathcal{LS}(A, b)$)
If $A$ is the coefficient matrix of a system of linear equations and $b$ is the vector of constants, then we will write $\mathcal{LS}(A, b)$ as a shorthand expression for the system of linear equations.

**Notation AMN**
Augmented Matrix ($[A | b]$)
If $A$ is the coefficient matrix of a system of linear equations and $b$ is the vector of constants, then we will write the augmented matrix of the system as $[A | b]$.

**Example NSLE**
Notation for systems of linear equations
The system of linear equations
\[
\begin{align*}
2x_1 + 4x_2 - 3x_3 + 5x_4 + x_5 &= 9 \\
3x_1 + x_2 + x_4 - 3x_5 &= 0 \\
-2x_1 + 7x_2 - 5x_3 + 2x_4 + 2x_5 &= -3
\end{align*}
\]
has coefficient matrix
\[
A = \begin{bmatrix}
2 & 4 & -3 & 5 & 1 \\
3 & 1 & 0 & 1 & -3 \\
-2 & 7 & -5 & 2 & 2
\end{bmatrix}
\]
and vector of constants
\[
b = \begin{bmatrix}
9 \\
0 \\
-3
\end{bmatrix}
\]
and so will be referenced as $\mathcal{LS}(A, b)$.

With these definitions and notation a homogeneous system will be indicated by $\mathcal{LS}(A, 0)$. Its augmented matrix will be $[A | 0]$, which when converted to reduced row-echelon form will still have the final column of zeros. So in this case, we may be as likely to just reference only the coefficient matrix.

**Subsection NSM**
Null Space of a Matrix

The set of solutions to a homogeneous system (which by Theorem HSC 64 is never empty) is of enough interest to warrant its own name. However, we define it as a property of the coefficient matrix, not as a property of some system of equations.

**Definition NSM**
Null Space of a Matrix
The null space of a matrix $A$, denoted $\mathcal{N}(A)$, is the set of all the vectors that are solutions to the homogeneous system $\mathcal{LS}(A, 0)$.
In the Archetypes (Chapter A) each example that is a system of equations also has a corresponding homogeneous system of equations listed, and several sample solutions are given. These solutions will be elements of the null space of the coefficient matrix. We’ll look at one example.

Example NSEAI
Null space elements of Archetype I

The write-up for Archetype I lists several solutions of the corresponding homogeneous system. Here are two, written as solution vectors. We can say that they are in the null space of the coefficient matrix for the system of equations in Archetype I.

\[
\begin{pmatrix}
3 \\
0 \\
-5 \\
-6 \\
0 \\
0 \\
1
\end{pmatrix}
\quad \begin{pmatrix}
-4 \\
1 \\
-3 \\
-2 \\
1 \\
1 \\
1
\end{pmatrix}
\]

However, the vector

\[
\begin{pmatrix}
1 \\
0 \\
0 \\
0 \\
0 \\
0 \\
2
\end{pmatrix}
\]

is not in the null space, since it is not a solution to the homogeneous system. For example, it fails to even make the first equation true.

Here are two (prototypical) examples of the computation of the null space of a matrix. Notice that we will now begin writing solutions as vectors.

Example CNS1
Computing a null space, #1

Let’s compute the null space of

\[
A = \begin{bmatrix}
2 & -1 & 7 & -3 & -8 \\
1 & 0 & 2 & 4 & 9 \\
2 & 2 & -2 & -1 & 8
\end{bmatrix}
\]

which we write as \(\mathcal{N}(A)\). Translating Definition NSM, we simply desire to solve the homogeneous system \(\mathcal{L}\mathcal{S}(A, 0)\). So we row-reduce the augmented matrix to obtain

\[
\begin{bmatrix}
1 & 0 & 2 & 0 & 1 & 0 \\
0 & 1 & -3 & 0 & 4 & 0 \\
0 & 0 & 0 & 1 & 2 & 0
\end{bmatrix}
\]

The variables (of the homogeneous system) \(x_3\) and \(x_5\) are free (since columns 1, 2 and 5 are pivot columns), so we arrange the equations represented by the matrix in reduced...
row-echelon form to

\[
\begin{align*}
    x_1 &= -2x_3 - x_5 \\
    x_2 &= 3x_3 - 4x_5 \\
    x_4 &= -2x_5
\end{align*}
\]

So we can write the infinite solution set as sets using column vectors,

\[
\mathcal{N}(A) = \left\{ \begin{bmatrix} -2x_3 - x_5 \\ 3x_3 - 4x_5 \\ x_3 \\ -2x_5 \\ x_5 \end{bmatrix} \middle| x_3, x_5 \in \mathbb{C} \right\}
\]

Example CNS2
Computing a null space, #2
Let’s compute the null space of

\[
C = \begin{bmatrix}
-4 & 6 & 1 \\
-1 & 4 & 1 \\
5 & 6 & 7 \\
4 & 7 & 1
\end{bmatrix}
\]

which we write as \(\mathcal{N}(C)\). Translating Definition NSM [68], we simply desire to solve the homogeneous system \(\mathcal{L}S(C, 0)\). So we row-reduce the augmented matrix to obtain

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0
\end{bmatrix}
\]

There are no free variables in the homogenous system represented by the row-reduced matrix, so there is only the trivial solution, the zero vector, \(0\). So we can write the (trivial) solution set as

\[
\mathcal{N}(C) = \{0\} = \left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \right\}
\]

Subsection READ
Reading Questions

1. What is always true of the solution set for a homogenous system of equations?
2. Suppose a homogenous sytem of equations has 13 variables and 8 equations. How many solutions will it have? Why?
3. Describe in words (not symbols) the null space of a matrix.
Subsection EXC
Exercises

C10 Each archetype (Chapter A [559]) that is a system of equations has a corresponding homogeneous system with the same coefficient matrix. Compute the set of solutions for each. Notice that these solution sets are the null spaces of the coefficient matrices.

| Archetype A | 563 |
| Archetype B | 568 |
| Archetype C | 573 |
| Archetype D | 577 |
| Archetype E | 581 |
| Archetype F | 585 |
| Archetype G | 590 |
| Archetype H | 594 |
| Archetype I | 599 |
| Archetype J | 604 |

Contributed by Robert Beezer

C20 Archetype K [609] and Archetype L [613] are simply $5 \times 5$ matrices (i.e. they are not systems of equations). Compute the null space of each matrix.

Contributed by Robert Beezer

M45 Without doing any computations, and without examining any solutions, say as much as possible about the form of the solution set for corresponding homogeneous system of equations of each archetype that is a system of equations.

| Archetype A | 563 |
| Archetype B | 568 |
| Archetype C | 573 |
| Archetype D | 577 |
| Archetype E | 581 |
| Archetype F | 585 |
| Archetype G | 590 |
| Archetype H | 594 |
| Archetype I | 599 |
| Archetype J | 604 |

Contributed by Robert Beezer

For Exercises M50–M52 say as much as possible about each system’s solution set. Be sure to make it clear which theorems you are using to reach your conclusions.

M50 A homogeneous system of 8 equations in 8 variables.

Contributed by Robert Beezer Solution 73

M51 A homogeneous system of 8 equations in 9 variables.

Contributed by Robert Beezer

M52 A homogeneous system of 8 equations in 7 variables.

Contributed by Robert Beezer

T10 Prove or disprove: A system of linear equations is homogeneous if and only if the system has the zero vector as a solution.

Contributed by Martin Jackson Solution 73
Subsection SOL
Solutions

M50 Contributed by Robert Beezer Statement 71
Since the system is homogeneous, we know it has the trivial solution (Theorem HSC 64).
We cannot say anymore based on the information provided, except to say that there
is either a unique solution or infinitely many solutions (Theorem PSSLS 56). See
Archetype A 563 and Archetype B 568 to understand the possibilities.

T10 Contributed by Robert Beezer Statement 71
This is a true statement. A proof is:

(⇐) Suppose we have a homogeneous system $\mathcal{L}S(A, 0)$. Then by substituting the
scalar zero for each variable, we arrive at true statements for each equation. So the zero
vector is a solution. This is the content of Theorem HSC 64.

(⇒) Suppose now that we have a generic (i.e. not necessarily homogeneous) system
of equations, $\mathcal{L}S(A, b)$ that has the zero vector as a solution. Upon substituting this
solution into the system, we discover that each component of $b$ must be also zero. So
$b = 0$. 
Section NSM
NonSingular Matrices

In this section we specialize and consider matrices with equal numbers of rows and columns, which when considered as coefficient matrices lead to systems with equal numbers of equations and variables. We will see in the second half of the course (Chapter D 361, Chapter E 373, Chapter LT 429, Chapter R 505) that these matrices are especially important.

Subsection NSM
NonSingular Matrices

Our theorems will now establish connections between systems of equations (homogeneous or otherwise), augmented matrices representing those systems, coefficient matrices, constant vectors, the reduced row-echelon form of matrices (augmented and coefficient) and solution sets. Be very careful in your reading, writing and speaking about systems of equations, matrices and sets of vectors. A system of equations is not a matrix, a matrix is not a solution set, and a solution set is not a system of equations. Now would be a good time to review the discussion about speaking and writing mathematics in Technique L 22.

Definition SQM
Square Matrix
A matrix with $m$ rows and $n$ columns is square if $m = n$. In this case, we say the matrix has size $n$. To emphasize the situation when a matrix is not square, we will call it rectangular.

We can now present one of the central definitions of linear algebra.

Definition NM
Nonsingular Matrix
Suppose $A$ is a square matrix. Suppose further that the solution set to the homogeneous linear system of equations $LS(A, 0)$ is $\{0\}$, i.e. the system has only the trivial solution. Then we say that $A$ is a nonsingular matrix. Otherwise we say $A$ is a singular matrix. △

We can investigate whether any square matrix is nonsingular or not, no matter if the matrix is derived somehow from a system of equations or if it is simply a matrix. The definition says that to perform this investigation we must construct a very specific system of equations (homogenous, with the matrix as the coefficient matrix) and look at its solution set. We will have theorems in this section that connect nonsingular matrices with systems of equations, creating more opportunities for confusion. Convince yourself now of two observations, (1) we can decide nonsingularity for any square matrix, and (2) the determination of nonsingularity involves the solution set for a certain homogenous system of equations.
Notice that it makes no sense to call a system of equations nonsingular (the term does not apply to a system of equations), nor does it make any sense to call a $5 \times 7$ matrix singular (the matrix is not square).

**Example S**  
**A singular matrix, Archetype A**  
Example [HISAA](#) shows that the coefficient matrix derived from [Archetype A](#), specifically the $3 \times 3$ matrix,

$$A = \begin{bmatrix} 1 & -1 & 2 \\ 2 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

is a singular matrix since there are nontrivial solutions to the homogeneous system $\mathcal{L}S(A, 0)$.

**Example NS**  
**A nonsingular matrix, Archetype B**  
Example [HUSAB](#) shows that the coefficient matrix derived from [Archetype B](#), specifically the $3 \times 3$ matrix,

$$B = \begin{bmatrix} -7 & -6 & -12 \\ 5 & 5 & 7 \\ 1 & 0 & 4 \end{bmatrix}$$

is a nonsingular matrix since the homogeneous system, $\mathcal{L}S(B, 0)$, has only the trivial solution.

Notice that we will not discuss [Example HISAD](#) as being a singular or nonsingular coefficient matrix since the matrix is not square.

The next theorem combines with our main computational technique (row-reducing a matrix) to make it easy to recognize a nonsingular matrix. But first a definition.

**Definition IM**  
**Identity Matrix**  
The $m \times m$ **identity matrix**, $I_m$ is defined by

$$[I_m]_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

**Example IM**  
**An identity matrix**  
The $4 \times 4$ identity matrix is

$$I_4 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Notice that an identity matrix is square, and in reduced row-echelon form. So in particular, if we were to arrive at the identity matrix while bringing a matrix to reduced row-echelon form, then it would have all of the diagonal entries circled as leading 1’s.
Theorem NSRRI
NonSingular matrices Row Reduce to the Identity matrix
Suppose that $A$ is a square matrix and $B$ is a row-equivalent matrix in reduced row-echelon form. Then $A$ is nonsingular if and only if $B$ is the identity matrix. □

Proof ($\iff$) Suppose $B$ is the identity matrix. When the augmented matrix $[A | 0]$ is row-reduced, the result is $[B | 0] = [I_n | 0]$. The number of nonzero rows is equal to the number of variables in the linear system of equations $\mathcal{L}(A, 0)$, so $n = r$ and Theorem FVCS [55] gives $n - r = 0$ free variables. Thus, the homogeneous system $\mathcal{L}(A, 0)$ has just one solution, which must be the trivial solution. This is exactly the definition of a nonsingular matrix.

($\Rightarrow$) If $A$ is nonsingular, then the homogeneous system $\mathcal{L}(A, 0)$ has a unique solution, and has no free variables in the description of the solution set. The homogeneous system is consistent (Theorem HSC [64]) so Theorem FVCS [55] applies and tells us there are $n - r$ free variables. Thus, $n - r = 0$, and so $n = r$. So $B$ has $n$ pivot columns among its total of $n$ columns. This is enough to force $B$ to be the $n \times n$ identity matrix $I_n$. ■

Notice that since this theorem is an equivalence it will always allow us to determine if a matrix is either nonsingular or singular. Here are two examples of this, continuing our study of Archetype A and Archetype B.

Example SRR
Singular matrix, row-reduced
The coefficient matrix for Archetype A [563] is

$$A = \begin{bmatrix} 1 & -1 & 2 \\ 2 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

which when row-reduced becomes the row-equivalent matrix

$$B = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix}.$$ 

Since this matrix is not the $3 \times 3$ identity matrix, Theorem NSRRI [77] tells us that $A$ is a singular matrix. ⊗

Example NSRR
NonSingular matrix, row-reduced
The coefficient matrix for Archetype B [568] is

$$A = \begin{bmatrix} -7 & -6 & -12 \\ 5 & 5 & 7 \\ 1 & 0 & 4 \end{bmatrix}$$

which when row-reduced becomes the row-equivalent matrix

$$B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$ 

Since this matrix is the $3 \times 3$ identity matrix, Theorem NSRRI [77] tells us that $A$ is a nonsingular matrix. ⊗
Example NSS
Null space of a singular matrix
Given the coefficient matrix from Archetype A [563],
\[
A = \begin{bmatrix}
1 & -1 & 2 \\
2 & 1 & 1 \\
1 & 1 & 0
\end{bmatrix}
\]
the null space is the set of solutions to the homogeneous system of equations \(\mathcal{L}S(A, 0)\) has a solution set and null space constructed in Example HISAA [64] as
\[
\mathcal{N}(A) = \left\{ \begin{bmatrix}
-x_3 \\
x_3 \\
x_3
\end{bmatrix} \bigg| x_3 \in \mathbb{C} \right\}
\]

Example NSNS
Null space of a nonsingular matrix
Given the coefficient matrix from Archetype B [568],
\[
A = \begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{bmatrix}
\]
the homogeneous system \(\mathcal{L}S(A, 0)\) has a solution set constructed in Example HUSAB [64] that contains only the trivial solution, so the null space has only a single element,
\[
\mathcal{N}(A) = \left\{ \begin{bmatrix}
0 \\
0 \\
0
\end{bmatrix} \right\}
\]

These two examples illustrate the next theorem, which is another equivalence.

Theorem NSTNS
NonSingular matrices have Trivial Null Spaces
Suppose that \(A\) is a square matrix. Then \(A\) is nonsingular if and only if the null space of \(A\), \(\mathcal{N}(A)\), contains only the zero vector, i.e. \(\mathcal{N}(A) = \{0\}\). □

Proof The null space of a square matrix, \(A\), is equal to the set of solutions to the homogeneous system, \(\mathcal{L}S(A, 0)\). A matrix is nonsingular if and only if the set of solutions to the homogeneous system, \(\mathcal{L}S(A, 0)\), has only a trivial solution. These two observations may be chained together to construct the two proofs necessary for each of half of this theorem.

Proof Technique U
Uniqueness
A theorem will sometimes claim that some object, having some desirable property, is unique. In other words, there should be only one such object. To prove this, a standard technique is to assume there are two such objects and proceed to analyze the consequences. The end result may be a contradiction, or the conclusion that the two allegedly different objects really are equal.
The next theorem pulls a lot of ideas together. It tells us that we can learn a lot about solutions to a system of linear equations with a square coefficient matrix by examining a similar homogeneous system.

**Theorem NSMUS**

**NonSingular Matrices and Unique Solutions**

Suppose that $A$ is a square matrix. $A$ is a nonsingular matrix if and only if the system $\mathcal{L}S(A, b)$ has a unique solution for every choice of the constant vector $b$. □

**Proof** ($\iff$) The hypothesis for this half of the proof is that the system $\mathcal{L}S(A, b)$ has a unique solution for every choice of the constant vector $b$. We will make a very specific choice for $b$: $b = 0$. Then we know that the system $\mathcal{L}S(A, 0)$ has a unique solution. But this is precisely the definition of what it means for $A$ to be nonsingular (Definition NM [75]). That almost seems too easy! Notice that we have not used the full power of our hypothesis, but there is nothing that says we must use a hypothesis to its fullest.

If the first half of the proof seemed easy, perhaps we’ll have to work a bit harder to get the implication in the opposite direction. We provide two different proofs for the second half. The first is suggested by Asa Scherer and relies on the uniqueness of the reduced row-echelon form of a matrix (Theorem RREFU [112]), a result that we could have proven earlier, but we have decided to delay until later. The second proof is lengthier and more involved, but does not rely on the uniqueness of the reduced row-echelon form of a matrix, a result we have not proven yet. It is also a good example of the types of proofs we will encounter throughout the course.

($\implies$, Round 1) We assume that $A$ is nonsingular, so we know there is a sequence of row operations that will convert $A$ into the identity matrix $I_n$ (Theorem NSRRI [77]). Form the augmented matrix $A’ = [A | b]$ and apply this same sequence of row operations to $A’$. The result will be the matrix $B’ = [I_n | c]$, which is in reduced row-echelon form. It should be clear that $c$ is a solution to $\mathcal{L}S(A, b)$. Furthermore, since $B’$ is unique (Theorem RREFU [112]), the vector $c$ must be unique, and therefore is a unique solution of $\mathcal{L}S(A, b)$.

($\implies$, Round 2) We will assume $A$ is nonsingular, and try to solve the system $\mathcal{L}S(A, b)$ without making any assumptions about $b$. To do this we will begin by constructing a new homogeneous linear system of equations that looks very much like the original. Suppose $A$ has size $n$ (why must it be square?) and write the original system as,

\[
\begin{align*}
a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
\vdots \\
a_{n1}x_1 + a_{n2}x_2 + a_{n3}x_3 + \cdots + a_{nn}x_n &= b_n
\end{align*}
\]

form the new, homogeneous system in $n$ equations with $n + 1$ variables, by adding a new
variable \( y \), whose coefficients are the negatives of the constant terms,
\[
\begin{align*}
  a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n - b_1y &= 0 \\
  a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n - b_2y &= 0 \\
  a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n - b_3y &= 0 \\
  &\vdots \\
  a_{n1}x_1 + a_{n2}x_2 + a_{n3}x_3 + \cdots + a_{nn}x_n - b_ny &= 0
\end{align*}
\]

Since this is a homogeneous system with more variables than equations \((m = n + 1 > n)\), Theorem HMVEI\footnote{HMVEI} says that the system has infinitely many solutions. We will choose one of these solutions, \textit{any} one of these solutions, so long as it is \textit{not} the trivial solution. Write this solution as
\[
x_1 = c_1 \quad x_2 = c_2 \quad x_3 = c_3 \quad \cdots \quad x_n = c_n \quad y = c_{n+1}
\]

We know that at least one value of the \( c_i \) is nonzero, but we will now show that in particular \( c_{n+1} \neq 0 \). We do this using a proof by contradiction. So suppose the \( c_i \) form a solution as described, and in addition that \( c_{n+1} = 0 \). Then we can write the \( i \)-th equation of system (**) as,
\[
a_{i1}c_1 + a_{i2}c_2 + a_{i3}c_3 + \cdots + a_{in}c_n - b_i(0) = 0
\]

which becomes
\[
a_{i1}c_1 + a_{i2}c_2 + a_{i3}c_3 + \cdots + a_{in}c_n = 0
\]

Since this is true for each \( i \), we have that \( x_1 = c_1, x_2 = c_2, x_3 = c_3, \ldots, x_n = c_n \) is a solution to the homogeneous system \( LS(A, 0) \) formed with a nonsingular coefficient matrix. This means that the only possible solution is the trivial solution, so \( c_1 = 0, c_2 = 0, c_3 = 0, \ldots, c_n = 0 \). So, assuming simply that \( c_{n+1} = 0 \), we conclude that \textit{all} of the \( c_i \) are zero. But this contradicts our choice of the \( c_i \) as not being the trivial solution to the system (**). So \( c_{n+1} \neq 0 \).

We now propose and verify a solution to the original system (*). Set
\[
x_1 = \frac{c_1}{c_{n+1}} \quad x_2 = \frac{c_2}{c_{n+1}} \quad x_3 = \frac{c_3}{c_{n+1}} \quad \cdots \quad x_n = \frac{c_n}{c_{n+1}}
\]

Notice how it was necessary that we know that \( c_{n+1} \neq 0 \) for this step to succeed. Now, evaluate the \( i \)-th equation of system (*) with this proposed solution, and recognize in the third line that \( c_1 \) through \( c_{n+1} \) appear as if they were substituted into the left-hand side of the \( i \)-th equation of system (**),
\[
a_{i1} \frac{c_1}{c_{n+1}} + a_{i2} \frac{c_2}{c_{n+1}} + a_{i3} \frac{c_3}{c_{n+1}} + \cdots + a_{in} \frac{c_n}{c_{n+1}} = \frac{1}{c_{n+1}} (a_{i1}c_1 + a_{i2}c_2 + a_{i3}c_3 + \cdots + a_{in}c_n)
\]
\[
= \frac{1}{c_{n+1}} (a_{i1}c_1 + a_{i2}c_2 + a_{i3}c_3 + \cdots + a_{in}c_n - b_i(c_{n+1}) + b_i
\]
\[
= \frac{1}{c_{n+1}} (0) + b_i
\]
\[
= b_i
\]
Since this equation is true for every \( i \), we have found a solution to system (\( \ast \)). To finish, we still need to establish that this solution is unique.

With one solution in hand, we will entertain the possibility of a second solution. So assume system (\( \ast \)) has two solutions,

\[
\begin{align*}
    x_1 &= d_1, & x_2 &= d_2, & x_3 &= d_3, & \ldots & x_n &= d_n, \\
    x_1 &= e_1, & x_2 &= e_2, & x_3 &= e_3, & \ldots & x_n &= e_n.
\end{align*}
\]

Then,

\[
\begin{align*}
    (a_{i1}(d_1 - e_1) + a_{i2}(d_2 - e_2) + a_{i3}(d_3 - e_3) + \cdots + a_{in}(d_n - e_n)) \\
    = (a_{i1}d_1 + a_{i2}d_2 + a_{i3}d_3 + \cdots + a_{in}d_n) - (a_{i1}e_1 + a_{i2}e_2 + a_{i3}e_3 + \cdots + a_{in}e_n) \\
    = b_i - b_i \\
    = 0.
\end{align*}
\]

This is the \( i \)-th equation of the homogeneous system \( L\!S(A, \mathbf{0}) \) evaluated with \( x_j = d_j - e_j \), \( 1 \leq j \leq n \). Since \( A \) is nonsingular, we must conclude that this solution is the trivial solution, and so \( 0 = d_j - e_j \), \( 1 \leq j \leq n \). That is, \( d_j = e_j \) for all \( j \) and the two solutions are identical, meaning any solution to (\( \ast \)) is unique. \( \blacksquare \)

This important theorem deserves several comments. First, notice that the proposed solution (\( x_i = \frac{c_i}{c_{n+1}} \)) appeared in the Round 2 proof with no motivation whatsoever. This is just fine in a proof. A proof should convince you that a theorem is true. It is your job to read the proof and be convinced of every assertion. Questions like “Where did that come from?” or “How would I think of that?” have no bearing on the validity of the proof.

Second, this theorem helps to explain part of our interest in nonsingular matrices. If a matrix is nonsingular, then no matter what vector of constants we pair it with, using the matrix as the coefficient matrix will always yield a linear system of equations with a solution, and the solution is unique. To determine if a matrix has this property (nonsingularity) it is enough to just solve one linear system, the homogeneous system with the matrix as coefficient matrix and the zero vector as the vector of constants (or any other vector of constants, see Exercise MM.T10 \( \text{[203]} \)).

Finally, formulating the negation of the second part of this theorem is a good exercise. A singular matrix has the property that for some value of the vector \( \mathbf{b} \), the system \( L\!S(A, \mathbf{b}) \) does not have a unique solution (which means that it has no solution or infinitely many solutions). We will be able to say more about this case later (see the discussion following Theorem PSPHS \( \text{[199]} \)).

**Proof Technique ME**

**Multiple Equivalences**

A very specialized form of a theorem begins with the statement “The following are equivalent…” and then follows a list of statements. Informally, this lead-in sometimes gets abbreviated by “TFAE.” This formulation means that any two of the statements on the list can be connected with an “if and only if” to form a theorem. So if the list has \( n \) statements then there are \( \frac{n(n-1)}{2} \) possible equivalences that can be constructed (and are claimed to be true).

Suppose a theorem of this form has statements denoted as \( A, B, C, \ldots Z \). To prove the entire theorem, we can prove \( A \Rightarrow B, B \Rightarrow C, C \Rightarrow D, \ldots, Y \Rightarrow Z \) and finally,
Z ⇒ A. This circular chain of $n$ equivalences would allow us, logically, if not practically, to form any one of the $\frac{n(n-1)}{2}$ possible equivalences by chasing the equivalences around the circle as far as required.

Square matrices that are nonsingular have a long list of interesting properties, which we will start to catalog in the following, recurring, theorem. Of course, singular matrices will then have all of the opposite properties.

**Theorem NSME1**  
**NonSingular Matrix Equivalences, Round 1**  
Suppose that $A$ is a square matrix. The following are equivalent.

1. $A$ is nonsingular.
2. $A$ row-reduces to the identity matrix.
3. The null space of $A$ contains only the zero vector, $N(A) = \{0\}$.
4. The linear system $LS(A, b)$ has a unique solution for every possible choice of $b$. □

**Proof** That $A$ is nonsingular is equivalent to each of the subsequent statements by, in turn, Theorem NSRRI \[77\], Theorem NSTNS \[78\] and Theorem NSMUS \[79\]. So the statement of this theorem is just a convenient way to organize all these results. ■

**Subsection READ**  
**Reading Questions**

1. What is the definition of a nonsingular matrix?
2. What is the easiest way to recognize a nonsingular matrix?
3. Suppose we have a system of equations and its coefficient matrix is nonsingular. What can you say about the solution set for this system?
Subsection EXC
Exercises

C30  Is the matrix below singular or nonsingular? Why?

\[
\begin{bmatrix}
-3 & 1 & 2 & 8 \\
2 & 0 & 3 & 4 \\
1 & 2 & 7 & -4 \\
5 & -1 & 2 & 0 \\
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution 85

C31  Is the matrix below singular or nonsingular? Why?

\[
\begin{bmatrix}
2 & 3 & 1 & 4 \\
1 & 1 & 1 & 0 \\
-1 & 2 & 3 & 5 \\
1 & 2 & 1 & 3 \\
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution 85

C32  Is the matrix below singular or nonsingular? Why?

\[
\begin{bmatrix}
9 & 3 & 2 & 4 \\
5 & -6 & 1 & 3 \\
4 & 1 & 3 & -5 \\
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution 85

C40  Each of the archetypes below is a system of equations with a square coefficient matrix, or is itself a square matrix. Determine if these matrices are nonsingular, or singular. Comment on the null space of each matrix.

Archetype A 563
Archetype B 568
Archetype F 585
Archetype K 609
Archetype L 613

Contributed by Robert Beezer

For Exercises M51–M51 say as much as possible about each system's solution set. Be sure to make it clear which theorems you are using to reach your conclusions.

M51  6 equations in 6 variables, singular coefficient matrix.

Contributed by Robert Beezer  Solution 85
Subsection SOL

Solutions

C30 Contributed by Robert Beezer Statement S3
The matrix row-reduces to
\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]
which is the $4 \times 4$ identity matrix. By Theorem NSRRI the original matrix must be nonsingular.

C31 Contributed by Robert Beezer Statement S3
Row-reducing the matrix yields,
\[
\begin{bmatrix}
1 & 0 & 0 & -2 \\
0 & 1 & 0 & 3 \\
0 & 0 & 1 & -1 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]
Since this is not the $4 \times 4$ identity matrix, Theorem NSRRI tells us the matrix is singular.

C32 Contributed by Robert Beezer Statement S3
The matrix is not square, so neither term is applicable. See Definition NM, which is stated for just square matrices.

M51 Contributed by Robert Beezer Statement S3
Theorem NSRRI tells us that the coefficient matrix will not row-reduce to the identity matrix. So if were to row-reduce the augmented matrix of this system of equations, we would not get a unique solution. So by Theorem PSSLS there remaining possibilities are no solutions, or infinitely many.
V: Vectors

Section VO
Vector Operations

We have worked extensively in the last chapter with matrices, and some with vectors. In this chapter we will develop the properties of vectors, while preparing to study vector spaces. Initially we will depart from our study of systems of linear equations, but in Section LC [99] we will forge a connection between linear combinations and systems of linear combinations in Theorem SLSLC [103]. This connection will allow us to understand systems of linear equations at a higher level, while consequently discussing them less frequently.

In the current section we define some new operations involving vectors, and collect some basic properties of these operations. Begin by recalling our definition of a column vector as a matrix with just one column (Definition CV [66]). The collection of all possible vectors of a fixed size is a commonly used set, so we start with its definition.

Definition VSCV
Vector Space of Column Vectors
The vector space \( \mathbb{C}^m \) is the set of all column vectors (Definition CV [66]) of size \( m \) with entries from the set of complex numbers, \( \mathbb{C} \).

When this set is defined using only entries from the real numbers, it is written as \( \mathbb{R}^m \) and is known as Euclidean \( m \)-space.

The term “vector” is used in a variety of different ways. We have defined it as a matrix with a single column. It could simply be an ordered list of numbers, and written like \((2, 3, -1, 6)\). Or it could be interpreted as a point in \( m \) dimensions, such as \((3, 4, -2)\) representing a point in three dimensions relative to \( x, y \) and \( z \) axes. With an interpretation as a point, we can construct an arrow from the origin to the point which is consistent with the notion that a vector has direction and magnitude.

All of these ideas can be shown to be related and equivalent, so keep that in mind as you connect the ideas of this course with ideas from other disciplines. For now, we’ll stick with the idea that a vector is a just a list of numbers, in some particular order.
We start our study of this set by first defining what it means for two vectors to be the same.

**Definition CVE**

Column Vector Equality

The vectors

\[
\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \quad \text{and} \quad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}
\]

are **equal**, written \( \mathbf{u} = \mathbf{v} \) provided that \( u_i = v_i \) for all \( 1 \leq i \leq m \).

Now this may seem like a silly (or even stupid) thing to say so carefully. Of course two vectors are equal if they are equal for each corresponding entry! Well, this is not as silly as it appears. We will see a few occasions later where the obvious definition is *not* the right one. And besides, in doing mathematics we need to be very careful about making all the necessary definitions and making them unambiguous. And we’ve done that here.

Notice now that the symbol ‘\( = \)’ is now doing triple-duty. We know from our earlier education what it means for two numbers (real or complex) to be equal, and we take this for granted. Earlier, in **Technique SE** [17] we discussed at some length what it meant for two sets to be equal. Now we have defined what it means for two vectors to be equal, and that definition builds on our definition for when two numbers are equal when we use the condition \( u_i = v_i \) for all \( 1 \leq i \leq m \). So think carefully about your objects when you see an equal sign and think about just which notion of equality you have encountered. This will be especially important when you are asked to construct proofs whose conclusion states that two objects are equal.

OK, let’s do an example of vector equality that begins to hint at the utility of this definition.

**Example VESE**

Vector equality for a system of equations

Consider the system of linear equations in **Archetype B** [568],

\[
\begin{align*}
-7x_1 - 6x_2 - 12x_3 &= -33 \\
5x_1 + 5x_2 + 7x_3 &= 24 \\
x_1 + 4x_3 &= 5
\end{align*}
\]

Note the use of three equals signs — each indicates an equality of numbers (the linear expressions are numbers when we evaluate them with fixed values of the variable quantities). Now write the vector equality,

\[
\begin{bmatrix}
-7x_1 - 6x_2 - 12x_3 \\
5x_1 + 5x_2 + 7x_3 \\
x_1 + 4x_3
\end{bmatrix} =
\begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}.
\]
By [Definition CVE][88], this single equality (of two column vectors) translates into three simultaneous equalities of numbers that form the system of equations. So with this new notion of vector equality we can become less reliant on referring to systems of simultaneous equations. There’s more to vector equality than just this, but this is a good example for starters and we will develop it further.

We will now define two operations on the set $\mathbb{C}^m$. By this we mean well-defined procedures that somehow convert vectors into other vectors. Here are two of the most basic definitions of the entire course.

**Definition CVA**

**Column Vector Addition**

Given the vectors

\[ u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \quad v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix} \]

the sum of $u$ and $v$ is the vector

\[ u + v = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} u_1 + v_1 \\ u_2 + v_2 \\ u_3 + v_3 \\ \vdots \\ u_m + v_m \end{bmatrix}. \]

So vector addition takes two vectors of the same size and combines them (in a natural way!) to create a new vector of the same size. Notice that this definition is required, even if we agree that this is the obvious, right, natural or correct way to do it. Notice too that the symbol ‘$+$’ is being recycled. We all know how to add numbers, but now we have the same symbol extended to double-duty and we use it to indicate how to add two new objects, vectors. And this definition of our new meaning is built on our previous meaning of addition via the expressions $u_i + v_i$. Think about your objects, especially when doing proofs. Vector addition is easy, here’s an example from $\mathbb{C}^4$.

**Example VA**

**Addition of two vectors in $\mathbb{C}^4$**

If

\[ u = \begin{bmatrix} 2 \\ -3 \\ 4 \\ 2 \end{bmatrix} \quad v = \begin{bmatrix} -1 \\ 5 \\ 2 \\ -7 \end{bmatrix} \]

then

\[ u + v = \begin{bmatrix} 2 \\ -3 \\ 4 \\ 2 \end{bmatrix} + \begin{bmatrix} -1 \\ 5 \\ 2 \\ -7 \end{bmatrix} = \begin{bmatrix} 2 + (-1) \\ -3 + 5 \\ 4 + 2 \\ 2 + (-7) \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 6 \\ -5 \end{bmatrix}. \]
Our second operation takes two objects of different types, specifically a number and a vector, and combines them to create another vector. In this context we call a number a scalar in order to emphasize that it is not a vector.

**Definition CVSM**
Column Vector Scalar Multiplication
Given the vector

\[
\mathbf{u} = \begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
\vdots \\
u_m
\end{bmatrix}
\]

and the scalar \( \alpha \in \mathbb{C} \), the scalar multiple of \( \mathbf{u} \) by \( \alpha \) is

\[
\alpha \mathbf{u} = \alpha \begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
\vdots \\
u_m
\end{bmatrix} = \begin{bmatrix}
\alpha u_1 \\
\alpha u_2 \\
\alpha u_3 \\
\vdots \\
\alpha u_m
\end{bmatrix}.
\]

Notice that we are doing a kind of multiplication here, but we are defining a new type, perhaps in what appears to be a natural way. We use juxtaposition (smashing two symbols together side-by-side) to denote this operation rather than using a symbol like we did with vector addition. So this can be another source of confusion. When two symbols are next to each other, are we doing regular old multiplication, the kind we’ve done for years, or are we doing scalar vector multiplication, the operation we just defined? Think about your objects — if the first object is a scalar, and the second is a vector, then it must be that we are doing our new operation, and the result of this operation will be another vector.

Notice how consistency in notation can be an aid here. If we write scalars as lower case Greek letters from the start of the alphabet (such as \( \alpha, \beta, \ldots \)) and write vectors in bold Latin letters from the end of the alphabet (\( \mathbf{u}, \mathbf{v}, \ldots \)), then we have some hints about what type of objects we are working with. This can be a blessing and a curse, since when we go read another book about linear algebra, or read an application in another discipline (physics, economics, \ldots) the types of notation employed may be very different and hence unfamiliar.

Again, computationally, vector scalar multiplication is very easy.

**Example CVSM**
Scalar multiplication in \( \mathbb{C}^5 \)
If

\[
\mathbf{u} = \begin{bmatrix}3 \\1 \\ -2 \\ 4 \\ -1\end{bmatrix}
\]
and $\alpha = 6$, then

$$\alpha \mathbf{u} = 6 \begin{bmatrix} 3 \\ 1 \\ -2 \\ 4 \\ -1 \end{bmatrix} = 6 \begin{bmatrix} 6(3) \\ 6(1) \\ 6(-2) \\ 6(4) \\ 6(-1) \end{bmatrix} = \begin{bmatrix} 18 \\ 6 \\ -12 \\ 24 \\ -6 \end{bmatrix}.$$

It is usually straightforward to effect these computations with a calculator or program.

**Computation Note VLC.MMA**

**Vector Linear Combinations (Mathematica)**

Contributed by Robert Beezer

Vectors in *Mathematica* are represented as lists, written and displayed horizontally. For example, the vector

$$\mathbf{v} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

would be entered and named via the command

$$\mathbf{v} = \{1, 2, 3, 4\}$$

Vector addition and scalar multiplication are then very natural. If $\mathbf{u}$ and $\mathbf{v}$ are two lists of equal length, then

$$2\mathbf{u} + (-3)\mathbf{v}$$

will compute the correct vector and return it as a list. If $\mathbf{u}$ and $\mathbf{v}$ have different sizes, then *Mathematica* will complain about “objects of unequal length.”

**Computation Note VLC.TI86**

**Vector Linear Combinations (TI-86)**

Contributed by Robert Beezer

Vector operations on the TI-86 can be accessed via the *VECTR* key, which is *Yellow-8*. The *EDIT* tool appears when the *F2* key is pressed. After providing a name and giving a “dimension” (the size) then you can enter the individual entries, one at a time. Vectors can also be entered on the home screen using brackets (*[]*). To create the vector

$$\mathbf{v} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

use brackets and the store key (*STO*),

$$[1, 2, 3, 4] \rightarrow \mathbf{v}$$

Vector addition and scalar multiplication are then very natural. If $\mathbf{u}$ and $\mathbf{v}$ are two vectors of equal size, then

$$2 \mathbf{u} + (-3) \mathbf{v}$$

will compute the correct vector and display the result as a vector.
Computation Note VLC.TI83
Vector Linear Combinations (TI-83)
Contributed by Douglas Phelps
Entering a vector on the TI-83 is the same process as entering a matrix. You press 4 ENTER 3 ENTER for a $4 \times 3$ matrix. Likewise, you press 4 ENTER 1 ENTER for a vector of size 4. To multiply a vector by 8, press the number 8, then press the MATRX key, then scroll down to the letter you named your vector (A, B, C, etc) and press ENTER.

To add vectors $A$ and $B$ for example, press the MATRX key, then ENTER. Then press the + key. Then press the MATRX key, then the down arrow once, then ENTER. $[A] + [B]$ will appear on the screen. Press ENTER.

Subsection VSP
Vector Space Properties

With definitions of vector addition and scalar multiplication we can state, and prove, several properties of each operation, and some properties that involve their interplay. We now collect ten of them here for later reference.

Theorem VSPCV
Vector Space Properties of Column Vectors
Suppose that $\mathbb{C}^m$ is the set of column vectors of size $m$ (Definition VSCV 87) with addition and scalar multiplication as defined in Definition CVA 89 and Definition CVSM 90. Then

- **ACC** Additive Closure, Column Vectors
  If $u, v \in \mathbb{C}^m$, then $u + v \in \mathbb{C}^m$.

- **SCC** Scalar Closure, Column Vectors
  If $\alpha \in \mathbb{C}$ and $u \in \mathbb{C}^m$, then $\alpha u \in \mathbb{C}^m$.

- **CC** Commutativity, Column Vectors
  If $u, v \in \mathbb{C}^m$, then $u + v = v + u$.

- **AAC** Additive Associativity, Column Vectors
  If $u, v, w \in \mathbb{C}^m$, then $u + (v + w) = (u + v) + w$.

- **ZC** Zero Vector, Column Vectors
  There is a vector, 0, called the **zero vector**, such that $u + 0 = u$ for all $u \in \mathbb{C}^m$.

- **AIC** Additive Inverses, Column Vectors
  If $u \in \mathbb{C}^m$, then there exists a vector $-u \in \mathbb{C}^m$ so that $u + (-u) = 0$.

- **SMAC** Scalar Multiplication Associativity, Column Vectors
  If $\alpha, \beta \in \mathbb{C}$ and $u \in \mathbb{C}^m$, then $\alpha(\beta u) = (\alpha\beta)u$.

- **DVAC** Distributivity across Vector Addition, Column Vectors
  If $\alpha \in \mathbb{C}$ and $u, v \in \mathbb{C}^m$, then $\alpha(u + v) = \alpha u + \alpha v$.

- **DSAC** Distributivity across Scalar Addition, Column Vectors
  If $\alpha, \beta \in \mathbb{C}$ and $u \in \mathbb{C}^m$, then $(\alpha + \beta)u = \alpha u + \beta u$. 

Version 0.52
OC One, Column Vectors
If \( u \in \mathbb{C}^m \), then \( 1u = u \).

Proof While some of these properties seem very obvious, they all require proof. However, the proofs are not very interesting, and border on tedious. We’ll prove one version of distributivity very carefully, and you can test your proof-building skills on some of the others. We need to establish an equality, so we will do so by beginning with one side of the equality, apply various definitions and theorems (listed to the left of each step) to massage the expression from the left into the expression on the right. Now would be a good time to read Technique [??], just below. Here we go,

\[
(\alpha + \beta)u = (\alpha + \beta) \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} = \begin{bmatrix} (\alpha + \beta)u_1 \\ (\alpha + \beta)u_2 \\ (\alpha + \beta)u_3 \\ \vdots \\ (\alpha + \beta)u_m \end{bmatrix} \quad \text{Definition CVSM [90]}
\]

\[
= \begin{bmatrix} \alpha u_1 + \beta u_1 \\ \alpha u_2 + \beta u_2 \\ \alpha u_3 + \beta u_3 \\ \vdots \\ \alpha u_m + \beta u_m \end{bmatrix} = \begin{bmatrix} \alpha u_1 \\ \alpha u_2 \\ \alpha u_3 \\ \vdots \\ \alpha u_m \end{bmatrix} + \begin{bmatrix} \beta u_1 \\ \beta u_2 \\ \beta u_3 \\ \vdots \\ \beta u_m \end{bmatrix} \quad \text{Distributivity in } \mathbb{C}^m
\]

\[
= \alpha \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} + \beta \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} = \alpha u + \beta u \quad \text{Definition CVSM [90]}
\]
example. Let’s prove that \(3 = -3\).

\[
\begin{align*}
3 &= -3 & \text{(This is a bad start)} \\
3^2 &= (-3)^2 & \text{Square both sides} \\
9 &= 9 \\
0 &= 0 & \text{Subtract 9 from both sides}
\end{align*}
\]

So because \(0 = 0\) is a true statement, does it follow that \(3 = -3\) is a true statement? Nope. Of course, we didn’t really expect a legitimate proof of \(3 = -3\), but this attempt should illustrate the dangers of this (incorrect) approach.

What you have just seen in the proof of Theorem VSPCV [92], and what you will see consistently throughout this text, is proofs of the following form. To prove that \(A = D\) we write

\[
\begin{align*}
A &= B & \text{Theorem, Definition or Hypothesis justifying } A = B \\
\quad &= C & \text{Theorem, Definition or Hypothesis justifying } B = C \\
\quad &= D & \text{Theorem, Definition or Hypothesis justifying } C = D
\end{align*}
\]

In your scratch work exploring possible approaches to proving a theorem you may massage a variety of expressions, sometimes making connections to various bits and pieces, while some parts get abandoned. Once you see a line of attack, rewrite your proof carefully mimicking this style.

Be careful with the notion of the vector \(-\mathbf{u}\). This is a vector that we add to \(\mathbf{u}\) so that the result is the particular vector \(\mathbf{0}\). This is basically a property of vector addition. It happens that we can compute \(-\mathbf{u}\) using the other operation, scalar multiplication. We can prove this directly by writing that

\[
\mathbf{-u} = \begin{bmatrix}
    -u_1 \\
    -u_2 \\
    \vdots \\
    -u_m
\end{bmatrix} = (-1) \begin{bmatrix}
    u_1 \\
    u_2 \\
    \vdots \\
    u_m
\end{bmatrix} = (-1)\mathbf{u}
\]

We will see later how to derive this property as a consequence of several of the ten properties listed in Theorem VSPCV [92].

**Subsection READ**

**Reading Questions**

1. Where have you seen vectors used before in other courses? How were they different?

2. In words, when are two vectors equal?

3. Perform the following computation with vector operations

\[
2 \begin{bmatrix}
    1 \\
    5 \\
    0
\end{bmatrix} + (-3) \begin{bmatrix}
    7 \\
    6 \\
    5
\end{bmatrix}
\]
Subsection EXC
Exercises

C10  Compute

\[
\begin{bmatrix}
2 \\
-3 \\
4 \\
1 \\
0
\end{bmatrix}
+ (-2)
\begin{bmatrix}
1 \\
-5 \\
2 \\
2 \\
4
\end{bmatrix}
+ \begin{bmatrix}
1 \\
3 \\
-5 \\
1 \\
2
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution 97

T13  Prove Property CC 92 of Theorem VSPCV 92.

Contributed by Robert Beezer

T17  Prove Property SMAC 92 of Theorem VSPCV 92.

Contributed by Robert Beezer

T18  Prove Property DVAC 92 of Theorem VSPCV 92.

Contributed by Robert Beezer
Subsection SOL
Solutions

C10 Contributed by Robert Beezer Statement 95

$$\begin{bmatrix} 5 \\ -13 \\ 26 \\ 1 \\ -6 \end{bmatrix}$$
Section LC
Linear Combinations

Subsection LC
Linear Combinations

In Section VO we defined vector addition and scalar multiplication. These two operations combine nicely to give us a construction known as a linear combination, a construct that we will work with throughout this course.

Definition LCCV
Linear Combination of Column Vectors
Given \( n \) vectors \( u_1, u_2, u_3, \ldots, u_n \) from \( \mathbb{C}^m \) and \( n \) scalars \( \alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n \), their linear combination is the vector

\[
\alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_n u_n.
\]

So this definition takes an equal number of scalars and vectors, combines them using our two new operations (scalar multiplication and vector addition) and creates a single brand-new vector, of the same size as the original vectors. When a definition or theorem employs a linear combination, think about the nature of the objects that go into its creation (lists of scalars and vectors), and the type of object that results (a single vector). Computationally, a linear combination is pretty easy.

Example TLC
Two linear combinations in \( \mathbb{C}^6 \)
Suppose that

\[
\alpha_1 = 1 \quad \alpha_2 = -4 \quad \alpha_3 = 2 \quad \alpha_4 = -1
\]

and

\[
\begin{align*}
\mathbf{u}_1 &= \begin{bmatrix} 2 \\ 4 \\ -3 \\ 1 \\ 2 \\ 9 \end{bmatrix} & \mathbf{u}_2 &= \begin{bmatrix} 6 \\ 3 \\ 0 \\ -2 \\ 1 \\ 4 \end{bmatrix} & \mathbf{u}_3 &= \begin{bmatrix} -5 \\ 2 \\ 1 \\ 1 \\ -3 \\ 0 \end{bmatrix} & \mathbf{u}_4 &= \begin{bmatrix} 3 \\ 2 \\ -5 \\ 7 \\ 1 \\ 3 \end{bmatrix}
\end{align*}
\]
then their linear combination is

\[
\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \alpha_4 \mathbf{u}_4 = (1) \begin{bmatrix} 2 \\ 4 \\ -3 \\ 1 \\ 2 \\ 9 \end{bmatrix} + (-4) \begin{bmatrix} 6 \\ 3 \\ 0 \\ 1 \\ 0 \end{bmatrix} + (2) \begin{bmatrix} -5 \\ 2 \\ 1 \\ 1 \end{bmatrix} + (-1) \begin{bmatrix} 3 \\ 2 \\ -5 \\ 7 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ -3 \\ 1 \\ 2 \\ 9 \end{bmatrix} + \begin{bmatrix} -24 \\ -12 \\ 0 \\ 2 \\ 8 \\ -16 \end{bmatrix} + \begin{bmatrix} -10 \\ 4 \\ 2 \\ -6 \\ -6 \\ 0 \end{bmatrix} + \begin{bmatrix} -3 \\ -2 \\ 5 \\ -7 \\ -1 \\ -3 \end{bmatrix} + \begin{bmatrix} -35 \\ -6 \\ -4 \end{bmatrix}.
\]

A different linear combination, of the same set of vectors, can be formed with different scalars. Take

\[
\beta_1 = 3 \quad \beta_2 = 0 \quad \beta_3 = 5 \quad \beta_4 = -1
\]

and form the linear combination

\[
\beta_1 \mathbf{u}_1 + \beta_2 \mathbf{u}_2 + \beta_3 \mathbf{u}_3 + \beta_4 \mathbf{u}_4 = (3) \begin{bmatrix} 2 \\ 4 \\ -3 \\ 1 \\ 2 \\ 9 \end{bmatrix} + (0) \begin{bmatrix} 6 \\ 3 \\ 0 \\ 1 \\ 0 \end{bmatrix} + (5) \begin{bmatrix} -5 \\ 2 \\ 1 \\ 1 \end{bmatrix} + (-1) \begin{bmatrix} 3 \\ 2 \\ -5 \\ 7 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ -3 \\ 1 \\ 2 \\ 9 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -25 \\ 10 \\ 5 \\ 5 \end{bmatrix} + \begin{bmatrix} -3 \\ -10 \\ -3 \\ -3 \end{bmatrix} + \begin{bmatrix} -22 \\ -2 \end{bmatrix}.
\]

Notice how we could keep our set of vectors fixed, and use different sets of scalars to construct different vectors. You might build a few new linear combinations of \( \mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \mathbf{u}_4 \) right now. We’ll be right here when you get back. What vectors were you able to create? Do you think you could create the vector

\[
\mathbf{w} = \begin{bmatrix} 13 \\ 15 \\ 5 \\ -17 \\ 2 \\ 25 \end{bmatrix}
\]

with a “suitable” choice of four scalars? Do you think you could create any possible vector from \( \mathbb{C}^6 \) by choosing the proper scalars? These last two questions are very fundamental, and time spent considering them now will prove beneficial later.
**Proof Technique DC**

Decompositions

Much of your mathematical upbringing, especially once you began a study of algebra, revolved around simplifying expressions — combining like terms, obtaining common denominators so as to add fractions, factoring in order to solve polynomial equations. However, as often as not, we will do the opposite. Many theorems and techniques will revolve around taking some object and “decomposing” it into some combination of other objects, ostensibly in a more complicated fashion. When we say something can “be written as” something else, we mean that the one object can be decomposed into some combination of other objects. This may seem unnatural at first, but results of this type will give us insight into the structure of the original object by exposing its inner workings. An appropriate analogy might be stripping the wallboards away from the interior of a building to expose the structural members supporting the whole building.

**Example ABLC**

Archetype B as a linear combination

In this example we will rewrite Archetype B [568] in the language of vectors, vector equality and linear combinations. In Example VESE [88] we wrote the system of $m = 3$ equations as the vector equality

\[
\begin{bmatrix}
-7x_1 - 6x_2 - 12x_3 \\
5x_1 + 5x_2 + 7x_3 \\
x_1 + 4x_3
\end{bmatrix} = \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}.
\]

Now we will bust up the linear expressions on the left, first using vector addition,

\[
\begin{bmatrix}
-7x_1 \\
5x_1 \\
x_1
\end{bmatrix} + \begin{bmatrix}
-6x_2 \\
5x_2 \\
0x_2
\end{bmatrix} + \begin{bmatrix}
-12x_3 \\7x_3 \\4x_3
\end{bmatrix} = \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}.
\]

Now we can rewrite each of these $n = 3$ vectors as a scalar multiple of a fixed vector, where the scalar is one of the unknown variables, converting the left-hand side into a linear combination

\[
x_1 \begin{bmatrix}
-7 \\
5 \\
1
\end{bmatrix} + x_2 \begin{bmatrix}
-6 \\
5 \\
0
\end{bmatrix} + x_3 \begin{bmatrix}
-12 \\
7 \\
4
\end{bmatrix} = \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}.
\]

We can now interpret the problem of solving the system of equations as determining values for the scalar multiples that make the vector equation true. In the analysis of Archetype B [568], we were able to determine that it had only one solution. A quick way to see this is to row-reduce the coefficient matrix to the $3 \times 3$ identity matrix and apply Theorem NSRRI [77] to determine that the coefficient matrix is nonsingular. Then Theorem NSMUS [79] tells us that the system of equations has a unique solution. This solution is

\[
x_1 = -3 \\
x_2 = 5 \\
x_3 = 2.
\]

So, in the context of this example, we can express the fact that these values of the variables are a solution by writing the linear combination,

\[
(-3) \begin{bmatrix}
-7 \\
5 \\
1
\end{bmatrix} + (5) \begin{bmatrix}
-6 \\
5 \\
0
\end{bmatrix} + (2) \begin{bmatrix}
-12 \\
7 \\
4
\end{bmatrix} = \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}.
\]
Furthermore, these are the only three scalars that will accomplish this equality, since they come from a unique solution.

Notice how the three vectors in this example are the columns of the coefficient matrix of the system of equations. This is our first hint of the important interplay between the vectors that form the columns of a matrix, and the matrix itself.

With any discussion of Archetype A 563 or Archetype B 568 we should be sure to contrast with the other.

**Example AALC**

**Archetype A as a linear combination**

As a vector equality, Archetype A 563 can be written as

\[
\begin{bmatrix}
  x_1 - x_2 + 2x_3 \\
  2x_1 + x_2 + x_3 \\
  x_1 + x_2
\end{bmatrix}
= \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix}.
\]

Now bust up the linear expressions on the left, first using vector addition,

\[
\begin{bmatrix} x_1 \\ 2x_1 \\ x_1 \end{bmatrix} + \begin{bmatrix} -x_2 \\ x_2 \\ x_2 \end{bmatrix} + \begin{bmatrix} 2x_3 \\ x_3 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix}.
\]

Rewrite each of these \( n = 3 \) vectors as a scalar multiple of a fixed vector, where the scalar is one of the unknown variables, converting the left-hand side into a linear combination

\[
x_1 \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + x_3 \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix}.
\]

Row-reducing the augmented matrix for Archetype A 563 leads to the conclusion that the system is consistent and has free variables, hence infinitely many solutions. So for example, the two solutions

\[
\begin{align*}
  x_1 &= 2 & x_2 &= 3 & x_3 &= 1 \\
  x_1 &= 3 & x_2 &= 2 & x_3 &= 0
\end{align*}
\]

can be used together to say that,

\[
\begin{align*}
  (2) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (3) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (1) \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} &= \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix} \\
  (3) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (2) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (0) \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} &= \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix}.
\end{align*}
\]

Ignore the middle of this equation, and move all the terms to the left-hand side,

\[
\begin{align*}
  (2) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (3) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (1) \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} + (-3) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (-2) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (0) \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.
\end{align*}
\]

Regrouping gives

\[
\begin{align*}
  (-1) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (1) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (1) \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.
\end{align*}
\]
Notice that these three vectors are the columns of the coefficient matrix for the system of equations in Archetype A. This equality says there is a linear combination of those columns that equals the vector of all zeros. Give it some thought, but this says that \( x_1 = -1 \), \( x_2 = 1 \), \( x_3 = 1 \) is a nontrivial solution to the homogeneous system of equations with the coefficient matrix for the original system in Archetype A. In particular, this demonstrates that this coefficient matrix is singular.

There’s a lot going on in the last two examples. Come back to them in a while and make some connections with the intervening material. For now, we will summarize and explain some of this behavior with a theorem.

**Theorem SLSLC**

**Solutions to Linear Systems are Linear Combinations**

Denote the columns of the \( m \times n \) matrix \( A \) as the vectors \( A_1, A_2, A_3, \ldots, A_n \). Then \( x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} \) is a solution to the linear system of equations \( \mathcal{L}S(A, b) \) if and only if

\[
\alpha_1 A_1 + \alpha_2 A_2 + \alpha_3 A_3 + \cdots + \alpha_n A_n = b
\]

**Proof** Write the system of equations \( \mathcal{L}S(A, b) \) as

\[
\begin{align*}
    a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n &= b_1 \\
    a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n &= b_2 \\
    a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n &= b_3 \\
    \vdots \\
    a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n &= b_m.
\end{align*}
\]

Now use vector equality (Definition CVE) to replace the \( m \) simultaneous equalities by one vector equality,

\[
\begin{bmatrix} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1n}x_n \\ a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2n}x_n \\ a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3n}x_n \\ \vdots \\ a_{m1}x_1 + a_{m2}x_2 + a_{m3}x_3 + \cdots + a_{mn}x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_m \end{bmatrix}
\]

Use vector addition (Definition CVA) to rewrite,

\[
\begin{bmatrix} a_{11}x_1 \\ a_{21}x_1 \\ a_{31}x_1 \\ \vdots \\ a_{m1}x_1 \end{bmatrix} + \begin{bmatrix} a_{12}x_2 \\ a_{22}x_2 \\ a_{32}x_2 \\ \vdots \\ a_{m2}x_2 \end{bmatrix} + \begin{bmatrix} a_{13}x_3 \\ a_{23}x_3 \\ a_{33}x_3 \\ \vdots \\ a_{m3}x_3 \end{bmatrix} + \cdots + \begin{bmatrix} a_{1n}x_n \\ a_{2n}x_n \\ a_{3n}x_n \\ \vdots \\ a_{mn}x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_m \end{bmatrix}
\]
And finally, use the definition of vector scalar multiplication [Definition CVSM],

\[
x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \\ \vdots \\ a_{m1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ a_{32} \\ \vdots \\ a_{m2} \end{bmatrix} + x_3 \begin{bmatrix} a_{13} \\ a_{23} \\ a_{33} \\ \vdots \\ a_{m3} \end{bmatrix} + \cdots + x_m \begin{bmatrix} a_{1n} \\ a_{2n} \\ a_{3n} \\ \vdots \\ a_{mn} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_m \end{bmatrix}.
\]

and use notation for the various column vectors,

\[
x_1 A_1 + x_2 A_2 + x_3 A_3 + \cdots + x_n A_n = b.
\]

Each of the expressions above is just a rewrite of another one. So if we begin with a solution to the system of equations, substituting its values into the original system will make the equations simultaneously true. But then these same values will also make the final expression with the linear combination true. Reversing the argument, and employing the equations in reverse, will give the other half of the proof.

In other words, this theorem tells us that solutions to systems of equations are linear combinations of the column vectors of the coefficient matrix \((A_i)\) which yield the constant vector \(b\). Or said another way, a solution to a system of equations \(\text{LS}(A, b)\) is an answer to the question “How can I form the vector \(b\) as a linear combination of the columns of \(A\)?” Look through the archetypes that are systems of equations and examine a few of the advertised solutions. In each case use the solution to form a linear combination of the columns of the coefficient matrix and verify that the result equals the constant vector.

Subsection VFSS

Vector Form of Solution Sets

We have recently begun writing solutions to systems of equations as column vectors. For example [Archetype B 568] has the solution \(x_1 = -3, \ x_2 = 5, \ x_3 = 2\) which we now write as

\[
x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -3 \\ 5 \\ 2 \end{bmatrix}.
\]

Now, we will use column vectors and linear combinations to express all of the solutions to a linear system of equations in a compact and understandable way. First, here’s an example that will motivate our next theorem. This is a valuable technique, almost the equal of row-reducing a matrix, so be sure you get comfortable with it over the course of this section.

Example VFSAD

Vector form of solutions for Archetype D

[Archetype D 577] is a linear system of 3 equations in 4 variables. Row-reducing the augmented matrix yields

\[
\begin{bmatrix} 1 & 0 & 3 & -2 & 4 \\ 0 & 1 & 1 & -3 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\]
and we see \( r = 2 \) nonzero rows. Also, \( D = \{1, 2\} \) so the dependent variables are then \( x_1 \) and \( x_2 \). \( F = \{3, 4, 5\} \) so the two free variables are \( x_3 \) and \( x_4 \). We will express a generic solution for the system by two slightly different methods, though both arrive at the same conclusion.

First, we will decompose \( \text{Technique DC} \) a solution vector. Rearranging each equation represented in the row-reduced form of the augmented matrix by solving for the dependent variable in each row yields the vector equality,

\[
\begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 
\end{bmatrix}
= \begin{bmatrix}
  4 - 3x_3 + 2x_4 \\
  -x_3 + 3x_4 \\
  x_3 \\
  x_4 
\end{bmatrix}
\]

Now we will use the definitions of column vector addition and scalar multiplication \( \text{Definition CVA} \) \( \text{Definition CVSM} \) to express this vector as a linear combination,

\[
\begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 
\end{bmatrix}
= \begin{bmatrix}
  4 \\
  0 \\
  0 \\
  0 
\end{bmatrix}
+ x_3 \begin{bmatrix}
  -3x_3 \\
  -x_3 \\
  x_3 \\
  0 
\end{bmatrix}
+ 2x_4 \begin{bmatrix}
  2x_4 \\
  3x_4 \\
  0 \\
  x_4 
\end{bmatrix}
\]

\[
= \begin{bmatrix}
  4 \\
  0 \\
  0 \\
  0 
\end{bmatrix}
+ x_3 \begin{bmatrix}
  -3 \\
  -1 \\
  1 \\
  0 
\end{bmatrix}
+ x_4 \begin{bmatrix}
  2 \\
  3 \\
  0 \\
  1 
\end{bmatrix}
\]

We will develop the same linear combination a bit quicker, using three steps. While the method above is instructive, the method below will be our preferred approach.

Step 1. Write the vector of variables as a fixed vector, plus a linear combination of \( n - r \) vectors, using the free variables as the scalars.

\[
\mathbf{x} = \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 
\end{bmatrix}
= \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 
\end{bmatrix}
+ x_3 \begin{bmatrix}
  0 \\
  0 \\
  -3 \\
  -1 
\end{bmatrix}
+ x_4 \begin{bmatrix}
  0 \\
  1 \\
  2 \\
  3 
\end{bmatrix}
\]

Step 2. For each free variable, use 0’s and 1’s to ensure equality for the corresponding entry of the vectors.

\[
\mathbf{x} = \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 
\end{bmatrix}
= \begin{bmatrix}
  0 \\
  0 \\
  0 \\
  0 
\end{bmatrix}
+ x_3 \begin{bmatrix}
  1 \\
  1 \\
  0 \\
  0 
\end{bmatrix}
+ x_4 \begin{bmatrix}
  0 \\
  0 \\
  1 \\
  1 
\end{bmatrix}
\]

Step 3. For each dependent variable, use the augmented matrix to formulate an equation expressing the dependent variable as a constant plus multiples of the free variables. Convert this equation into entries of the vectors that ensure equality for each dependent
variable, one at a time.

\[ x_1 = 4 - 3x_3 + 2x_4 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -3 \\ 1 \\ 0 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 2 \\ 0 \\ 0 \\ 1 \end{bmatrix} \]

\[ x_2 = 0 - 1x_3 + 3x_4 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 2 \\ 3 \\ 0 \\ 0 \end{bmatrix} \]

This final form of a typical solution is especially pleasing and useful. For example, we can build solutions quickly by choosing values for our free variables, and then compute a linear combination. Such as

\[ x_3 = 2, \quad x_4 = -5 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} + (2) \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + (-5) \begin{bmatrix} 2 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -12 \\ -17 \\ 7 \\ 2 \end{bmatrix} \]

or,

\[ x_3 = 1, \quad x_4 = 3 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} + (1) \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + (3) \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 7 \\ 8 \\ 1 \\ 3 \end{bmatrix}. \]

You’ll find the second solution listed in the write-up for Archetype D [577], and you might check the first solution by substituting it back into the original equations.

While this form is useful for quickly creating solutions, its even better because it tells us exactly what every solution looks like. We know the solution set is infinite, which is pretty big, but now we can say that a solution is some multiple of

\[ \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} \]

plus a multiple of

\[ \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix} \]

plus the fixed vector \[ \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} \]. Period. So it only takes us three vectors to describe the entire infinite solution set, provided we also agree on how to combine the three vectors into a linear combination. ☐

We’ll now formalize the last example as a theorem.

**Theorem VFSLS**

**Vector Form of Solutions to Linear Systems**

Suppose that \([A \mid b]\) is the augmented matrix for a consistent linear system \(\mathcal{L}S(A, b)\) of \(m\) equations in \(n\) variables. Let \(B\) be a row-equivalent \(m \times (n + 1)\) matrix in reduced row-echelon form. Suppose that \(B\) has \(r\) nonzero rows, columns without leading 1’s with...
indices \( F = \{ f_1, f_2, f_3, \ldots, f_{n-r}, n+1 \} \), and columns with leading 1's (pivot columns) having indices \( D = \{ d_1, d_2, d_3, \ldots, d_r \} \). Define vectors \( c, u_j, 1 \leq j \leq n-r \) of size \( n \) by

\[
[c]_i = \begin{cases} 
0 & \text{if } i \in F \\
[B]_{k,n+1} & \text{if } i \in D, i = d_k \\
1 & \text{if } i \in F, i = f_j \\
0 & \text{if } i \in F, i \neq f_j \\
-[B]_{k,f_j} & \text{if } i \in D, i = d_k
\end{cases}
\]

Then the set of solutions to the system of equations \( LS(A, b) \) is

\[
S = \left\{ c + x_{f_1}u_1 + x_{f_2}u_2 + x_{f_3}u_3 + \cdots + x_{f_{n-r}}u_{n-r} \mid x_{f_1}, x_{f_2}, x_{f_3}, \ldots, x_{f_{n-r}}, \in \mathbb{C} \right\}
\]

**Proof** We are being asked to prove that the solution set has a particular form. First, \( LS(A, b) \) is equivalent to the linear system of equations that has the matrix \( B \) as its augmented matrix (Theorem REMES [32]), so we need only show that \( S \) is the solution set for the system with \( B \) as its augmented matrix.

We begin by showing that every element of \( S \) is a solution to the system. Let \( x_{f_1} = \alpha_1, x_{f_2} = \alpha_2, x_{f_3} = \alpha_3, \ldots, x_{f_{n-r}} = \alpha_{n-r} \) be one choice of the values of \( x_{f_1}, x_{f_2}, x_{f_3}, \ldots, x_{f_{n-r}} \). So a proposed solution is

\[
x = c + \alpha_1u_1 + \alpha_2u_2 + \alpha_3u_3 + \cdots + \alpha_{n-r}u_{n-r}
\]

So we evaluate equation \( \ell \) of the system represented by \( B \) with the solution vector \( x \),

\[
\beta = [B]_{\ell f_1} [x]_1 + [B]_{\ell f_2} [x]_2 + [B]_{\ell f_3} [x]_3 + \cdots + [B]_{\ell n} [x]_n
\]

When \( r + 1 \leq \ell \leq m \), row \( \ell \) of the matrix \( B \) is a zero row, so the equation represented by that row is always true, no matter which solution vector we propose. So assume \( 1 \leq \ell \leq r \). Then \( [B]_{\ell d_i} = 0 \) for all \( 1 \leq i \leq r \), except that \( [B]_{\ell d_r} = 1 \), so \( \beta \) simplifies to

\[
\beta = [x]_{d_r} + [B]_{\ell f_1} [x]_{f_1} + [B]_{\ell f_2} [x]_{f_2} + [B]_{\ell f_3} [x]_{f_3} + \cdots + [B]_{\ell f_{n-r}} [x]_{f_{n-r}}
\]

Notice that for \( 1 \leq i \leq n-r \)

\[
[x]_{f_i} = [c]_{f_i} + \alpha_{f_1} [u_1]_{f_i} + \alpha_{f_2} [u_2]_{f_i} + \alpha_{f_3} [u_3]_{f_i} + \cdots + \alpha_{f_{n-r}} [u_{n-r}]_{f_i}
= 0 + \alpha_{f_1}(0) + \alpha_{f_2}(0) + \alpha_{f_3}(0) + \cdots + \alpha_{f_{n-r}}(0)
= \alpha_{f_i}
\]

So \( \beta \) simplifies further to

\[
\beta = [x]_{d_r} + [B]_{\ell f_1} \alpha_{f_1} + [B]_{\ell f_2} \alpha_{f_2} + [B]_{\ell f_3} \alpha_{f_3} + \cdots + [B]_{\ell f_{n-r}} \alpha_{f_{n-r}}
\]

Now examine the \( [x]_{d_r} \) term of \( \beta \),

\[
[x]_{d_r} = [c]_{d_r} + \alpha_{f_1} [u_1]_{d_r} + \alpha_{f_2} [u_2]_{d_r} + \alpha_{f_3} [u_3]_{d_r} + \cdots + \alpha_{f_{n-r}} [u_{n-r}]_{d_r}
= [B]_{\ell,n+1} + \alpha_{f_1} (-[B]_{\ell,f_1}) + \alpha_{f_2} (-[B]_{\ell,f_2}) + \alpha_{f_3} (-[B]_{\ell,f_3}) + \cdots + \alpha_{f_{n-r}} (-[B]_{\ell,f_{n-r}})
\]
Replacing this term into the expression for \( \beta \), we obtain

\[
\beta = [x]_d + [B]_{\ell f_1} \alpha f_1 + [B]_{\ell f_2} \alpha f_2 + [B]_{\ell f_3} \alpha f_3 + \cdots + [B]_{\ell f_{n-r}} \alpha f_{n-r} \\
= [B]_{\ell,n+1} + \alpha f_1 (-[B]_{\ell,f_1}) + \alpha f_2 (-[B]_{\ell,f_2}) + \alpha f_3 (-[B]_{\ell,f_3}) + \cdots + \alpha f_{n-r} (-[B]_{\ell,f_{n-r}}) + \\
[B]_{\ell f_1} \alpha f_1 + [B]_{\ell f_2} \alpha f_2 + [B]_{\ell f_3} \alpha f_3 + \cdots + [B]_{\ell f_{n-r}} \alpha f_{n-r} \\
= [B]_{\ell,n+1}
\]

So \( \beta \) began as the left-hand side of equation \( \ell \) from the system represented by \( B \) and we now know it equals \([B]_{\ell,n+1}\), the constant term for equation \( \ell \). So this arbitrarily chosen vector from \( S \) makes every equation true, and therefore is a solution to the system.

TODO: Prove that any solution can be written in the form described in \( S \).

**Theorem VFSLS** formalizes what happened in the three steps of Example VFSAD. The theorem will be useful in proving other theorems, and it is useful since it tells us an exact procedure for simply describing an infinite solution set. We could program a computer to implement it, once we have the augmented matrix row-reduced and have checked that the system is consistent. By Knuth’s definition, this completes our conversion of linear equation solving from art into science. Notice that it even applies (but is overkill) in the case of a unique solution. However, as a practical matter, I prefer the three-step process of Example VFSAD when I need to describe an infinite solution set. So let’s practice some more, but with a bigger example.

**Example VFSAI**

**Vector form of solutions for Archetype I**

Archetype I is a linear system of \( m = 4 \) equations in \( n = 7 \) variables. Row-reducing the augmented matrix yields

\[
\begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 & 4 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 & 2 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

and we see \( r = 3 \) nonzero rows. The columns with leading 1’s are \( D = \{1, 3, 4\} \) so the \( r \) dependent variables are \( x_1, x_3, x_4 \). The columns without leading 1’s are \( F = \{2, 5, 6, 7, 8\} \), so the \( n - r = 4 \) free variables are \( x_2, x_5, x_6, x_7 \).

Step 1. Write the vector of variables \( \mathbf{x} \) as a fixed vector \( \mathbf{c} \), plus a linear combination of \( n - r = 4 \) vectors \( (\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \mathbf{u}_4) \), using the free variables as the scalars.

\[
\mathbf{x} = \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4 \\
  x_5 \\
  x_6 \\
  x_7 
\end{bmatrix} = \begin{bmatrix}
  \mathbf{c} \\
  + x_2 \mathbf{u}_1 \\
  + x_5 \mathbf{u}_2 \\
  + x_6 \mathbf{u}_3 \\
  + x_7 \mathbf{u}_4 
\end{bmatrix}
\]

Step 2. For each free variable, use 0’s and 1’s to ensure equality for the corresponding entry of the the vectors. Take note of the pattern of 0’s and 1’s at this stage, because this is the best look you’ll have at it. We’ll state an important theorem in the next section.
and the proof will essentially rely on this observation.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ +x_2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ +x_5 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 0 \\ +x_6 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ +x_7 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

Step 3. For each dependent variable, use the augmented matrix to formulate an equation expressing the dependent variable as a constant plus multiples of the free variables. Convert this equation into entries of the vectors that ensure equality for each dependent variable, one at a time.

$$x_1 = 4 - 4x_2 - 2x_5 - 1x_6 + 3x_7 \Rightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ +x_2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -4 \\ 1 \\ 0 \\ +x_5 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -2 \\ 0 \\ 0 \\ +x_6 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -1 \\ 0 \\ 0 \\ +x_7 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

$$x_3 = 2 + 0x_2 - x_5 + 3x_6 - 5x_7 \Rightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 2 \\ +x_2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -4 \\ 1 \\ 0 \\ +x_5 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -2 \\ 0 \\ -1 \\ +x_6 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -1 \\ 0 \\ 3 \\ +x_7 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

$$x_4 = 1 + 0x_2 - 2x_5 + 6x_6 - 6x_7 \Rightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 2 \\ +x_2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -4 \\ 1 \\ 0 \\ +x_5 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} -2 \\ 0 \\ -1 \\ +x_6 \\ -2 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} -1 \\ 0 \\ 3 \\ +x_7 \\ 6 \\ 6 \\ -6 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ +x_7 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

We can now use this final expression to quickly build solutions to the system. You might try to recreate each of the solutions listed in the write-up for Archetype II 599. (Hint: look at the values of the free variables in each solution, and notice that the vector c has 0’s in these locations.)

Even better, we have a description of the infinite solution set, based on just 5 vectors, which we combine in linear combinations to produce solutions.
Whenever we discuss Archetype 1 you know that’s your cue to go work through Archetype J by yourself. Remember to take note of the 0/1 pattern at the conclusion of Step 2. Have fun — we won’t go anywhere while you’re away.

This technique is so important, that we’ll do one more example. However, an important distinction will be that this system is homogeneous.

**Example VFSAL**

**Vector form of solutions for Archetype L**

Archetype L is presented simply as the $5 \times 5$ matrix

$$L = \begin{bmatrix} -2 & -1 & -2 & -4 & 4 \\ -6 & -5 & -4 & -4 & 6 \\ 10 & 7 & 7 & 10 & -13 \\ -7 & -5 & -6 & -9 & 10 \\ -4 & -3 & -4 & -6 & 6 \end{bmatrix}$$

We’ll interpret it here as the coefficient matrix of a homogeneous system and reference this matrix as $L$. So we are solving the homogeneous system $LS(L, 0)$ having $m = 5$ equations in $n = 5$ variables. If we built the augmented matrix, we would add a sixth column to $L$ containing all zeros. As we did row operations, this sixth column would remain all zeros. So instead we will row-reduce the coefficient matrix, and mentally remember the missing sixth column of zeros. This row-reduced matrix is

$$\begin{bmatrix} 1 & 0 & 0 & 1 & -2 \\ 0 & 1 & 0 & -2 & 2 \\ 0 & 0 & 1 & 2 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

and we see $r = 3$ nonzero rows. The columns with leading 1’s are $D = \{1, 2, 3\}$ so the $r$ dependent variables are $x_1, x_2, x_3$. The columns without leading 1’s are $F = \{4, 5\}$, so the $n - r = 2$ free variables are $x_4, x_5$. Notice that if we had included the all-zero vector of constants to form the augmented matrix for the system, then the index 6 would have appeared in the set $F$, and subsequently would have been ignored when listing the free variables.

**Step 1.** Write the vector of variables ($\mathbf{x}$) as a fixed vector ($\mathbf{c}$), plus a linear combination of $n - r = 2$ vectors ($\mathbf{u}_1, \mathbf{u}_2$), using the free variables as the scalars.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} \end{bmatrix} + x_4 \begin{bmatrix} \end{bmatrix} + x_5 \begin{bmatrix} \end{bmatrix}$$

**Step 2.** For each free variable, use 0’s and 1’s to ensure equality for the corresponding entry of the the vectors. Take note of the pattern of 0’s and 1’s at this stage, even if it is not as illuminating as in other examples.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_4 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} \end{bmatrix} + x_4 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$
Step 3. For each dependent variable, use the augmented matrix to formulate an equation expressing the dependent variable as a constant plus multiples of the free variables. Don’t forget about the “missing” sixth column being full of zeros. Convert this equation into entries of the vectors that ensure equality for each dependent variable, one at a time.

\[
\begin{align*}
x_1 &= 0 - 1x_4 + 2x_5 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 2 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \\
x_2 &= 0 + 2x_4 - 2x_5 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 2 \\ -2 \\ 0 \\ 0 \\ 1 \end{bmatrix} \\
x_3 &= 0 - 2x_4 + x_5 \quad \Rightarrow \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ 2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 2 \\ -2 \\ 0 \\ 0 \\ 1 \end{bmatrix}
\end{align*}
\]

The vector \( \mathbf{c} \) will always have 0’s in the entries corresponding to free variables. However, since we are solving a homogeneous system, the row-reduced augmented matrix has zeros in column \( n + 1 = 6 \), and hence all the entries of \( \mathbf{c} \) are zero. So we can write

\[
\mathbf{x} = \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = 0 + x_4 \begin{bmatrix} -1 \\ 2 \\ -2 \\ 1 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 2 \\ -2 \\ 0 \\ 1 \\ 1 \end{bmatrix} = x_4 \begin{bmatrix} -1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 2 \\ -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}.
\]

It will always happen that the solutions to a homogeneous system has \( \mathbf{c} = 0 \) (even in the case of a unique solution?). So our expression for the solutions is a bit more pleasing. In this example it says that the solutions are all possible linear combinations of the two vectors \( \mathbf{u}_1 = \begin{bmatrix} -1 \\ 2 \\ -2 \\ 1 \\ 0 \end{bmatrix} \) and \( \mathbf{u}_2 = \begin{bmatrix} 2 \\ -2 \\ 1 \\ 0 \\ 1 \end{bmatrix} \), with no mention of any fixed vector entering into the linear combination.

This observation will motivate our next section and the main definition of that section, and after that we will conclude the section by formalizing this situation.

**Subsection URREF**

**Uniqueness of Reduced Row-Echelon Form**

We are now in a position to establish that the reduced row-echelon form of a matrix is unique. Going forward, we will emphasize the point-of-view that a matrix is a collection
of columns. But there are two occasions when we need to work carefully with the rows of a matrix. This is the first such occasion. We could define something called a row vector that would equal a given row of a matrix, and might be written as a horizontal list. Then we could define vector equality, the basic operations of vector addition and scalar multiplication, followed by a definition of a linear combination of row vectors. We will not incur the overhead of stating all these definitions, but will instead convert the rows of a matrix to column vectors and use our definitions that are already in place. This was our reason for delaying this proof until now. Remind yourself as you work through this proof that it only relies only on the definition of equivalent matrices, reduced row-echelon form and linear combinations. So in particular, we are not guilty of circular reasoning. Should we have defined vector operations and linear combinations just prior to discussing reduced row-echelon form, then the following proof of uniqueness could have been presented at that time. OK, here we go.

**Theorem RREFU**

**Reduced Row-Echelon Form is Unique**

Suppose that $A$ is an $m \times n$ matrix and that $B$ and $C$ are $m \times n$ matrices that are row-equivalent to $A$ and in reduced row-echelon form. Then $B = C$.

**Proof** Denote the pivot columns of $B$ as $D = \{d_1, d_2, d_3, \ldots, d_r\}$ and the pivot columns of $C$ as $D' = \{d'_1, d'_2, d'_3, \ldots, d'_{r'}\}$ (Notation RREFA [49]). We begin by showing that $D = D'$.

For both $B$ and $C$, we can take the elements of a row of the matrix and use them to construct a column vector. We will denote these by $b_i$ and $c_i$, respectively, $1 \leq i \leq m$. Since $B$ and $C$ are both row-equivalent to $A$, there is a sequence of row operations that will convert $B$ to $C$, and vice-versa, since row operations are reversible. If we can convert $B$ into $C$ via a sequence of row operations, then any row of $C$ expressed as a column vector, say $c_k$, is a linear combination of the column vectors derived from the rows of $B$, $\{b_1, b_2, b_3, \ldots, b_m\}$. Similarly, any row of $B$ is a linear combination of the set of rows of $C$. Our principal device in this proof is to carefully analyze individual entries of vector equalities between a single row of either $B$ or $C$ and a linear combination of the rows of the other matrix.

Let's first show that $d_1 = d'_1$. Suppose that $d_1 < d'_1$. We can write the first row of $B$ as a linear combination of the rows of $C$, that is, there are scalars $a_1$, $a_2$, $a_3$, $\ldots$, $a_m$ such that

$$b_1 = a_1 c_1 + a_2 c_2 + a_3 c_3 + \cdots + a_m c_m$$

Consider the entry in location $d_1$ on both sides of this equality. Since $B$ is in reduced row-echelon form (Definition RREF [34]) we find a one in $b_1$ on the left. Since $d_1 < d'_1$, and $C$ is in reduced row-echelon form (Definition RREF [34]) each vector $c_i$ has a zero in location $d_1$, and therefore the linear combination on the right also has a zero in location $d_1$. This is a contradiction, so we know that $d_1 \geq d'_1$. By an entirely similar argument, we could conclude that $d_1 = d'_1$. This means that $d_1 = d'_1$.

Suppose that we have determined that $d_1 = d'_1$, $d_2 = d'_2$, $d_3 = d'_3$, $\ldots$, $d_k = d'_k$. Let’s now show that $d_{k+1} = d'_{k+1}$. To achieve a contradiction, suppose that $d_{k+1} < d'_{k+1}$. Row $k+1$ of $B$ is a linear combination of the rows of $C$, so there are scalars $a_1$, $a_2$, $a_3$, $\ldots$, $a_m$ such that

$$b_{k+1} = a_1 c_1 + a_2 c_2 + a_3 c_3 + \cdots + a_m c_m$$

...
Since $B$ is in reduced row-echelon form (Definition RREF [34]), the entries of $b_{k+1}$ in locations $d_1, d_2, d_3, \ldots, d_k$ are all zero. Since $C$ is in reduced row-echelon form (Definition RREF [34]), location $d_i$ of $c_i$ is one for each $1 \leq i \leq k$. The equality of these vectors in locations $d_1, d_2, d_3, \ldots, d_k$ then implies that $a_1 = 0, a_2 = 0, a_3 = 0, \ldots, a_k = 0$.

Now consider location $d_{k+1}$ in this vector equality. The vector $b_{k+1}$ on the left is one in this location since $B$ is in reduced row-echelon form (Definition RREF [34]). Vectors $c_1, c_2, c_3, \ldots, c_k$, are multiplied by zero scalars in the linear combination on the right. The remaining vectors, $c_{k+1}, c_{k+2}, c_{k+3}, \ldots, c_m$, each has a zero in location $d_{k+1}$ since $d_{k+1} < d'_{k+1}$ and $C$ is in reduced row-echelon form (Definition RREF [34]). So the right hand side of the vector equality is zero in location $d_{k+1}$, a contradiction. Thus $d_{k+1} \geq d'_{k+1}$. By an entirely similar argument, we could conclude that $d_{k+1} \leq d'_{k+1}$, and therefore $d_{k+1} = d'_{k+1}$.

Now we establish that $r = r'$. Suppose that $r < r'$. By the arguments above we can show that $d_1 = d'_1, d_2 = d'_2, d_3 = d'_3, \ldots, d_r = d'_r$. Row $r'$ of $C$ is a linear combination of the $r$ non-zero rows of $B$, so there are scalars $a_1, a_2, a_3, \ldots, a_r$ so that

$$c_{r'} = a_1 b_1 + a_2 b_2 + a_3 b_3 + \cdots + a_r b_r$$

Locations $d_1, d_2, d_3, \ldots, d_r$ of $c_{r'}$ are all zero since $r < r'$ and $C$ is in reduced row-echelon form (Definition RREF [34]). For a given index $i$, $1 \leq i \leq r$, the vectors $b_1, b_2, b_3, \ldots, b_r$ have zeros in location $d_i$, except that the vector $b_i$ is one in location $d_i$ since $B$ is in reduced row-echelon form (Definition RREF [34]). This consideration of location $d_i$ implies that $a_i = 0, 1 \leq i \leq r$. With all the scalars in the linear combination equal to zero, we conclude that $c_{r'} = 0$, contradicting the existence of a leading 1 in $c_{r'}$. So $r \geq r'$. By a similar argument, we conclude that $r \leq r'$ and therefore $r = r'$. Thus $D = D'$.

To finally show that $B = C$, we will show that the rows of the two matrices are equal. Row $k$ of $C$, $c_k$, is a linear combination of the $r$ non-zero rows of $B$, so there are scalars $a_1, a_2, a_3, \ldots, a_r$ such that

$$c_k = a_1 b_1 + a_2 b_2 + a_3 b_3 + \cdots + a_r b_r$$

Because $C$ is in reduced row-echelon form (Definition RREF [34]), location $d_i$ of $c_k$ is zero for $1 \leq i \leq r$, except in location $d_k$ where the entry is one. In the linear combination on the right of the vector equality, the vectors $b_1, b_2, b_3, \ldots, b_r$ have zeros in location $d_i$, except that $b_k$ has a one in location $d_k$, since $B$ is in reduced row-echelon form (Definition RREF [34]). This implies that $a_1 = 0, a_2 = 0, \ldots, a_{k-1} = 0, a_{k+1} = 0, a_{k+2} = 0, \ldots, a_r = 0$ and $a_k = 1$. Then the vector equality reduces to simply $c_k = b_k$. Since $k$ was arbitrary, $B$ and $C$ have equal rows and so are equal matrices. \[
\boxed{\phantom{0}}
\]
Subsection READ

Reading Questions

1. Earlier, a reading question asked you to solve the system of equations

\begin{align*}
2x_1 + 3x_2 - x_3 &= 0 \\
x_1 + 2x_2 + x_3 &= 3 \\
x_1 + 3x_2 + 3x_3 &= 7
\end{align*}

Use a linear combination to rewrite this system of equations as a vector equality.

2. Find a linear combination of the vectors

\[ S = \left\{ \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \\ 4 \end{bmatrix}, \begin{bmatrix} -1 \\ 3 \\ -5 \end{bmatrix} \right\} \]

that equals the vector \[ \begin{bmatrix} 1 \\ -9 \\ 11 \end{bmatrix}. \]

3. The matrix below is the augmented matrix of a system of equations, row-reduced to reduced row-echelon form. Write the vector form of the solutions to the system.

\[
\begin{bmatrix}
1 & 3 & 0 & 6 & 0 & 9 \\
0 & 0 & 1 & -2 & 0 & -8 \\
0 & 0 & 0 & 0 & 1 & 3
\end{bmatrix}
\]
Subsection EXC
Exercises

C21  Consider each archetype that is a system of equations. For individual solutions listed (both for the original system and the corresponding homogeneous system) express the vector of constants as a linear combination of the columns of the coefficient matrix, as guaranteed by Theorem SLSLC 103. Verify this equality by computing the linear combination. For systems with no solutions, recognize that it is then impossible to write the vector of constants as a linear combination of the columns of the coefficient matrix. Note too, for homogeneous systems, that the solutions give rise to linear combinations that equal the zero vector.

Archetype A  [563]
Archetype B  [568]
Archetype C  [573]
Archetype D  [577]
Archetype E  [581]
Archetype F  [585]
Archetype G  [590]
Archetype H  [594]
Archetype I  [599]
Archetype J  [604]

Contributed by Robert Beezer  Solution 117

C22  Consider each archetype that is a system of equations. Write elements of the solution set in vector form, as guaranteed by Theorem VFSLS 106.

Archetype A  [563]
Archetype B  [568]
Archetype C  [573]
Archetype D  [577]
Archetype E  [581]
Archetype F  [585]
Archetype G  [590]
Archetype H  [594]
Archetype I  [599]
Archetype J  [604]

Contributed by Robert Beezer  Solution 117

C40  Find the vector form of the solutions to the system of equations below.

\[
\begin{align*}
2x_1 - 4x_2 + 3x_3 + x_5 &= 6 \\
x_1 - 2x_2 - 2x_3 + 14x_4 - 4x_5 &= 15 \\
x_1 - 2x_2 + x_3 + 2x_4 + x_5 &= -1 \\
-2x_1 + 4x_2 - 12x_4 + x_5 &= -7
\end{align*}
\]

Contributed by Robert Beezer  Solution 117
M10  Example TLC 99 asks if the vector
\[
\mathbf{w} = \begin{bmatrix}
  13 \\
  15 \\
  5 \\
  -17 \\
  2 \\
  25
\end{bmatrix}
\]
can be written as a linear combination of the four vectors
\[
\mathbf{u}_1 = \begin{bmatrix}
  2 \\
  4 \\
  -3 \\
  1 \\
  2 \\
  9
\end{bmatrix} \quad \mathbf{u}_2 = \begin{bmatrix}
  6 \\
  3 \\
  0 \\
  -2 \\
  1 \\
  4
\end{bmatrix} \quad \mathbf{u}_3 = \begin{bmatrix}
  -5 \\
  2 \\
  1 \\
  -3 \\
  1 \\
  0
\end{bmatrix} \quad \mathbf{u}_4 = \begin{bmatrix}
  3 \\
  2 \\
  -5 \\
  7 \\
  1 \\
  3
\end{bmatrix}
\]
Can it?  Can any vector in \( \mathbb{C}^6 \) be written as a linear combination of the four vectors \( \mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \mathbf{u}_4 \)?
Contributed by Robert Beezer  Solution 117
Subsection LC.SOL  Solutions  117

Subsection SOL  Solutions

C21  Contributed by Robert Beezer  Statement [115]
Solutions for Archetype A [563] and Archetype B [568] are described carefully in Example AALC [102] and Example ABLC [101].

C22  Contributed by Robert Beezer  Statement [115]
Solutions for Archetype D [577] and Archetype I [599] are described carefully in Example VFSAD [104] and Example VFSAI [108]. The technique described in these examples is probably more useful than carefully deciphering the notation of Theorem VFSLS [106]. The solution for each archetype is contained in its description. So now you can check-off the box for that item.

C40  Contributed by Robert Beezer  Statement [115]
Row-reduce the augmented matrix representing this system, to find
\[
\begin{bmatrix}
1 & -2 & 0 & 6 & 0 & 1 \\
0 & 0 & 1 & -4 & 0 & 3 \\
0 & 0 & 0 & 0 & 1 & -5 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]
The system is consistent (no leading one in column 6, Theorem RCLS [53]). \(x_2\) and \(x_4\) are the free variables. Now apply Theorem VFSLS [106], or follow the three-step process of Example VFSAD [104], Example VFSAI [108], or Example VFSAL [110] to obtain
\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5
\end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 3 \\ 0 \\ -5 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -6 \\ 0 \\ 4 \\ 0 \\ 1 \end{bmatrix}
\]

M10  Contributed by Robert Beezer  Statement [116]
No, it is not possible to create \(w\) as a linear combination of the four vectors \(u_1, u_2, u_3, u_4\). By creating the desired linear combination with unknowns as scalars, Theorem SLSLC [103] provides a system of equations that has no solution. This one computation is enough to show us that it is not possible to create all the vectors of \(\mathbb{C}^6\) through linear combinations of the four vectors \(u_1, u_2, u_3, u_4\).
Section SS
Spanning Sets

In this section we will describe a compact way to indicate the elements of an infinite set of vectors, making use of linear combinations. This will give us a convenient way to describe the elements of a set of solutions to a linear system, or the elements of the null space of a matrix.

Subsection SSV
Span of a Set of Vectors

In Example VFSAL we saw the solution set of a homogeneous system described as all possible linear combinations of two particular vectors. This happens to be a useful way to construct or describe infinite sets of vectors, so we encapsulate this idea in a definition.

Definition SSCV
Span of a Set of Column Vectors
Given a set of vectors \( S = \{u_1, u_2, u_3, \ldots, u_t\} \), their span, \( S_p(S) \), is the set of all possible linear combinations of \( u_1, u_2, u_3, \ldots, u_t \). Symbolically,

\[
S_p(S) = \{ \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t \}
\]

\[
= \left\{ \sum_{i=1}^{t} \alpha_i u_i \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t \right\}
\]

The span is just a set of vectors, though in all but one situation it is an infinite set. (Just when is it not infinite?) So we start with a finite collection of vectors (\( t \) of them to be precise), and use this finite set to describe an infinite set of vectors. We will see this construction repeatedly, so let’s work through some examples to get comfortable with it. The most obvious question about a set is if a particular item of the correct type is in the set, or not.

Example SCAA
Span of the columns of Archetype A
Begin with the finite set of three vectors of size 3

\[
S = \{u_1, u_2, u_3\} = \left\{ \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} \right\}
\]

and consider the infinite set \( U = S_p(S) \). The vectors of \( S \) could have been chosen to be anything, but for reasons that will become clear later, we have chosen the three columns...
of the coefficient matrix in Archetype A \[563\]. First, as an example, note that
\[
\mathbf{v} = (5) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (-3) \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} + (7) \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 22 \\ 14 \\ 2 \end{bmatrix}
\]
is in $Sp(S)$, since it is a linear combination of $\mathbf{u}_1$, $\mathbf{u}_2$, $\mathbf{u}_3$. We write this succinctly as $\mathbf{v} \in Sp(S)$. There is nothing magical about the scalars $\alpha_1 = 5$, $\alpha_2 = -3$, $\alpha_3 = 7$, they could have been chosen to be anything. So repeat this part of the example yourself, using different values of $\alpha_1$, $\alpha_2$, $\alpha_3$. What happens if you choose all three scalars to be zero?

So we know how to quickly construct sample elements of the set $Sp(S)$. A slightly different question arises when you are handed a vector of the correct size and asked if it is an element of $Sp(S)$. For example, is $\mathbf{w} = \begin{bmatrix} 1 \\ 8 \\ 5 \end{bmatrix}$ in $Sp(S)$? More succinctly, $\mathbf{w} \in Sp(S)$?

To answer this question, we will look for scalars $\alpha_1$, $\alpha_2$, $\alpha_3$ so that
\[
\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 = \mathbf{w}.
\]
By Theorem SLSLC \[103\] solutions to this vector equality are solutions to the system of equations
\[
\begin{align*}
\alpha_1 - \alpha_2 + 2\alpha_3 &= 1 \\
2\alpha_1 + \alpha_2 + \alpha_3 &= 8 \\
\alpha_1 + \alpha_2 &= 5.
\end{align*}
\]
Building the augmented matrix for this linear system, and row-reducing, gives
\[
\begin{bmatrix}
1 & 0 & 1 & 3 \\
0 & 1 & -1 & 2 \\
0 & 0 & 0 & 0
\end{bmatrix}.
\]
This system has infinitely many solutions (there’s a free variable), but all we need is one. The solution,
\[
\alpha_1 = 2 \quad \alpha_2 = 3 \quad \alpha_3 = 1
\]
tells us that
\[
(2)\mathbf{u}_1 + (3)\mathbf{u}_2 + (1)\mathbf{u}_3 = \mathbf{w}
\]
so we are convinced that $\mathbf{w}$ really is in $Sp(S)$. Let’s ask the same question again, but this time with $\mathbf{y} = \begin{bmatrix} 2 \\ 4 \\ 3 \end{bmatrix}$, i.e. is $\mathbf{y} \in Sp(S)$?

So we’ll look for scalars $\alpha_1$, $\alpha_2$, $\alpha_3$ so that
\[
\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 = \mathbf{y}.
\]
By Theorem SLSLC \[103\] this linear combination becomes the system of equations
\[
\begin{align*}
\alpha_1 - \alpha_2 + 2\alpha_3 &= 2 \\
2\alpha_1 + \alpha_2 + \alpha_3 &= 4 \\
\alpha_1 + \alpha_2 &= 3.
\end{align*}
\]
Building the augmented matrix for this linear system, and row-reducing, gives
\[
\begin{bmatrix}
1 & 0 & 1 & 0 \\
0 & 1 & -1 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]
This system is inconsistent (there’s a leading 1 in the last column, Theorem RCLS [53]), so there are no scalars \(\alpha_1, \alpha_2, \alpha_3\) that will create a linear combination of \(u_1, u_2, u_3\) that equals \(y\). More precisely, \(y \notin S_p(S)\).

There are three things to observe in this example. (1) It is easy to construct vectors in \(S_p(S)\). (2) It is possible that some vectors are in \(S_p(S)\) (e.g. \(w\)), while others are not (e.g. \(y\)). (3) Deciding if a given vector is in \(S_p(S)\) leads to solving a linear system of equations and asking if the system is consistent.

With a computer program in hand to solve systems of linear equations, could you create a program to decide if a vector was, or wasn’t, in the span of a given set of vectors? Is this art or science?

This example was built on vectors from the columns of the coefficient matrix of Archetype A [563]. Study the determination that \(v \in S_p(S)\) and see if you can connect it with some of the other properties of Archetype A [563].

Let’s do a similar example to Example SCAA [119], only now with Archetype B [568].

**Example SCAB**

**Span of the columns of Archetype B**

Begin with the finite set of three vectors of size 3
\[
R = \{v_1, v_2, v_3\} = \left\{ \begin{bmatrix} -7 \\ 5 \\ 1 \end{bmatrix}, \begin{bmatrix} -6 \\ 5 \\ 0 \end{bmatrix}, \begin{bmatrix} -12 \\ 7 \\ 4 \end{bmatrix} \right\}
\]
and consider the infinite set \(V = S_p(R)\). The vectors of \(R\) have been chosen as the three columns of the coefficient matrix in Archetype B [568]. First, as an example, note that
\[
x = (2) \begin{bmatrix} -7 \\ 5 \\ 1 \end{bmatrix} + (4) \begin{bmatrix} -6 \\ 5 \\ 0 \end{bmatrix} + (-3) \begin{bmatrix} -12 \\ 7 \\ 4 \end{bmatrix} = \begin{bmatrix} -2 \\ 9 \\ -10 \end{bmatrix}
\]
is in \(S_p(R)\), since it is a linear combination of \(v_1, v_2, v_3\). In other words, \(x \in S_p(R)\). Try some different values of \(\alpha_1, \alpha_2, \alpha_3\) yourself, and see what vectors you can create as elements of \(S_p(R)\).

Now ask if a given vector is an element of \(S_p(R)\). For example, is \(z = \begin{bmatrix} -33 \\ 24 \\ 5 \end{bmatrix} \in S_p(R)\)? Is \(z \in S_p(R)\)?

To answer this question, we will look for scalars \(\alpha_1, \alpha_2, \alpha_3\) so that
\[
\alpha_1 v_1 + \alpha_2 v_2 + \alpha_3 v_3 = z.
\]
By Theorem SLSLC [103] this linear combination becomes the system of equations
\[
\begin{align*}
-7\alpha_1 - 6\alpha_2 - 12\alpha_3 &= -33 \\
5\alpha_1 + 5\alpha_2 + 7\alpha_3 &= 24 \\
\alpha_1 + 4\alpha_3 &= 5.
\end{align*}
\]
Building the augmented matrix for this linear system, and row-reducing, gives
\[
\begin{bmatrix}
1 & 0 & 0 & -3 \\
0 & 1 & 0 & 5 \\
0 & 0 & 1 & 2
\end{bmatrix}.
\]
This system has a unique solution,
\[
\alpha_1 = -3 \quad \alpha_2 = 5 \quad \alpha_3 = 2
\]
telling us that
\[
(-3)v_1 + (5)v_2 + (2)v_3 = z
\]
so we are convinced that \( z \) really is in \( S_p(R) \).

There is no point in replacing \( z \) with another vector and doing this again. A question about membership in \( S_p(R) \) inevitably leads to a system of three equations in the three variables \( \alpha_1, \alpha_2, \alpha_3 \) with a coefficient matrix whose columns are the vectors \( v_1, v_2, v_3 \). This particular coefficient matrix is nonsingular, so by Theorem NSMUS [79], it is guaranteed to have a solution. (This solution is unique, but that’s not important here.) So no matter which vector we might have chosen for \( z \), we would have been certain to discover that it was an element of \( S_p(R) \). Stated differently, every vector of size 3 is in \( S_p(R) \), or \( S_p(R) = \mathbb{C}^3 \).

Compare this example with Example SCAA [119], and see if you can connect \( z \) with some aspects of the write-up for Archetype B [568].

### Subsection SSNS
#### Spanning Sets of Null Spaces

We saw in Example VFSAL [110] that when a system of equations is homogeneous the solution set can be expressed in the form described by Theorem VFSLS [106], where the vector \( c \) is the zero vector. We can essentially ignore this vector, so that the remainder of the typical expression for a solution looks like an arbitrary linear combination, where the scalars are the free variables and the vectors are \( u_1, u_2, u_3, \ldots, u_{n-r} \). Which sounds a lot like a span. This is the substance of the next theorem.

**Theorem SSNS**

**Spanning Sets for Null Spaces**

Suppose that \( A \) is an \( m \times n \) matrix, and \( B \) is a row-equivalent matrix in reduced row-echelon form with \( r \) nonzero rows. Let \( D = \{d_1, d_2, d_3, \ldots, d_r\} \) and \( F = \{f_1, f_2, f_3, \ldots, f_{n-r}\} \) be the sets of column indices where \( B \) does and does not (respectively) have leading 1’s. Construct the \( n-r \) vectors \( u_j = (u_{ij}), 1 \leq j \leq n-r \) of size \( n \) as

\[
u_{ij} = \begin{cases} 
1 & \text{if } i \in F, i = f_j \\
0 & \text{if } i \in F, i \neq f_j \\
-b_{kj} & \text{if } i \in D, i = d_k
\end{cases}.
\]

Then the null space of \( A \) is given by

\[
N(A) = S_p(\{u_1, u_2, u_3, \ldots, u_{n-r}\}).
\]
Proof Consider the homogeneous system with $A$ as a coefficient matrix, $\mathcal{L}\mathcal{S}(A, 0)$. Its set of solutions is, by definition, the null space of $A$, $\mathcal{N}(A)$. Row-reducing the augmented matrix of this homogeneous system will create the row-equivalent matrix $B'$. Row-reducing the augmented matrix that has a final column of all zeros, yields $B'$, which is the matrix $B$, along with an additional column (index $n+1$) that is still totally zero.

Now apply Theorem VFSLS [106], noting that our homogeneous system is consistent (Theorem HSC [64]). The vector $c$ has zeros for each entry that corresponds to an index in $F$. For entries that correspond to an index in $D$, the value is $-b'_{k,n+1}$, but for $B'$ these entries in the final column are all zero. So $c = 0$. This says that a solution of the homogeneous system is of the form

$$x = c + x_{f_1}u_1 + x_{f_2}u_2 + x_{f_3}u_3 + \cdots + x_{f_{n-r}}u_{n-r} = x_{f_1}u_1 + x_{f_2}u_2 + x_{f_3}u_3 + \cdots + x_{f_{n-r}}u_{n-r}$$

where the free variables $x_{f_j}$ can each take on any value. Rephrased this says

$$\mathcal{N}(A) = \{ x_{f_1}u_1 + x_{f_2}u_2 + x_{f_3}u_3 + \cdots + x_{f_{n-r}}u_{n-r} \mid x_{f_1}, x_{f_2}, x_{f_3}, \ldots, x_{f_{n-r}} \in \mathbb{C} \} = \mathcal{S}p(\{u_1, u_2, u_3, \ldots, u_{n-r}\})$$

Example SSNS
Spanning set of a null space
Find a set of vectors, $S$, so that the null space of the matrix $A$ below is the span of $S$, that is, $\mathcal{S}p(S) = \mathcal{N}(A)$.

$$A = \begin{bmatrix}
1 & 3 & 3 & -1 & -5 \\
2 & 5 & 7 & 1 & 1 \\
1 & 1 & 5 & 1 & 5 \\
-1 & -4 & -2 & 0 & 4
\end{bmatrix}$$

The null space of $A$ is the set of all solutions to the homogeneous system $\mathcal{L}\mathcal{S}(A, 0)$. If we find the vector form of the solutions to this homogenous system (Theorem VFSLS [106]) then the fixed vectors in the linear combination are exactly the vectors $u_j$, $1 \leq j \leq n-r$ described in Theorem SSNS [122]. So we can mimic Example VFSAL [110] to arrive at these vectors (rather than being a slave to the formulas in the statement of the theorem).

Begin by row-reducing $A$. The result is

$$\begin{bmatrix}
1 & 0 & 6 & 0 & 4 \\
0 & 1 & -1 & 0 & -2 \\
0 & 0 & 0 & 1 & 3 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

With $D = \{1, 2, 4\}$ and $F = \{3, 5\}$ we recognize that $x_3$ and $x_5$ are free variables and we can express each nonzero row as an expression for the dependent variables $x_1, x_2, x_4$ (respectively) in the free variables $x_3$ and $x_5$. With this we can write the vector form of a solution vector as

$$\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5
\end{bmatrix} = \begin{bmatrix}
-6x_3 - 4x_5 \\
x_3 + 2x_5 \\
x_3 \\
-3x_5 \\
x_5
\end{bmatrix} = x_3 \begin{bmatrix}
-6 \\
1 \\
1 \\
0 \\
0
\end{bmatrix} + x_5 \begin{bmatrix}
-4 \\
2 \\
0 \\
-3 \\
1
\end{bmatrix}$$
Then in the notation of Theorem SSNS \[122\],

\[
\begin{bmatrix}
-6 \\
1 \\
1 \\
0 \\
0
\end{bmatrix}
\quad \begin{bmatrix}
-4 \\
2 \\
0 \\
-3 \\
1
\end{bmatrix}
\]

and

\[
N(A) = Sp(\{u_1, u_2\}) = Sp \left( \begin{bmatrix}
-6 \\
1 \\
1 \\
0 \\
-3 \\
1
\end{bmatrix}, \begin{bmatrix}
-4 \\
2 \\
0 \\
-3 \\
1
\end{bmatrix} \right)
\]

Here’s an example that will simultaneously exercise the span construction and Theorem SSNS \[122\], while also pointing the way to the next section.

**Example SCAD**

**Span of the columns of Archetype D**

Begin with the set of four vectors of size 3

\[
T = \{w_1, w_2, w_3, w_4\} = \left\{ \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 1 \end{bmatrix}, \begin{bmatrix} 7 \\ -5 \\ 4 \end{bmatrix}, \begin{bmatrix} -7 \\ -6 \\ -5 \end{bmatrix} \right\}
\]

and consider the infinite set \(W = Sp(T)\). The vectors of \(T\) have been chosen as the four columns of the coefficient matrix in Archetype D \[577\]. Check that the vector

\[
u_2 = \begin{bmatrix}
2 \\
3 \\
0 \\
1
\end{bmatrix}
\]

is a solution to the homogeneous system \(LS(D, 0)\) (it is the second vector of the spanning set for the null space of the coefficient matrix \(D\), as described in Theorem SSNS \[122\]). Applying Theorem SLSLC \[103\], we can write the linear combination,

\[
2w_1 + 3w_2 + 0w_3 + 1w_4 = 0
\]

which we can solve for \(w_4\),

\[
w_4 = (-2)w_1 + (-3)w_2.
\]

This equation says that whenever we encounter the vector \(w_4\), we can replace it with a specific linear combination of the vectors \(w_1\) and \(w_2\). So using \(w_4\) in the set \(T\), along with \(w_1\) and \(w_2\), is excessive. An example of what we mean here can be illustrated by the computation,

\[
5w_1 + (-4)w_2 + 6w_3 + (-3)w_4 = 5w_1 + (-4)w_2 + 6w_3 + (-3)((-2)w_1 + (-3)w_2) \\
= 5w_1 + (-4)w_2 + 6w_3 + (6w_1 + 9w_2) \\
= 11w_1 + 5w_2 + 6w_3.
\]
So what began as a linear combination of the vectors $w_1, w_2, w_3, w_4$ has been reduced to a linear combination of the vectors $w_1, w_2, w_4$. A careful proof using our definition of set equality (Technique SE [17]) would now allow us to conclude that this reduction is possible for any vector in $W$, so

$$W = Sp\{w_1, w_2, w_3\}.$$ 

So the span of our set of vectors, $W$, has not changed, but we have described it by the span of a set of three vectors, rather than four. Furthermore, we can achieve yet another, similar, reduction.

Check that the vector

$$u_1 = \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix}$$

is a solution to the homogeneous system $LS(D, 0)$ (it is the first vector of the spanning set for the null space of the coefficient matrix $D$, as described in Theorem SSNS [122]). Applying Theorem SLSLC [103], we can write the linear combination,

$$(-3)w_1 + (-1)w_2 + 1w_3 = 0$$

which we can solve for $w_3$,

$$w_3 = 3w_1 + 1w_2.$$ 

This equation says that whenever we encounter the vector $w_3$, we can replace it with a specific linear combination of the vectors $w_1$ and $w_2$. So, as before, the vector $w_3$ is not needed in the description of $W$, provided we have $w_1$ and $w_2$ available. In particular, a careful proof would show that

$$W = Sp\{w_1, w_2\}.$$ 

So $W$ began life as the span of a set of four vectors, and we have now shown (utilizing solutions to a homogeneous system) that $W$ can also be described as the span of a set of just two vectors. Convince yourself that we cannot go any further. In other words, it is not possible to dismiss either $w_1$ or $w_2$ in a similar fashion and winnow the set down to just one vector.

What was it about the original set of four vectors that allowed us to declare certain vectors as surplus? And just which vectors were we able to dismiss? And why did we have to stop once we had two vectors remaining? The answers to these questions motivate “linear independence,” our next section and next definition, and so are worth considering carefully now.
Subsection READ
Reading Questions

1. Let $S$ be the set of three vectors below.

$$S = \left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ -4 \\ 2 \end{bmatrix}, \begin{bmatrix} 4 \\ -2 \\ 1 \end{bmatrix} \right\}$$

Let $W = \mathcal{S}p(S)$ be the span of $S$. Is the vector \begin{bmatrix} -1 \\ 8 \\ -4 \end{bmatrix} in $W$? Give an explanation of the reason for your answer.

2. Use $S$ and $W$ from the previous question. Is the vector \begin{bmatrix} 6 \\ 5 \\ -1 \end{bmatrix} in $W$? Give an explanation of the reason for your answer.

3. For the matrix $A$ below, find a set $S$ that spans the null space of $A$, $\mathcal{N}(A)$. That is, $S$ should be such that $\mathcal{S}p(S) = \mathcal{N}(A)$. (See Theorem SSNS [122].)

$$A = \begin{bmatrix} 1 & 3 & 1 & 9 \\ 2 & 1 & -3 & 8 \\ 1 & 1 & -1 & 5 \end{bmatrix}$$
Subsection EXC
Exercises

C22 For each archetype that is a system of equations, consider the corresponding homogeneous system of equations. Write elements of the solution set to these homogeneous systems in vector form, as guaranteed by Theorem VFSLS [106].
Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577
Archetype E 581
Archetype F 585
Archetype G 590
Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer  Solution 129

C40 Suppose that \( S = \left\{ \begin{pmatrix} 2 \\ -1 \\ 3 \\ 3 \\ 4 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \\ -2 \\ -1 \end{pmatrix} \right\} \). Let \( W = \mathcal{S}(S) \) and let \( x = \begin{pmatrix} 5 \\ 8 \\ -12 \\ -5 \end{pmatrix} \). Is \( x \in W \)? If so, provide an explicit linear combination that demonstrates this. Contributed by Robert Beezer  Solution 129

C41 Suppose that \( S = \left\{ \begin{pmatrix} 2 \\ -1 \\ 3 \\ 3 \\ 4 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \\ -2 \\ -1 \end{pmatrix} \right\} \). Let \( W = \mathcal{S}(S) \) and let \( y = \begin{pmatrix} 5 \\ 1 \\ 3 \\ 5 \end{pmatrix} \). Is \( y \in W \)? If so, provide an explicit linear combination that demonstrates this. Contributed by Robert Beezer  Solution 129

C42 Suppose \( R = \left\{ \begin{pmatrix} 2 \\ -1 \\ 3 \\ 4 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \\ 2 \\ 3 \\ -1 \end{pmatrix} \right\} \). Is \( y = \begin{pmatrix} 1 \\ -1 \\ -8 \\ -4 \\ -3 \end{pmatrix} \) in \( \mathcal{S}(R) \)? Contributed by Robert Beezer  Solution 130

C43 Suppose \( R = \left\{ \begin{pmatrix} 2 \\ -1 \\ 3 \\ 4 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 2 \\ 2 \\ -1 \end{pmatrix} \right\} \). Is \( z = \begin{pmatrix} 1 \\ 1 \\ 5 \\ 3 \\ 1 \end{pmatrix} \) in \( \mathcal{S}(R) \)? Contributed by Robert Beezer  Solution 131

C60 For the matrix \( A \) below, find a set of vectors \( S \) so that the span of \( S \) equals the
null space of $A$, $\mathcal{S}p(S) = \mathcal{N}(A)$.

\[
A = \begin{bmatrix}
1 & 1 & 6 & -8 \\
1 & -2 & 0 & 1 \\
-2 & 1 & -6 & 7
\end{bmatrix}
\]

Contributed by Robert Beezer  
Solution [131]

**M20**  In Example SCAD [124] we began with the four columns of the coefficient matrix of Archetype D [577], and used these columns in a span construction. Then we methodically argued that we could remove the last column, then the third column, and create the same set by just doing a span construction with the first two columns. We claimed we could not go any further, and had removed as many vectors as possible. Provide a convincing argument for why a third vector cannot be removed.

Contributed by Robert Beezer

**M21**  In the spirit of Example SCAD [124], begin with the four columns of the coefficient matrix of Archetype C [573], and use these columns in a span construction to build the set $S$. Argue that $S$ can be expressed as the span of just three of the columns of the coefficient matrix (saying exactly which three) and in the spirit of Exercise SS.M20 [128] argue that no one of these three vectors can be removed and still have a span construction create $S$.

Contributed by Robert Beezer  
Solution [132]

**T10**  Suppose that $v_1, v_2 \in \mathbb{C}^m$. Prove that

\[
\mathcal{S}p(\{v_1, v_2\}) = \mathcal{S}p(\{v_1, v_2, 5v_1 + 3v_2\})
\]

Contributed by Robert Beezer  
Solution [132]
Subsection SOL
Solutions

C22 Contributed by Robert Beezer Statement 127
The vector form of the solutions obtained in this manner will involve precisely the vectors described in Theorem SSNS 122 as providing the null space of the coefficient matrix of the system as a span. These vectors occur in each archetype in a description of the null space. Studying Example VFSAL 110 may be of some help.

C40 Contributed by Robert Beezer Statement 127
Rephrasing the question, we want to know if there are scalars \( \alpha_1 \) and \( \alpha_2 \) such that

\[
\alpha_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \end{bmatrix} + \alpha_2 \begin{bmatrix} 3 \\ 2 \\ -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 5 \\ 8 \\ -12 \\ -5 \end{bmatrix}
\]

Theorem SLSLC 103 allows us to rephrase the question again as a quest for solutions to the system of four equations in two unknowns with an augmented matrix given by

\[
\begin{bmatrix} 2 & 3 & 5 \\ -1 & 2 & 8 \\ 3 & -2 & -12 \\ 4 & 1 & -5 \end{bmatrix}
\]

This matrix row-reduces to

\[
\begin{bmatrix} 1 & 0 & -2 \\ 0 & 1 & 3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

From the form of this matrix, we can see that \( \alpha_1 = -2 \) and \( \alpha_2 = 3 \) is an affirmative answer to our question. More convincingly,

\[
(-2) \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \end{bmatrix} + (3) \begin{bmatrix} 3 \\ 2 \\ -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 5 \\ 8 \\ -12 \\ -5 \end{bmatrix}
\]

C41 Contributed by Robert Beezer Statement 127
Rephrasing the question, we want to know if there are scalars \( \alpha_1 \) and \( \alpha_2 \) such that

\[
\alpha_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \end{bmatrix} + \alpha_2 \begin{bmatrix} 3 \\ 2 \\ -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 5 \\ 1 \\ 3 \\ 5 \end{bmatrix}
\]

Theorem SLSLC 103 allows us to rephrase the question again as a quest for solutions
to the system of four equations in two unknowns with an augmented matrix given by

\[
\begin{bmatrix}
2 & 3 & 5 \\
-1 & 2 & 1 \\
3 & -2 & 3 \\
4 & 1 & 5
\end{bmatrix}
\]

This matrix row-reduces to

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0
\end{bmatrix}
\]

With a leading 1 in the last column of this matrix (Theorem RCLS [53]) we can see that the system of equations has no solution, so there are no values for \(\alpha_1\) and \(\alpha_2\) that will allow us to conclude that \(y\) is in \(W\). So \(y \notin W\).

C42 Contributed by Robert Beezer Statement [127]
Form a linear combination, with unknown scalars, of \(R\) that equals \(y\),

\[
a_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 1 \\ 2 \\ 2 \\ -1 \end{bmatrix} + a_3 \begin{bmatrix} 3 \\ -1 \\ 0 \\ 3 \\ -2 \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \\ -8 \\ -4 \\ -3 \end{bmatrix}
\]

We want to know if there are values for the scalars that make the vector equation true since that is the definition of membership in \(S_p(R)\). By Theorem SLSLC [103] any such values will also be solutions to the linear system represented by the augmented matrix,

\[
\begin{bmatrix}
2 & 1 & 3 & 1 \\
-1 & 1 & -1 & -1 \\
3 & 2 & 0 & -8 \\
4 & 2 & 3 & -4 \\
0 & -1 & -2 & -3
\end{bmatrix}
\]

Row-reducing the matrix yields,

\[
\begin{bmatrix}
1 & 0 & 0 & -2 \\
0 & 1 & 0 & -1 \\
0 & 0 & 1 & 2 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

From this we see that the system of equations is consistent (Theorem RCLS [53]), and has a unique solution. This solution will provide a linear combination of the vectors in \(R\) that equals \(y\). So \(y \in R\).

C43 Contributed by Robert Beezer Statement [127]
Form a linear combination, with unknown scalars, of $R$ that equals $z$,

$$
a_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 2 \\ 2 \\ -1 \end{bmatrix} + a_3 \begin{bmatrix} 3 \\ -1 \\ 0 \\ -2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 3 \\ 3 \end{bmatrix}
$$

We want to know if there are values for the scalars that make the vector equation true since that is the definition of membership in $S_p(R)$. By Theorem SLSLC, any such values will also be solutions to the linear system represented by the augmented matrix,

$$
\begin{bmatrix}
2 & 1 & 3 & 1 \\
-1 & 1 & -1 & 1 \\
3 & 2 & 0 & 5 \\
4 & 2 & 3 & 3 \\
0 & -1 & -2 & 1
\end{bmatrix}
$$

Row-reducing the matrix yields,

$$
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
$$

With a leading 1 in the last column, the system is inconsistent, so there are no scalars $a_1, a_2, a_3$ that will create a linear combination of the vectors in $R$ that equal $z$. So $z \not\in R$.

**C60** Contributed by Robert Beezer Statement [127]

Theorem SSNS says that if we find the vector form of the solutions to the homogeneous system $LS(A, 0)$, then the fixed vectors (one per free variable) will have the desired property. Row-reduce $A$, viewing it as the augmented matrix of a homogeneous system with an invisible columns of zeros as the last column,

$$
\begin{bmatrix}
1 & 0 & 4 & -5 \\
0 & 1 & 2 & -3 \\
0 & 0 & 0 & 0
\end{bmatrix}
$$

Moving to the vector form of the solutions, with free variables $x_3$ and $x_4$, solutions to the consistent system (it is homogeneous, Theorem HSC) can be expressed as

$$
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4
\end{bmatrix} = x_3 \begin{bmatrix} -4 \\ -2 \\ 1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 5 \\ 3 \\ 0 \\ 1 \end{bmatrix}
$$

Then with $S$ given by

$$
S = \begin{bmatrix}
-4 & 5 \\
-2 & 3 \\
1 & 0 \\
0 & 1
\end{bmatrix}
$$
Theorem SSNS \[122\] guarantees that

$$N(A) = S_p(S) = S_p\left( \begin{bmatrix} -4 & 5 \\ -2 & 3 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \right)$$

M21 Contributed by Robert Beezer Statement \[128\] If the columns of the coefficient matrix from Archetype C \[573\] are named \(u_1, u_2, u_3, u_4\) then we can discover the equation

$$(-2)u_1 + (-3)u_2 + u_3 + u_4 = 0$$

by building a homogeneous system of equations and viewing a solution to the system as scalars in a linear combination via Theorem SLSLC \[103\]. This particular vector equation can be rearranged to read

$$u_4 = (2)u_1 + (3)u_2 + (-1)u_3$$

This can be interpreted to mean that \(u_4\) is unnecessary in \(S_p(\{u_1, u_2, u_3, u_4\})\), so that

$$S_p(\{u_1, u_2, u_3, u_4\}) = S_p(\{u_1, u_2, u_3\})$$

If we try to repeat this process and find a linear combination of \(u_1, u_2, u_3\) that equals the zero vector, we will fail. The required homogeneous system of equations (via Theorem SLSLC \[103\]) has only a trivial solution, which will not provide the kind of equation we need to remove one of the three remaining vectors.

T10 Contributed by Robert Beezer Statement \[128\] This is an equality of sets, so Technique SE \[17\] applies.

First show that \(X = S_p(\{v_1, v_2\}) \subseteq S_p(\{v_1, v_2, 5v_1 + 3v_2\}) = Y\).

Choose \(x \in X\). Then \(x = a_1v_1 + a_2v_2\) for some scalars \(a_1\) and \(a_2\). Then,

$$x = a_1v_1 + a_2v_2 = a_1v_1 + a_2v_2 + 0(5v_1 + 3v_2)$$

which qualifies \(x\) for membership in \(Y\), as it is a linear combination of \(v_1, v_2, 5v_1 + 3v_2\).

Now show the opposite inclusion, \(Y = S_p(\{v_1, v_2, 5v_1 + 3v_2\}) \subseteq S_p(\{v_1, v_2\}) = X\).

Choose \(y \in Y\). Then there are scalars \(a_1, a_2, a_3\) such that

$$y = a_1v_1 + a_2v_2 + a_3(5v_1 + 3v_2)$$

Rearranging, we obtain,

$$y = a_1v_1 + a_2v_2 + a_3(5v_1 + 3v_2)$$

$$= a_1v_1 + a_2v_2 + 5a_3v_1 + 3a_3v_2 \quad \text{Property DVAC} \[92\]$$

$$= a_1v_1 + 5a_3v_1 + a_2v_2 + 3a_3v_2 \quad \text{Property CC} \[92\]$$

$$= (a_1 + 5a_3)v_1 + (a_2 + 3a_3)v_2 \quad \text{Property DSAC} \[93\]$$

This is an expression for \(y\) as a linear combination of \(v_1\) and \(v_2\), earning \(y\) membership in \(X\). Since \(X\) is a subset of \(Y\), and vice versa, we see that \(X = Y\), as desired.


Section LI
Linear Independence

Subsection LIV
Linearly Independent Vectors

**Theorem SLSLC** [103] tells us that a solution to a homogeneous system of equations is a linear combination of the columns of the coefficient matrix that equals the zero vector. We used just this situation to our advantage (twice!) in Example SCAD [124] where we reduced the set of vectors used in a span construction from four down to two, by declaring certain vectors as surplus. The next two definitions will allow us to formalize this situation.

**Definition RLDCV**
Relation of Linear Dependence for Column Vectors
Given a set of vectors \( S = \{ u_1, u_2, u_3, \ldots, u_n \} \), an equation of the form
\[
\alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_n u_n = 0
\]
is a relation of linear dependence on \( S \). If this equation is formed in a trivial fashion, i.e. \( \alpha_i = 0 \), \( 1 \leq i \leq n \), then we say it is a trivial relation of linear dependence on \( S \).

**Definition LICV**
Linear Independence of Column Vectors
The set of vectors \( S = \{ u_1, u_2, u_3, \ldots, u_n \} \) is linearly dependent if there is a relation of linear dependence on \( S \) that is not trivial. In the case where the only relation of linear dependence on \( S \) is the trivial one, then \( S \) is a linearly independent set of vectors. \( \triangle \)

Notice that a relation of linear dependence is an equation. Though most of it is a linear combination, it is not a linear combination (that would be a vector). Linear independence is a property of a set of vectors. It is easy to take a set of vectors, and an equal number of scalars, all zero, and form a linear combination that equals the zero vector. When the easy way is the only way, then we say the set is linearly independent. Here’s a couple of examples.

**Example LDS**
Linearly dependent set in \( \mathbb{C}^5 \)
Consider the set of \( n = 4 \) vectors from \( \mathbb{C}^5 \),
\[
S = \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ -1 \\ 5 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ -3 \\ 6 \\ 1 \end{bmatrix}, \begin{bmatrix} -6 \\ 7 \\ -1 \\ 0 \\ 1 \end{bmatrix} \right\}.
\]
To determine linear independence we first form a relation of linear dependence,

\[
\alpha_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 1 \\ 2 \end{bmatrix} + \alpha_2 \begin{bmatrix} 1 \\ 2 \\ -1 \\ 5 \\ 2 \end{bmatrix} + \alpha_3 \begin{bmatrix} 2 \\ 1 \\ -3 \\ 6 \\ 1 \end{bmatrix} + \alpha_4 \begin{bmatrix} -6 \\ 7 \\ -1 \\ 0 \\ 1 \end{bmatrix} = 0.
\]

We know that \( \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0 \) is a solution to this equation, but that is of no interest whatsoever. That is always the case, no matter what four vectors we might have chosen. We are curious to know if there are other, nontrivial, solutions. Theorem SLSLC \[103\] tells us that we can find such solutions as solutions to the homogeneous system \( \mathbf{L}(A, \mathbf{0}) \) where the coefficient matrix has these four vectors as columns,

\[
A = \begin{bmatrix} 2 & 1 & 2 & -6 \\ -1 & 2 & 1 & 7 \\ 3 & -1 & -3 & -1 \\ 1 & 5 & 6 & 0 \\ 2 & 2 & 1 & 1 \end{bmatrix}.
\]

Row-reducing this coefficient matrix yields,

\[
\begin{bmatrix} 1 & 0 & 0 & -2 \\ 0 & 1 & 0 & 4 \\ 0 & 0 & 1 & -3 \\ 0 & 0 & 0 & 0 \end{bmatrix}.
\]

We could solve this homogeneous system completely, but for this example all we need is one nontrivial solution. Setting the lone free variable to any nonzero value, such as \( x_4 = 1 \), yields the nontrivial solution

\[
\mathbf{x} = \begin{bmatrix} 2 \\ -4 \\ 3 \\ 1 \end{bmatrix}.
\]

completing our application of Theorem SLSLC \[103\], we have

\[
2 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 1 \\ 2 \end{bmatrix} + (-4) \begin{bmatrix} 1 \\ 2 \\ -1 \\ 5 \\ 2 \end{bmatrix} + 3 \begin{bmatrix} 2 \\ 1 \\ -3 \\ 6 \\ 1 \end{bmatrix} + 1 \begin{bmatrix} -6 \\ 7 \\ -1 \\ 0 \\ 1 \end{bmatrix} = 0.
\]

This is a relation of linear dependence on \( S \) that is not trivial, so we conclude that \( S \) is linearly dependent.

\[\circ\]

**Example LIS**

Linearly independent set in \( \mathbb{C}^5 \)
Consider the set of $n = 4$ vectors from $\mathbb{C}^5$,

$$T = \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ -1 \\ 5 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ -3 \\ 6 \\ 1 \end{bmatrix}, \begin{bmatrix} -6 \\ 1 \\ -1 \\ 1 \\ 1 \end{bmatrix} \right\}.$$

To determine linear independence we first form a relation of linear dependence,

$$\alpha_1 \begin{bmatrix} 2 \\ -1 \\ 3 \\ 1 \\ 2 \end{bmatrix} + \alpha_2 \begin{bmatrix} 1 \\ 2 \\ -1 \\ 5 \\ 2 \end{bmatrix} + \alpha_3 \begin{bmatrix} 2 \\ 1 \\ -3 \\ 6 \\ 1 \end{bmatrix} + \alpha_4 \begin{bmatrix} -6 \\ 1 \\ -1 \\ 1 \\ 1 \end{bmatrix} = 0.$$

We know that $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$ is a solution to this equation, but that is of no interest whatsoever. That is always the case, no matter what four vectors we might have chosen. We are curious to know if there are other, nontrivial, solutions. Theorem SLSLC\ref{th:slslc} tells us that we can find such solutions as solution to the homogeneous system $\mathcal{L}(B, 0)$ where the coefficient matrix has these four vectors as columns,

$$B = \begin{bmatrix} 2 & 1 & 2 & -6 \\ -1 & 2 & 1 & 7 \\ 3 & -1 & -3 & -1 \\ 1 & 5 & 6 & 1 \\ 2 & 2 & 1 & 1 \end{bmatrix}.$$

Row-reducing this coefficient matrix yields,

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

From the form of this matrix, we see that there are no free variables, so the solution is unique, and because the system is homogeneous, this unique solution is the trivial solution. So we now know that there is but one way to combine the four vectors of $T$ into a relation of linear dependence, and that one way is the easy and obvious way. In this situation we say that the set, $T$, is linearly independent. \[\Box\]

Example LDS\ref{ex:lds} and Example LIS\ref{ex:lis} relied on solving a homogeneous system of equations to determine linear independence. We can codify this process in a time-saving theorem.

**Theorem LIVHS**

**Linearly Independent Vectors and Homogeneous Systems**

Suppose that $A$ is an $m \times n$ matrix and $S = \{A_1, A_2, A_3, \ldots, A_n\}$ is the set of vectors in $\mathbb{C}^m$ that are the columns of $A$. Then $S$ is a linearly independent set if and only if the homogeneous system $\mathcal{L}(A, 0)$ has a unique solution. \[\Box\]
Proof \((\Leftarrow)\) Suppose that \(LS(A, 0)\) has a unique solution. Since it is a homogeneous system, this solution must be the trivial solution \(x = 0\). By Theorem SLSLC 103, this means that the only relation of linear dependence on \(S\) is the trivial one. So \(S\) is linearly independent.

\((\Rightarrow)\) We will prove the contrapositive. Suppose that \(LS(A, 0)\) does not have a unique solution. Since it is a homogeneous system, it is consistent (Theorem HSC 64), and so must have infinitely many solutions (Theorem PSSLS 56). One of these infinitely many solutions must be nontrivial (in fact, almost all of them are), so choose one. By Theorem SLSLC 103 this nontrivial solution will give a nontrivial relation of linear dependence on \(S\), so we can conclude that \(S\) is a linearly dependent set.

Since Theorem LIVHS 135 is an equivalence, we can use it to determine the linear independence or dependence of any set of column vectors, just by creating a corresponding matrix and analyzing the row-reduced form. Let’s illustrate this with two more examples.

Example LIHS
Linearly independent, homogeneous system
Is the set of vectors
\[
S = \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \end{bmatrix}, \begin{bmatrix} 6 \\ 2 \\ -1 \\ 3 \end{bmatrix}, \begin{bmatrix} 4 \\ 3 \\ -4 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ 4 \\ 1 \end{bmatrix} \right\}
\]
linearly independent or linearly dependent?

Theorem LIVHS 135 suggests we study the matrix whose columns are the vectors in \(S\),
\[
A = \begin{bmatrix} 2 & 6 & 4 \\ -1 & 2 & 3 \\ 3 & -1 & -4 \\ 4 & 3 & 5 \\ 2 & 4 & 1 \end{bmatrix}
\]
Specifically, we are interested in the size of the solution set for the homogeneous system \(LS(A, 0)\). Row-reducing \(A\), we obtain
\[
\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}
\]
Now, \(r = 3\), so there are \(n - r = 3 - 3 = 0\) free variables and we see that \(LS(A, 0)\) has a unique solution (Theorem HSC 64, Theorem FVCS 55). By Theorem LIVHS 135, the set \(S\) is linearly independent.

Example LDHS
Linearly dependent, homogeneous system
Is the set of vectors
\[ S = \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 4 \\ 2 \end{bmatrix}, \begin{bmatrix} 6 \\ 2 \\ -1 \\ 3 \\ 4 \end{bmatrix}, \begin{bmatrix} 4 \\ 3 \\ -4 \\ -1 \\ 2 \end{bmatrix} \right\} \]
linearly independent or linearly dependent?

Theorem LIVHS [135] suggests we study the matrix whose columns are the vectors in \( S \),
\[ A = \begin{bmatrix} 2 & 6 & 4 \\ -1 & 2 & 3 \\ 3 & -1 & -4 \\ 4 & 3 & -1 \\ 2 & 4 & 2 \end{bmatrix} \]

Specifically, we are interested in the size of the solution set for the homogeneous system \( \mathcal{L}S(A, 0) \). Row-reducing \( A \), we obtain
\[ \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \]

Now, \( r = 2 \), so there are \( n - r = 3 - 2 = 1 \) free variables and we see that \( \mathcal{L}S(A, 0) \) has infinitely many solutions (Theorem HSC [64], Theorem FVCS [55]). By Theorem LIVHS [135], the set \( S \) is linearly dependent.

As an equivalence, Theorem LIVHS [135] gives us a straightforward way to determine if a set of vectors is linearly independent or dependent.

Review Example LIHS [136] and Example LDHS [136]. They are very similar, differing only in the last two slots of the third vector. This resulted in slightly different matrices when row-reduced, and slightly different values of \( r \), the number of nonzero rows. Notice, too, that we are less interested in the actual solution set, and more interested in its form or size. These observations allow us to make a slight improvement in Theorem LIVHS [135].

**Theorem LIVRN**

**Linearly Independent Vectors, \( r \) and \( n \)**

Suppose that \( A \) is an \( m \times n \) matrix and \( S = \{ A_1, A_2, A_3, \ldots, A_n \} \) is the set of vectors in \( \mathbb{C}^m \) that are the columns of \( A \). Let \( B \) be a matrix in reduced row-echelon form that is row-equivalent to \( A \) and let \( r \) denote the number of non-zero rows in \( B \). Then \( S \) is linearly independent if and only if \( n = r \).

**Proof** Theorem LIVHS [135] says the linear independence of \( S \) is equivalent to the homogeneous linear system \( \mathcal{L}S(A, 0) \) having a unique solution. Since \( \mathcal{L}S(A, 0) \) is consistent (Theorem HSC [64]) we can apply Theorem CSRN [54] to see that the solution is unique exactly when \( n = r \).

So now here’s an example of the most straightforward way to determine if a set of column vectors in linearly independent or linearly dependent. While this method can be quick
and easy, don’t forget the logical progression from the definition of linear independence through homogeneous system of equations which makes it possible.

Example LDRN
Linearly dependent, $r < n$
Is the set of vectors

\[ S = \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 0 \\ 3 \end{bmatrix}, \begin{bmatrix} 9 \\ -6 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -3 \\ 1 \\ 2 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 6 \\ -2 \\ 4 \\ 3 \\ 2 \end{bmatrix} \right\} \]

linearly independent or linearly dependent? Theorem LIVHS 135 suggests we place these vectors into a matrix as columns and analyze the row-reduced version of the matrix,

\[
\begin{bmatrix}
2 & 9 & 1 & -3 & 6 \\
-1 & -6 & 1 & 1 & -2 \\
3 & -2 & 1 & 4 & 1 \\
1 & 3 & 0 & 2 & 4 \\
0 & 2 & 0 & 1 & 3 \\
3 & 1 & 1 & 2 & 2
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & -1 \\
0 & 1 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 2 \\
0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Now we need only compute that $r = 4 < 5 = n$ to recognize, via Theorem LIVHS 135 that $S$ is a linearly dependent set. Boom!

Example LLDS
Large linearly dependent set in $\mathbb{C}^4$
Consider the set of $n = 9$ vectors from $\mathbb{C}^4$,

\[ R = \left\{ \begin{bmatrix} -1 \\ 3 \\ 1 \\ 2 \\ 6 \\ 1 \end{bmatrix}, \begin{bmatrix} 7 \\ -3 \\ -1 \\ -2 \\ 9 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 4 \\ 3 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 4 \\ 2 \\ 3 \\ 4 \\ 4 \end{bmatrix}, \begin{bmatrix} 5 \\ -2 \\ 4 \\ 1 \\ -2 \\ 0 \end{bmatrix}, \begin{bmatrix} -2 \\ -4 \\ -6 \\ 4 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \\ 6 \\ 3 \\ 4 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 2 \\ 1 \\ 3 \\ 3 \end{bmatrix}, \begin{bmatrix} -6 \\ 1 \\ 5 \\ 1 \\ 1 \\ 1 \end{bmatrix} \right\}. \]

To employ Theorem LIVHS 135, we form a $4 \times 9$ coefficient matrix, $C$,

\[
C = \begin{bmatrix}
-1 & 7 & 1 & 0 & 5 & 2 & 3 & 1 & -6 \\
3 & 1 & 2 & 4 & -2 & 1 & 0 & 1 & -1 \\
1 & -3 & 1 & 2 & 4 & -6 & -3 & 5 & 1 \\
2 & 6 & -2 & 9 & 3 & 4 & 1 & 3 & 1
\end{bmatrix}
\]

To determine if the homogeneous system $LS(C, 0)$ has a unique solution or not, we would normally row-reduce this matrix. But in this particular example, we can do better. Theorem HMVE1 65 tells us that since the system is homogeneous with $n = 9$ variables in $m = 4$ equations, and $n > m$, there must be infinitely many solutions. Since there is not a unique solution, Theorem LIVHS 135 says the set is linearly dependent.

The situation in Example LLDS 138 is slick enough to warrant formulating as a theorem.
Theorem MVSLD
More Vectors than Size implies Linear Dependence
Suppose that $S = \{u_1, u_2, u_3, \ldots, u_n\}$ is the set of vectors in $\mathbb{C}^m$, and that $n > m$. Then $S$ is a linearly dependent set.

\[ \square \]

Proof
Form the $m \times n$ coefficient matrix $A$ that has the column vectors $u_i$, $1 \leq i \leq n$ as its columns. Consider the homogeneous system $\mathcal{L}(A, 0)$. By Theorem HMVEI [165] this system has infinitely many solutions. Since the system does not have a unique solution, Theorem LIVHS [135] says the columns of $A$ form a linearly dependent set, which is the desired conclusion.

\[ \blacksquare \]

Subsection LI.LINSM
Linear Independence and NonSingular Matrices

We will now specialize to sets of $n$ vectors from $\mathbb{C}^n$. This will put Theorem MVSLD [139] off-limits, while Theorem LIVHS [135] will involve square matrices. Let’s begin by contrasting Archetype A [563] and Archetype B [568].

Example LDCAA
Linearly dependent columns in Archetype A

Archetype A [563] is a system of linear equations with coefficient matrix,

\[
A = \begin{bmatrix}
1 & -1 & 2 \\
2 & 1 & 1 \\
1 & 1 & 0
\end{bmatrix}.
\]

Do the columns of this matrix form a linearly independent or dependent set? By Example S [76] we know that $A$ is singular. According to the definition of nonsingular matrices, Definition NM [75], the homogeneous system $\mathcal{L}(A, 0)$ has infinitely many solutions. So by Theorem LIVHS [135], the columns of $A$ form a linearly dependent set.

\[ \odot \]

Example LICAB
Linearly independent columns in Archetype B

Archetype B [568] is a system of linear equations with coefficient matrix,

\[
B = \begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{bmatrix}.
\]

Do the columns of this matrix form a linearly independent or dependent set? By Example NS [76] we know that $B$ is nonsingular. According to the definition of nonsingular matrices, Definition NM [75], the homogeneous system $\mathcal{L}(A, 0)$ has a unique solution. So by Theorem LIVHS [135], the columns of $B$ form a linearly independent set.

\[ \odot \]

That Archetype A [563] and Archetype B [568] have opposite properties for the columns of their coefficient matrices is no accident. Here’s the theorem, and then we will update our equivalences for nonsingular matrices, Theorem NSME1 [82].

Theorem NSLIC
NonSingular matrices have Linearly Independent Columns

Suppose that $A$ is a square matrix. Then $A$ is nonsingular if and only if the columns of $A$ form a linearly independent set.

\[ \odot \]
Proof  This is a proof where we can chain together equivalences, rather than proving the two halves separately.

\[ A \text{ nonsingular} \iff \mathcal{LS}(A, \mathbf{0}) \text{ has a unique solution} \quad \text{Definition NM 75} \]
\[ \iff \text{columns of } A \text{ are linearly independent} \quad \text{Theorem LIVH5 135} \]

Here’s an update to Theorem NSME1 82.

Theorem NSME2
NonSingular Matrix Equivalences, Round 2
Suppose that \( A \) is a square matrix. The following are equivalent.

1. \( A \) is nonsingular.
2. \( A \) row-reduces to the identity matrix.
3. The null space of \( A \) contains only the zero vector, \( \mathcal{N}(A) = \{0\} \).
4. The linear system \( \mathcal{LS}(A, \mathbf{b}) \) has a unique solution for every possible choice of \( \mathbf{b} \).
5. The columns of \( A \) form a linearly independent set. □

Proof  Theorem NSLIC 139 is yet another equivalence for a nonsingular matrix, so we can add it to the list in Theorem NSME1 82. □

Subsection NSSLI
Null Spaces, Spans, Linear Independence

In Subsection SS.SSNS 122 we proved Theorem SSNS 122 which provided \( n-r \) vectors that could be used with the span construction to build the entire null space of a matrix. As we have seen in Theorem DLDS 151 and Example RSC5 152, linearly dependent sets carry redundant vectors with them when used in building a set as a span. Our aim now is to show that the vectors provided by Theorem SSNS 122 form a linearly independent set, so in one sense they are as efficient as possible a way to describe the null space. Notice that the vectors \( \mathbf{u}_j, 1 \leq j \leq n-r \) first appear in the vector form of solutions to arbitrary linear systems (Theorem VFSLS 106). The exact same vectors appear again in the span construction in the conclusion of Theorem SSNS 122. Since this second theorem specializes to homogeneous systems the only real difference is that the vector \( \mathbf{c} \) in Theorem VFSLS 106 is the zero vector for a homogeneous system. Finally, Theorem BNS 141 will now show that these same vectors are a linearly independent set.

The proof is really quite straightforward, and relies on the “pattern” of zeros and ones that arise in the vectors \( \mathbf{u}_i, 1 \leq i \leq n-r \) in the entries that correspond to the free variables. So take a look at Example VFSAD 104, Example VFSAI 108 and Example VFSAL 110, especially during the conclusion of Step 2 (temporarily ignore the construction of the constant vector, \( \mathbf{c} \)). It is a good exercise in showing how to prove a conclusion that states a set is linearly independent.
Theorem BNS

Basis for Null Spaces

Suppose that $A$ is an $m \times n$ matrix, and $B$ is a row-equivalent matrix in reduced row-echelon form with $r$ nonzero rows. Let $D = \{d_1, d_2, d_3, \ldots, d_r\}$ and $F = \{f_1, f_2, f_3, \ldots, f_{n-r}\}$ be the sets of column indices where $B$ does and does not (respectively) have leading 1’s. Construct the $n - r$ vectors $\mathbf{z}_j = (z_{ij})$, $1 \leq j \leq n - r$ of size $n$ as

$$
z_{ij} = \begin{cases} 
1 & \text{if } i \in F, \ i = f_j \\
0 & \text{if } i \in F, \ i \neq f_j \\
-b_{k,f_j} & \text{if } i \in D, \ i = d_k
\end{cases}
$$

Define the set $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_{n-r}\}$. Then

1. $\mathcal{N}(A) = \mathcal{S}p(S)$.

2. $S$ is a linearly independent set. \qed

Proof Notice first that the vectors $\mathbf{z}_j = (z_{ij})$, $1 \leq j \leq n - r$ are defined in exactly the same way that the vectors $\mathbf{u}_j = (u_{ij})$, $1 \leq j \leq n - r$ of Theorem SSNS [122] are defined. Other than this cosmetic change in the names of these vectors, the hypotheses of Theorem SSNS [122] are the same as the hypotheses of the theorem we are currently proving. So it is then simply the conclusion of Theorem SSNS [122] that tells us that $\mathcal{N}(A) = \mathcal{S}p(S)$. That was the easy half, but the second part is not much harder.

To prove the linear independence of a set, we need to start with a relation of linear dependence and somehow conclude that the scalars involved must all be zero, i.e. that the relation of linear dependence only happens in the trivial fashion. So to establish the linear independence of $S$, we start with

$$
\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_{n-r} \mathbf{u}_{n-r} = \mathbf{0}.
$$

For each $j$, $1 \leq j \leq n - r$, consider the entry of the vectors on both sides of this equality in position $f_j$. On the right, it is easy since the zero vector has a zero in each entry. On the left we find,

$$
\alpha_1 \mathbf{z}_{f_j,1} + \alpha_2 \mathbf{z}_{f_j,2} + \alpha_3 \mathbf{z}_{f_j,3} + \cdots + \alpha_{j-1} \mathbf{z}_{f_j,j-1} + \alpha_j \mathbf{z}_{f_j,j} + \alpha_{j+1} \mathbf{z}_{f_j,j+1} + \cdots + \alpha_{n-r} \mathbf{z}_{f_j,n-r} = \alpha_1(0) + \alpha_2(0) + \alpha_3(0) + \cdots + \alpha_{j-1}(0) + \alpha_j(1) + \alpha_{j+1}(0) + \cdots + \alpha_{n-r}(0) = \alpha_j
$$

So for all $j$, $1 \leq j \leq n - r$, we have $\alpha_j = 0$, which is the conclusion that tells us that the only relation of linear dependence on $S = \{\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \ldots, \mathbf{z}_{n-r}\}$ is the trivial one, hence the set is linearly independent, as desired. \[\blacksquare\]

Example NSLIL

Null space spanned by linearly independent set, Archetype L

In Example VFSAL [110] we previewed Theorem SSNS [122] by finding a set of two vectors such that their span was the null space for the matrix in Archetype L [613]. Writing the matrix as $L$, we have

$$
N(L) = \mathcal{S}p\left(\begin{bmatrix}
-1 & 2 \\
2 & -2 \\
-2 & 1 \\
1 & 0 \\
0 & 1
\end{bmatrix}\right).
$$
Solving the homogeneous system $LS(L, 0)$ resulted in recognizing $x_4$ and $x_5$ as the free variables. So look in entries 4 and 5 of the two vectors above and notice the pattern of zeros and ones that provides the linear independence of the set.

Subsection READ
Reading Questions

1. Let $S$ be the set of three vectors below.

$$S = \left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ -4 \\ 2 \end{bmatrix}, \begin{bmatrix} 4 \\ -2 \\ 1 \end{bmatrix} \right\}$$

Is $S$ linearly independent or linearly dependent? Explain why.

2. Let $S$ be the set of three vectors below.

$$S = \left\{ \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} 4 \\ 3 \\ -4 \end{bmatrix} \right\}$$

Is $S$ linearly independent or linearly dependent? Explain why.

3. Based on your answer to the previous question, is the matrix below singular or nonsingular? Explain.

$$\begin{bmatrix} 1 & 3 & 4 \\ -1 & 2 & 3 \\ 0 & 2 & -4 \end{bmatrix}$$
Determine if the sets of vectors in Exercises C20–C24 are linearly independent or linearly dependent.

**C20**
\[
\begin{bmatrix}
1 & 2 & 1 \\
-2 & -1 & 5 \\
1 & 3 & 0
\end{bmatrix}
\]
Contributed by Robert Beezer Solution 147

**C21**
\[
\begin{bmatrix}
-1 & 3 & 7 \\
2 & 3 & 3 \\
4 & -1 & -6 \\
2 & 3 & 4
\end{bmatrix}
\]
Contributed by Robert Beezer Solution 147

**C22**
\[
\begin{bmatrix}
1 & 6 & 9 & 2 & 3 \\
5 & -1 & -3 & 8 & -2 \\
1 & 2 & -1 & -1 & 0
\end{bmatrix}
\]
Contributed by Robert Beezer Solution 147

**C23**
\[
\begin{bmatrix}
1 & 3 & 2 & 1 \\
-2 & 3 & 1 & 0 \\
2 & 1 & 2 & 1 \\
5 & 2 & -1 & 2 \\
3 & -4 & 1 & 2
\end{bmatrix}
\]
Contributed by Robert Beezer Solution 147

**C24**
\[
\begin{bmatrix}
1 & 3 & 4 & -1 \\
-1 & -1 & -2 & 2 \\
0 & 2 & 2 & -2 \\
1 & 2 & 3 & 0
\end{bmatrix}
\]
Contributed by Robert Beezer Solution 147

**C30** For the matrix $B$ below, find a set $S$ that is linearly independent and spans the null space of $B$, that is, $N(B) = Sp(S)$.

\[
B = \begin{bmatrix}
-3 & 1 & -2 & 7 \\
-1 & 2 & 1 & 4 \\
1 & 1 & 2 & -1
\end{bmatrix}
\]

Contributed by Robert Beezer Solution 148

**C50** Consider each archetype that is a system of equations and consider the solutions listed for the homogeneous version of the archetype. (If only the trivial solution is listed, then assume this is the only solution to the system.) From the solution set, determine if the columns of the coefficient matrix form a linearly independent or linearly dependent set. In the case of a linearly dependent set, use one of the sample solutions to provide
a nontrivial relation of linear dependence on the set of columns of the coefficient matrix
(Definition RLD [309]). Indicate when Theorem MVSLD [139] applies and connect this
with the number of variables and equations in the system of equations.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577/Archetype E 581
Archetype F 585
Archetype G 590/Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer

C51 For each archetype that is a system of equations consider the homogeneous ver-
sion. Write elements of the solution set in vector form (Theorem VFSLS [106]) and from
this extract the vectors $z_j$ described in Theorem BNS [141]. These vectors are used in a
span construction to describe the null space of the coefficient matrix for each archetype.
What does it mean when we write a null space as $\text{Sp}(\{\})$?

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577/Archetype E 581
Archetype F 585
Archetype G 590/Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer

C52 For each archetype that is a system of equations consider the homogeneous ver-
sion. Sample solutions are given and a linearly independent spanning set is given for the
null space of the coefficient matrix. Write each of the sample solutions individually as a
linear combination of the vectors in the spanning set for the null space of the coefficient
matrix.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577/Archetype E 581
Archetype F 585
Archetype G 590/Archetype H 594
Archetype I 599
Archetype J 604

Contributed by Robert Beezer

C60 For the matrix $A$ below, find a set of vectors $S$ so that (1) $S$ is linearly in-
dependent, and (2) the span of $S$ equals the null space of $A$, $\text{Sp}(S) = \mathcal{N}(A)$. 

Version 0.52
Exercise SS.C60 127.)

\[
A = \begin{bmatrix}
1 & 1 & 6 & -8 \\
1 & -2 & 0 & 1 \\
-2 & 1 & -6 & 7
\end{bmatrix}
\]

Contributed by Robert Beezer Solution 148

M50  Consider the set of vectors from \( \mathbb{C}^3 \), \( W \), given below. Find a set \( T \) that contains three vectors from \( W \) and such that \( W = \text{sp}(T) \).

\[
W = \text{sp}(\{v_1, v_2, v_3, v_4, v_5\}) = \text{sp}\left(\left\{\begin{bmatrix}2 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix}-1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix}1 \\ 3 \\ 3 \end{bmatrix}, \begin{bmatrix}3 \\ 1 \\ -3 \end{bmatrix}\right\}\right)
\]

Contributed by Robert Beezer Solution 149

T10  Prove that if a set of vectors contains the zero vector, then the set is linearly dependent. (Ed. “The zero vector is death to linearly independent sets.”)

Contributed by Martin Jackson

T20  Suppose that \( \{v_1, v_2, v_3, v_4\} \) is a linearly independent set in \( \mathbb{C}^3 \). Prove that

\[
\{v_1, v_1 + v_2, v_1 + v_2 + v_3, v_1 + v_2 + v_3 + v_4\}
\]

is a linearly independent set.

Contributed by Robert Beezer Solution 149
Subsection SOL
Solutions

C20 Contributed by Robert Beezer Statement 143
With three vectors from $\mathbb{C}^3$, we can form a square matrix by making these three vectors the columns of a matrix. We do so, and row-reduce to obtain,

$$
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
$$

the $3 \times 3$ identity matrix. So by Theorem NSME2 140 the original matrix is nonsingular and its columns are therefore a linearly independent set.

C21 Contributed by Robert Beezer Statement 143
Theorem LIVRN 137 says we can answer this question by putting these vectors into a matrix as columns and row-reducing. Doing this we obtain,

$$
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
$$

With $n = 3$ (3 vectors, 3 columns) and $r = 3$ (3 leading 1’s) we have $n = r$ and the corollary says the vectors are linearly independent.

C22 Contributed by Robert Beezer Statement 143
Five vectors from $\mathbb{C}^3$. Theorem MVSLD 139 says the set is linearly dependent. Boom.

C23 Contributed by Robert Beezer Statement 143
Theorem LIVRN 137 suggests we analyze a matrix whose columns are the vectors of $S$,

$$
A = \begin{bmatrix}
1 & 3 & 2 & 1 \\
-2 & 3 & 1 & 0 \\
2 & 1 & 2 & 1 \\
5 & 2 & -1 & 2 \\
3 & -4 & 1 & 2
\end{bmatrix}
$$

Row-reducing the matrix $A$ yields,

$$
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
$$

We see that $r = 4 = n$, where $r$ is the number of nonzero rows and $n$ is the number of columns. By Theorem LIVRN 137, the set $S$ is linearly independent.

C24 Contributed by Robert Beezer Statement 143
Theorem LIVRN 137 suggests we analyze a matrix whose columns are the vectors from
the set,

\[
A = \begin{bmatrix}
1 & 3 & 4 & -1 \\
2 & 2 & 4 & 2 \\
-1 & -1 & -2 & -1 \\
0 & 2 & 2 & -2 \\
1 & 2 & 3 & 0
\end{bmatrix}
\]

Row-reducing the matrix \( A \) yields,

\[
\begin{bmatrix}
1 & 0 & 1 & 2 \\
0 & 1 & 1 & -1 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

We see that \( r = 2 \neq 4 = n \), where \( r \) is the number of nonzero rows and \( n \) is the number of columns. By Theorem LIVRN, the set \( S \) is linearly dependent.

C30 Contributed by Robert Beezer Statement

The requested set is described by Theorem BNS. It is easiest to find by using the procedure of Example VFSAL. Begin by row-reducing the matrix, viewing it as the coefficient matrix of a homogeneous system of equations. We obtain,

\[
\begin{bmatrix}
1 & 0 & 1 & -2 \\
0 & 1 & 1 & 1 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Now build the vector form of the solutions to this homogeneous system. The free variables are \( x_3 \) and \( x_4 \), corresponding to the columns without leading 1’s,

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4
\end{bmatrix} = x_3 \begin{bmatrix} -1 \\ -1 \\ 1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 2 \\ -1 \\ 0 \\ 1 \end{bmatrix}
\]

The desired set \( S \) is simply the constant vectors in this expression, and these are the vectors \( z_1 \) and \( z_2 \) described by Theorem BNS.

\[
S = \left\{ \begin{bmatrix} -1 \\ -1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 0 \\ 1 \end{bmatrix} \right\}
\]

C60 Contributed by Robert Beezer Statement

Theorem BNS says that if we find the vector form of the solutions to the homogeneous system \( LS(A, 0) \), then the fixed vectors (one per free variable) will have the desired properties. Row-reduce \( A \), viewing it as the augmented matrix of a homogeneous system with an invisible columns of zeros as the last column,

\[
\begin{bmatrix}
1 & 0 & 4 & -5 \\
0 & 1 & 2 & -3 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]
Moving to the vector form of the solutions (Theorem VFSLS [106]), with free variables $x_3$ and $x_4$, solutions to the consistent system (it is homogeneous, Theorem HSC [64]) can be expressed as

$$
\begin{bmatrix}
    x_1 \\
    x_2 \\
    x_3 \\
    x_4
\end{bmatrix}
= x_3
\begin{bmatrix}
    -4 \\
    -2 \\
    1 \\
    0
\end{bmatrix}
+ x_4
\begin{bmatrix}
    5 \\
    3 \\
    0 \\
    1
\end{bmatrix}
$$

Then with $S$ given by

$$
S = \left\{
\begin{bmatrix}
    -4 \\
    -2 \\
    1 \\
    0
\end{bmatrix},
\begin{bmatrix}
    5 \\
    3 \\
    0 \\
    1
\end{bmatrix}
\right\}
$$

Theorem BNS [141] guarantees the set has the desired properties.

We want to first find some relations of linear dependence on \{v_1, v_2, v_3, v_4, v_5\} that will allow us to “kick out” some vectors, in the spirit of Example SCAD [124]. To find relations of linear dependence, we formulate a matrix $A$ whose columns are $v_1, v_2, v_3, v_4, v_5$. Then we consider the homogeneous system of equations $LS(A, 0)$ by row-reducing its coefficient matrix (remember that if we formulated the augmented matrix we would just add a column of zeros). After row-reducing, we obtain

$$
\begin{bmatrix}
    1 & 0 & 0 & 2 & -1 \\
    0 & 1 & 0 & 1 & -2 \\
    0 & 0 & 1 & 0 & 0
\end{bmatrix}
$$

From this we that solutions can be obtained employing the free variables $x_4$ and $x_5$. With appropriate choices we will be able to conclude that vectors $v_4$ and $v_5$ are unnecessary for creating $W$ via a span. By Theorem SLSLC [103], the choice of free variables below lead to solutions and linear combinations, which are then rearranged.

$$
x_4 = 1, x_5 = 0 \Rightarrow (-2)v_1 + (-1)v_2 + (0)v_3 + (1)v_4 + (0)v_5 = 0 \Rightarrow v_4 = 2v_1 + v_2
$$

$$
x_4 = 0, x_5 = 1 \Rightarrow (1)v_1 + (2)v_2 + (0)v_3 + (0)v_4 + (1)v_5 = 0 \Rightarrow v_5 = -v_1 - 2v_2
$$

Since $v_4$ and $v_5$ can be expressed as linear combinations of $v_1$ and $v_2$ we can say that $v_4$ and $v_5$ are not needed for the linear combinations used to build $W$ (a claim that we could establish carefully with a pair of set equality arguments). Thus

$$
W = S\rho(\{v_1, v_2, v_3\}) = S\rho\left(\left\{\begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}\right\}\right)
$$

That the \{v_1, v_2, v_3\} is linearly independent set can be established quickly with Theorem LIVRN [137].

There are other answers to this question, but notice that any nontrivial linear combination of $v_1, v_2, v_3, v_4, v_5$ will have a zero coefficient on $v_3$, so this vector can never be eliminated from the set used to build the span.

Our hypothesis and our conclusion use the term linear independence, so it will get
To establish linear independence, we begin with the definition of linear independence (Definition LICV [133]) and write a relation of linear dependence (Definition RLDCV [133]),

$$\alpha_1 (v_1) + \alpha_2 (v_1 + v_2) + \alpha_3 (v_1 + v_2 + v_3) + \alpha_4 (v_1 + v_2 + v_3 + v_4) = 0$$

Using the distributive and commutative properties of vector addition and scalar multiplication (Theorem VSPCV [92]) this equation can be rearranged as

$$(\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4) v_1 + (\alpha_2 + \alpha_3 + \alpha_4) v_2 + (\alpha_3 + \alpha_4) v_3 + (\alpha_4) v_4 = 0$$

However, this is a relation of linear dependence on a linearly independent set, \(\{v_1, v_2, v_3, v_4\}\) (this was our lone hypothesis). By the definition of linear independence (Definition LICV [133]) the scalars must all be zero. This is the homogeneous system of equations,

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 0$$
$$\alpha_2 + \alpha_3 + \alpha_4 = 0$$
$$\alpha_3 + \alpha_4 = 0$$
$$\alpha_4 = 0$$

Row-reducing the coefficient matrix of this system (or backsolving) gives the conclusion

$$\alpha_1 = 0 \quad \alpha_2 = 0 \quad \alpha_3 = 0 \quad \alpha_4 = 0$$

This means, by Definition LICV [133], that the original set

$$\{v_1, v_1 + v_2, v_1 + v_2 + v_3, v_1 + v_2 + v_3 + v_4\}$$

is linearly independent.
In any linearly dependent set there is always one vector that can be written as a linear combination of the others. This is the substance of the upcoming Theorem DLDS [151]. Perhaps this will explain the use of the word “dependent.” In a linearly dependent set, at least one vector “depends” on the others (via a linear combination).

Indeed, because Theorem DLDS [151] is an equivalence (Technique E [52]) some authors use this condition as a definition (Technique D [13]) of linear dependence. Then linear independence is defined as the logical opposite of linear dependence. Of course, we have chosen to take Definition LICV [133] as our definition, and then present Theorem DLDS [151] as a theorem.

**Subsection LDSS**

**Linearly Dependent Sets and Spans**

If we use a linearly dependent set to construct a span, then we can *always* create the same infinite set with a starting set that is one vector smaller in size. We will illustrate this behavior in Example RSC5 [152]. However, this will not be possible if we build a span from a linearly independent set. So in a certain sense, using a linearly independent set to formulate a span is the best possible way to go about it — there aren’t any extra vectors being used to build up all the necessary linear combinations. OK, here’s the theorem, and then the example.

**Theorem DLDS**

**Dependency in Linearly Dependent Sets**

Suppose that \( S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_n\} \) is a set of vectors. Then \( S \) is a linearly dependent set if and only if there is an index \( t, 1 \leq t \leq n \) such that \( \mathbf{u}_t \) is a linear combination of the vectors \( \mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_{t-1}, \mathbf{u}_{t+1}, \ldots, \mathbf{u}_n \).

**Proof** \((\Rightarrow)\) Suppose that \( S \) is linearly dependent, so there is a nontrivial relation of linear dependence, 

\[
\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_n \mathbf{u}_n = \mathbf{0}.
\]

Since the \( \alpha_i \) cannot all be zero, choose one, say \( \alpha_t \), that is nonzero. Then,

\[
-\alpha_t \mathbf{u}_t = \alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_{t-1} \mathbf{u}_{t-1} + \alpha_{t+1} \mathbf{u}_{t+1} + \cdots + \alpha_n \mathbf{u}_n
\]

and we can multiply by \( \frac{1}{\alpha_t} \) since \( \alpha_t \neq 0 \),

\[
\mathbf{u}_t = \frac{-\alpha_1}{\alpha_t} \mathbf{u}_1 + \frac{-\alpha_2}{\alpha_t} \mathbf{u}_2 + \frac{-\alpha_3}{\alpha_t} \mathbf{u}_3 + \cdots + \frac{-\alpha_{t-1}}{\alpha_t} \mathbf{u}_{t-1} + \frac{-\alpha_{t+1}}{\alpha_t} \mathbf{u}_{t+1} + \cdots + \frac{-\alpha_n}{\alpha_t} \mathbf{u}_n.
\]
Since the values of \(\frac{a_i}{a_i}\) are again scalars, we have expressed \(u_t\) as the desired linear combination.

\((\Leftarrow)\) Suppose that the vector \(u_t\) is a linear combination of the other vectors in \(S\). Write this linear combination as

\[
\beta_1 u_1 + \beta_2 u_2 + \beta_3 u_3 + \cdots + \beta_{t-1} u_{t-1} + \beta_{t+1} u_{t+1} + \cdots + \beta_n u_n = u_t
\]

and move \(u_t\) to the other side of the equality

\[
\beta_1 u_1 + \beta_2 u_2 + \beta_3 u_3 + \cdots + \beta_{t-1} u_{t-1} + (-1)u_t + \beta_{t+1} u_{t+1} + \cdots + \beta_n u_n = 0.
\]

Then the scalars \(\beta_1, \beta_2, \beta_3, \ldots, \beta_{t-1}, \beta_t = -1, \beta_{t+1}, \ldots, \beta_n\) provide a nontrivial linear combination of the vectors in \(S\), thus establishing that \(S\) is a linearly dependent set. ■

This theorem can be used, sometimes repeatedly, to whittle down the size of a set of vectors used in a span construction. We have seen some of this already in Example SCAD [124], but in the next example we will detail some of the subtleties.

**Example RSC5**

**Reducing a span in \(\mathbb{C}^5\)**

Consider the set of \(n = 4\) vectors from \(\mathbb{C}^5\),

\[
R = \{v_1, v_2, v_3, v_4\} = \left\{ \begin{pmatrix} 1 \\ 2 \\ -1 \\ 3 \\ 2 \end{pmatrix}, \begin{pmatrix} 2 \\ 1 \\ 3 \\ 1 \\ 2 \end{pmatrix}, \begin{pmatrix} -7 \\ 6 \\ 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 1 \\ 6 \\ -11 \\ 1 \end{pmatrix}, \begin{pmatrix} 4 \\ 0 \\ 2 \end{pmatrix} \right\}
\]

and define \(V = \text{span}(R)\).

To employ Theorem LIVHS [135], we form a \(5 \times 4\) coefficient matrix, \(D\),

\[
D = \begin{bmatrix} 1 & 2 & 0 & 4 \\ 2 & 1 & -7 & 1 \\ -1 & 3 & 6 & 2 \\ 3 & 1 & -11 & 1 \\ 2 & 2 & -2 & 6 \end{bmatrix}
\]

and row-reduce to understand solutions to the homogeneous system \(\mathbf{LS}(D, 0)\),

\[
\begin{bmatrix} 1 & 0 & 0 & 4 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.
\]

We can find infinitely many solutions to this system, most of them nontrivial, and we choose any one we like to build a relation of linear dependence on \(R\). Let’s begin with \(x_4 = 1\), to find the solution

\[
\begin{bmatrix} -4 \\ 0 \\ -1 \\ 1 \end{bmatrix}.
\]
So we can write the relation of linear dependence,

\[ (-4)v_1 + 0v_2 + (-1)v_3 + 1v_4 = 0. \]

Theorem DLDS [151] guarantees that we can solve this relation of linear dependence for some vector in \( R \), but the choice of which one is up to us. Notice however that \( v_2 \) has a zero coefficient. In this case, we cannot choose to solve for \( v_2 \). Maybe some other relation of linear dependence would produce a nonzero coefficient for \( v_2 \) if we just had to solve for this vector. Unfortunately, this example has been engineered to always produce a zero coefficient here, as you can see from solving the homogeneous system. Every solution has \( x_2 = 0! \)

OK, if we are convinced that we cannot solve for \( v_2 \), let’s instead solve for \( v_3 \),

\[ v_3 = (-4)v_1 + 0v_2 + 1v_4 = (-4)v_1 + 1v_4. \]

We now claim that this particular equation will allow us to write

\[ V = Sp(R) = Sp(\{v_1, v_2, v_3, v_4\}) = Sp(\{v_1, v_2, v_4\}) \]

in essence declaring \( v_3 \) as surplus for the task of building \( V \) as a span. This claim is an equality of two sets, so we will use Technique SE [17] to establish it carefully. Let \( R' = \{v_1, v_2, v_4\} \) and \( V' = Sp(R') \). We want to show that \( V = V' \).

First show that \( V' \subseteq V \). Since every vector of \( R' \) is in \( R \), any vector we can construct in \( V' \) as a linear combination of vectors from \( R' \) can also be constructed as a vector in \( V \) by the same linear combination of the same vectors in \( R \). That was easy, now turn it around.

Next show that \( V \subseteq V' \). Choose any \( v \) from \( V \). Then there are scalars \( \alpha_1, \alpha_2, \alpha_3, \alpha_4 \) so that

\[ v = \alpha_1v_1 + \alpha_2v_2 + \alpha_3v_3 + \alpha_4v_4 \]

\[ = \alpha_1v_1 + \alpha_2v_2 + \alpha_3((-4)v_1 + 1v_4) + \alpha_4v_4 \]

\[ = \alpha_1v_1 + \alpha_2v_2 + ((-4\alpha_3)v_1 + \alpha_3v_4) + \alpha_4v_4 \]

\[ = (\alpha_1 - 4\alpha_3)v_1 + \alpha_2v_2 + (\alpha_3 + \alpha_4)v_4. \]

This equation says that \( v \) can then be written as a linear combination of the vectors in \( R' \) and hence qualifies for membership in \( V' \). So \( V \subseteq V' \) and we have established that \( V = V' \).

If \( R' \) was also linearly dependent (its not), we could reduce the set even further. Notice that we could have chosen to eliminate any one of \( v_1, v_3 \) or \( v_4 \), but somehow \( v_2 \) is essential to the creation of \( V \) since it cannot be replaced by any linear combination of \( v_1, v_3 \) or \( v_4 \).

\[ \textcircled{\text{\textbullet}} \]

In Example RSC5 [152] we used four vectors to create a span. With a relation of linear dependence in hand, we were able to “toss-out” one of these four vectors and create the
same span from a subset of just three vectors from the original set of four. We did have to take some care as to just which vector we tossed-out. In the next example, we will be more methodical about just how we choose to eliminate vectors from a linearly dependent set while preserving a span.

**Example COV**

**Casting out vectors**

We begin with a set \( S \) containing seven vectors from \( \mathbb{C}^4 \),

\[
S = \left\{ \begin{bmatrix} 1 \\ 2 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 4 \\ 8 \\ 0 \\ -4 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 3 \\ -3 \\ -4 \end{bmatrix}, \begin{bmatrix} 0 \\ 9 \\ -4 \\ 8 \end{bmatrix}, \begin{bmatrix} 7 \\ 12 \\ -31 \\ 37 \end{bmatrix}, \begin{bmatrix} -9 \\ 7 \end{bmatrix} \right\}
\]

and define \( W = S_{p}(S) \). The set \( S \) is obviously linearly dependent by Theorem MVSLD 139, since we have \( n = 7 \) vectors from \( \mathbb{C}^4 \). So we can slim down \( S \) some, and still create \( W \) as the span of a smaller set of vectors. As a device for identifying relations of linear dependence among the vectors of \( S \), we place the seven column vectors of \( S \) into a matrix as columns,

\[
A = [A_1|A_2|A_3|\ldots|A_7] = \begin{bmatrix}
1 & 4 & 0 & -1 & 0 & 7 & -9 \\
2 & 8 & -1 & 3 & 9 & -13 & 7 \\
0 & 0 & 2 & -3 & -4 & 12 & -8 \\
-1 & -4 & 2 & 4 & 8 & -31 & 37
\end{bmatrix}
\]

By Theorem SLSLC 103 a nontrivial solution to \( LS(A, 0) \) will give us a nontrivial relation of linear dependence (Definition RLDCV 133) on the columns of \( A \) (which are the elements of the set \( S \)). The row-reduced form for \( A \) is the matrix

\[
B = \begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

so we can easily create solutions to the homogeneous system \( LS(A, 0) \) using the free variables \( x_2, x_5, x_6, x_7 \). Any such solution will correspond to a relation of linear dependence on the columns of \( I \). These solutions will allow us to solve for one column vector as a linear combination of some others, in the spirit of Theorem DLDS 151, and remove that vector from the set. We’ll set about forming these linear combinations methodically. Set the free variable \( x_2 \) to one, and set the other free variables to zero. Then a solution to \( LS(A, 0) \) is

\[
x = \begin{bmatrix}
-4 \\
1 \\
0 \\
0 \\
0 \\
0 \\
0
\end{bmatrix}
\]

which can be used to create the linear combination

\[(-4)A_1 + 1A_2 + 0A_3 + 0A_4 + 0A_5 + 0A_6 + 0A_7 = 0\]
This can then be arranged and solved for $A_2$, resulting in $A_2$ expressed as a linear combination of \{$A_1, A_3, A_4$\},

$$A_2 = 4A_1 + 0A_3 + 0A_4$$

This means that $A_2$ is surplus, and we can create $W$ just as well with a smaller set with this vector removed,

$$W = Sp(\{A_1, A_3, A_4, A_5, A_6, A_7\})$$

Technically, this set equality for $W$ requires a proof, in the spirit of Example RSC5 \[152\], but we will bypass this requirement here, and in the next few paragraphs.

Now, set the free variable $x_5$ to one, and set the other free variables to zero. Then a solution to $LS(I, 0)$ is

$$x = \begin{bmatrix} -2 \\ 0 \\ -1 \\ -2 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

which can be used to create the linear combination

$$(-2)A_1 + 0A_2 + (-1)A_3 + (-2)A_4 + 1A_5 + 0A_6 + 0A_7 = 0$$

This can then be arranged and solved for $A_5$, resulting in $A_5$ expressed as a linear combination of \{$A_1, A_3, A_4$\},

$$A_5 = 2A_1 + 1A_3 + 2A_4$$

This means that $A_5$ is surplus, and we can create $W$ just as well with a smaller set with this vector removed,

$$W = Sp(\{A_1, A_3, A_4, A_6, A_7\})$$

Do it again, set the free variable $x_6$ to one, and set the other free variables to zero. Then a solution to $LS(I, 0)$ is

$$x = \begin{bmatrix} -1 \\ 0 \\ 3 \\ 6 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

which can be used to create the linear combination

$$(-1)A_1 + 0A_2 + 3A_3 + 6A_4 + 0A_5 + 1A_6 + 0A_7 = 0$$

This can then be arranged and solved for $A_6$, resulting in $A_6$ expressed as a linear combination of \{$A_1, A_3, A_4$\},

$$A_6 = 1A_1 + (-3)A_3 + (-6)A_4$$
This means that $A_6$ is surplus, and we can create $W$ just as well with a smaller set with this vector removed,

$$W = \text{sp}(\{A_1, A_3, A_4, A_7\})$$

Set the free variable $x_7$ to one, and set the other free variables to zero. Then a solution to $LS(I, 0)$ is

$$x = \begin{bmatrix} 3 \\ 0 \\ -5 \\ -6 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

which can be used to create the linear combination

$$3A_1 + 0A_2 + (-5)A_3 + (-6)A_4 + 0A_5 + 0A_6 + 1A_7 = 0$$

This can then be arranged and solved for $A_7$, resulting in $A_7$ expressed as a linear combination of $\{A_1, A_3, A_4\}$,

$$A_7 = (-3)A_1 + 5A_3 + 6A_4$$

This means that $A_7$ is surplus, and we can create $W$ just as well with a smaller set with this vector removed,

$$W = \text{sp}(\{A_1, A_3, A_4\})$$

You might think we could keep this up, but we have run out of free variables. And not coincidentally, the set $\{A_1, A_3, A_4\}$ is linearly independent (check this!). It should be clear how each free variable was used to eliminate the corresponding column from the set used to span the column space, as this will be the essence of the proof of the next theorem. The column vectors in $S$ were not chosen entirely at random, they are the columns of Archetype I [599]. See if you can mimic this example using the columns of Archetype J [604]. Go ahead, we’ll go grab a cup of coffee and be back before you finish up.

For extra credit, notice that the vector

$$b = \begin{bmatrix} 3 \\ 9 \\ 1 \\ 4 \end{bmatrix}$$

is the vector of constants in the definition of Archetype I [599]. Since the system $LS(I, b)$ is consistent, we know by Theorem SLSLC [103] that $b$ is a linear combination of the columns of $A$, or stated equivalently, $b \in W$. This means that $b$ must also be a linear combination of just the three columns $A_1, A_3, A_4$. Can you find such a linear combination? Did you notice that there is just a single (unique) answer? Hmmm.

Example COV [154] deserves your careful attention, since this important example motivates the following fundamental theorem.
Theorem RSS
Reducing a Spanning Set
Suppose that \( S = \{v_1, v_2, v_3, \ldots, v_n\} \) is a set of column vectors. Define \( W = Sp(S) \) and let \( A \) be the matrix whose columns are the vectors from \( S \). Let \( B \) be the reduced row-echelon form of \( A \), with \( D = \{d_1, d_2, d_3, \ldots, d_r\} \) be the set of column indices corresponding to the pivot columns of \( B \). Then

1. \( T = \{v_{d_1}, v_{d_2}, v_{d_3}, \ldots, v_{d_r}\} \) is a linearly independent set.

2. \( W = Sp(T) \).

Proof To prove that \( T \) is linearly independent, begin with a relation of linear dependence on \( T \),

\[
0 = \alpha_1 v_{d_1} + \alpha_2 v_{d_2} + \alpha_3 v_{d_3} + \ldots + \alpha_r v_{d_r}
\]

and we will try to conclude that the only possibility for the scalars \( \alpha_i \) is that they are all zero. Denote the non-pivot columns of \( B \) by \( F = \{f_1, f_2, f_3, \ldots, f_{n-r}\} \). Then we can preserve the equality by adding a big fat zero to the linear combination,

\[
0 = \alpha_1 v_{d_1} + \alpha_2 v_{d_2} + \alpha_3 v_{d_3} + \ldots + \alpha_r v_{d_r} + 0v_{f_1} + 0v_{f_2} + 0v_{f_3} + \ldots + 0v_{f_{n-r}}
\]

By Theorem SLSLC [103], the scalars in this linear combination give a solution to the homogeneous system \( LS(A, 0) \). But notice that in this solution every free variable has been set to zero. Applying Theorem VFSL [106] in the case of a homogeneous system, we lead to the conclusion that this solution is simply the trivial solution. So \( \alpha_i = 0 \), \( 1 \leq i \leq r \). This implies by Definition LICV [133] that \( T \) is a linearly independent set.

The second conclusion of this theorem is an equality of sets (Technique SE [17]). Since \( T \) is a subset of \( S \), any linear combination of elements of the set \( T \) can also be viewed as a linear combination of elements of the set \( S \). So \( Sp(T) \subseteq Sp(S) = W \). It remains to prove that \( W = Sp(S) \subseteq Sp(T) \).

For each \( k \in F \), form a solution \( x \) to \( LS(A, 0) \) by setting the free variables as follows:

\[
x_{f_1} = 0 \quad x_{f_2} = 0 \quad x_{f_3} = 0 \quad \ldots \quad x_{f_k} = 1 \quad \ldots \quad x_{f_{n-r}} = 0
\]

By Theorem VFSL [106], the remainder of this solution vector is given by,

\[
x_{d_1} = -b_{1,f_k} \quad x_{d_2} = -b_{2,f_k} \quad x_{d_3} = -b_{3,f_k} \quad \ldots \quad x_{d_r} = -b_{r,f_k}
\]

From this solution, we obtain a relation of linear dependence on the columns of \( A \),

\[-b_{1,f_k} v_{d_1} - b_{2,f_k} v_{d_2} - b_{3,f_k} v_{d_3} - \ldots - b_{r,f_k} v_{d_r} + 1 v_{f_k} = 0
\]

which can be arranged as the equality

\[v_{f_k} = b_{1,f_k} v_{d_1} + b_{2,f_k} v_{d_2} + b_{3,f_k} v_{d_3} + \ldots + b_{r,f_k} v_{d_r}\]

Now, suppose we take an arbitrary element, \( w \), of \( W = Sp(S) \) and write it as a linear combination of the elements of \( S \), but with the terms organized according to the indices in \( D \) and \( F \),

\[
w = \alpha_1 v_{d_1} + \alpha_2 v_{d_2} + \alpha_3 v_{d_3} + \ldots + \alpha_r v_{d_r} + \beta_1 v_{f_1} + \beta_2 v_{f_2} + \beta_3 v_{f_3} + \ldots + \beta_{n-r} v_{f_{n-r}}
\]
From the above, we can replace each \( \mathbf{v}_j \) by a linear combination of the \( \mathbf{v}_i \),

\[
\mathbf{w} = \alpha_1 \mathbf{v}_{d_1} + \alpha_2 \mathbf{v}_{d_2} + \alpha_3 \mathbf{v}_{d_3} + \ldots + \alpha_r \mathbf{v}_{d_r} + \\
\beta_1 (b_{1,j_1} \mathbf{v}_{d_1} + b_{2,j_1} \mathbf{v}_{d_2} + b_{3,j_1} \mathbf{v}_{d_3} + \ldots + b_{r,j_1} \mathbf{v}_{d_r}) + \\
\beta_2 (b_{1,j_2} \mathbf{v}_{d_1} + b_{2,j_2} \mathbf{v}_{d_2} + b_{3,j_2} \mathbf{v}_{d_3} + \ldots + b_{r,j_2} \mathbf{v}_{d_r}) + \\
\beta_3 (b_{1,j_3} \mathbf{v}_{d_1} + b_{2,j_3} \mathbf{v}_{d_2} + b_{3,j_3} \mathbf{v}_{d_3} + \ldots + b_{r,j_3} \mathbf{v}_{d_r}) + \\
\vdots \\
\beta_{n-r} (b_{1,j_{n-r}} \mathbf{v}_{d_1} + b_{2,j_{n-r}} \mathbf{v}_{d_2} + b_{3,j_{n-r}} \mathbf{v}_{d_3} + \ldots + b_{r,j_{n-r}} \mathbf{v}_{d_r})
\]

With repeated applications of several of the properties of Theorem VSPCV 92 we can rearrange this expression as,

\[
= (\alpha_1 + \beta_1 b_{1,j_1} + \beta_2 b_{1,j_2} + \beta_3 b_{1,j_3} + \ldots + \beta_{n-r} b_{1,j_{n-r}}) \mathbf{v}_{d_1} + \\
(\alpha_2 + \beta_1 b_{2,j_1} + \beta_2 b_{2,j_2} + \beta_3 b_{2,j_3} + \ldots + \beta_{n-r} b_{2,j_{n-r}}) \mathbf{v}_{d_2} + \\
(\alpha_3 + \beta_1 b_{3,j_1} + \beta_2 b_{3,j_2} + \beta_3 b_{3,j_3} + \ldots + \beta_{n-r} b_{3,j_{n-r}}) \mathbf{v}_{d_3} + \\
\vdots \\
(\alpha_r + \beta_1 b_{r,j_1} + \beta_2 b_{r,j_2} + \beta_3 b_{r,j_3} + \ldots + \beta_{n-r} b_{r,j_{n-r}}) \mathbf{v}_{d_r}
\]

This mess expresses the vector \( \mathbf{w} \) as a linear combination of the vectors in

\[
T = \{\mathbf{v}_{d_1}, \mathbf{v}_{d_2}, \mathbf{v}_{d_3}, \ldots \mathbf{v}_{d_r}\}
\]

thus saying that \( \mathbf{w} \in \mathcal{S}p(T) \). Therefore, \( W = \mathcal{S}p(S) \subseteq \mathcal{S}p(T) \). \( \square \)

In Example COV 154, we tossed-out vectors one at a time. But in each instance, we rewrote the offending vector as a linear combination of those vectors that corresponded to indices for the pivot columns of the reduced row-echelon form of the matrix of columns. In the proof of Theorem RSS 157, we accomplish this reduction in one big step. In Example COV 154 we arrived at a linearly independent set at exactly the same moment that we ran out of free variables to exploit. This was not a coincidence, it is the substance of our first conclusion in Theorem RSS 157.

Here’s a straightforward application of Theorem RSS 157.

Example RSSC4
Reducing a span in \( \mathbb{C}^4 \)

Begin with a set of five vectors from \( \mathbb{C}^4 \),

\[
S = \left\{ \begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 4 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 7 \\ 0 \\ -1 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}
\]

and let \( W = \mathcal{S}p(S) \). To arrive at a (smaller) linearly independent set, follow the procedure described in Theorem RSS 157. Place the vectors from \( S \) into a matrix as columns, and row-reduce,

\[
\begin{bmatrix}
1 & 2 & 2 & 7 & 0 \\
1 & 2 & 0 & 1 & 2 \\
2 & 4 & -1 & -1 & 5 \\
1 & 2 & 1 & 4 & 1 \\
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 2 & 0 & 1 & 2 \\
0 & 0 & 1 & 3 & -1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

Version 0.52
Columns 1 and 3 are the pivot columns \((D = \{1, 3\})\) so the set
\[
T = \left\{ \begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 0 \\ -1 \\ 1 \end{bmatrix} \right\}
\]
is linearly independent and \(S_p(T) = S_p(S) = W\). Boom!
Since the reduced row-echelon form of a matrix is unique (Theorem RREFU [112]),
the procedure of Theorem RSS [157] leads us to a unique set \(T\).
However, there is a wide variety of possibilities for sets \(T\) that are linearly independent and
which can be employed in a span to create \(W\). Without proof, we list two other possibilities:
\[
T' = \left\{ \begin{bmatrix} 2 \\ 2 \\ 4 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ -1 \\ 1 \end{bmatrix} \right\}
\]
\[
T^* = \left\{ \begin{bmatrix} 3 \\ 1 \\ 1 \\ 3 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 0 \end{bmatrix} \right\}
\]
Can you prove that \(T'\) and \(T^*\) are linearly independent sets and \(W = S_p(S) = S_p(T') = S_p(T^*)\)?

**Example RES**

**Reworking elements of a span**
Begin with a set of five vectors from \(\mathbb{C}^4\),
\[
R = \left\{ \begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \\ 3 \\ -1 \\ 1 \\ -9 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -8 \\ 1 \\ 4 \\ -2 \\ 1 \\ -1 \\ -1 \\ -2 \\ -4 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 0 \\ -1 \\ -2 \end{bmatrix}, \begin{bmatrix} -10 \\ -1 \\ -1 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} \right\}
\]
It is easy to create elements of \(X = S_p(R)\) — we will create one at random,
\[
y = 6 \begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \\ 3 \\ -1 \\ 1 \\ -9 \\ 0 \\ 0 \end{bmatrix} + (7) \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + 1 \begin{bmatrix} -8 \\ 1 \\ -9 \\ -4 \end{bmatrix} + 6 \begin{bmatrix} 3 \\ 1 \\ -1 \\ -4 \end{bmatrix} + 2 \begin{bmatrix} -10 \\ -1 \\ -1 \\ -2 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 9 \\ 2 \\ 1 \\ -3 \end{bmatrix}
\]
We know we can replace \(R\) by a smaller set (since it is obviously linearly dependent by
Theorem MVSLD [139]) that will create the same span. Here goes,
\[
\begin{bmatrix} 2 & -1 & -8 & 3 & -10 \\ 1 & 1 & -1 & 1 & -1 \\ 3 & 0 & -9 & -1 & -1 \\ 2 & 1 & -4 & -2 & 4 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & -3 & 0 & -1 \\ 0 & 1 & 2 & 0 & 2 \\ 0 & 0 & 0 & 1 & -2 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\]
So, if we collect the first, second and fourth vectors from \(R\),
\[
P = \left\{ \begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} \right\}
\]
then \( P \) is linearly independent and \( S_p(P) = S_p(R) = X \) by Theorem RSS\textsuperscript{157}. Since we built \( y \) as an element of \( S_p(R) \) it must also be an element of \( S_p(P) \). Can we write \( y \) as a linear combination of just the three vectors in \( P \)? The answer is, of course, yes. But let’s compute an explicit linear combination just for fun. By Theorem SLSLC\textsuperscript{103} we can get such a linear combination by solving a system of equations with the column vectors of \( R \) as the columns of a coefficient matrix, and \( y \) as the vector of constants. Employing an augmented matrix to solve this system,

\[
\begin{bmatrix}
2 & -1 & 3 & 9 \\
1 & 1 & 1 & 2 \\
3 & 0 & -1 & 1 \\
2 & 1 & -2 & -3
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 0 & -1 \\
0 & 0 & 1 & 2 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

So we see, as expected, that

\[
\begin{bmatrix}
1 \\
2 \\
3
\end{bmatrix}
+ (-1)
\begin{bmatrix}
1 \\
1 \\
0
\end{bmatrix}
+ 2
\begin{bmatrix}
3 \\
-1 \\
-2
\end{bmatrix}
= \begin{bmatrix}
9 \\
2 \\
1
\end{bmatrix}
= y
\]

A key feature of this example is that the linear combination that expresses \( y \) as a linear combination of the vectors in \( P \) is unique. This is a consequence of the linear independence of \( P \). The linearly independent set \( P \) is smaller than \( R \), but still just (barely) big enough to create elements of the set \( X = S_p(R) \). There are many, many ways to write \( y \) as a linear combination of the five vectors in \( R \) (the appropriate system of equations to verify this claim has two free variables in the description of the solution set), yet there is precisely one way to write \( y \) as a linear combination of the three vectors in \( P \).

**Subsection READ**

**Reading Questions**

1. Let \( S \) be the linearly dependent set of three vectors below.

\[
S = \left\{ \begin{bmatrix}
1 \\
10 \\
1000
\end{bmatrix}, \begin{bmatrix}
1 \\
11 \\
1001
\end{bmatrix}, \begin{bmatrix}
5 \\
23 \\
2003
\end{bmatrix} \right\}
\]

Write one vector from \( S \) as a linear combination of the other two (you should be able to do this on sight, rather than doing some computations). Convert this expression into a relation of linear dependence on \( S \).

2. Explain why the word “dependent” is used in the definition of linear dependence.

3. Suppose that \( Y = S_p(P) = S_p(Q) \), where \( P \) is a linearly dependent set and \( Q \) is linearly independent. Would you rather use \( P \) or \( Q \) to describe \( Y \)? Why?
Subsection EXC
Exercises

C20 Let $T$ be the set of columns of the matrix $B$ below. Define $W = \text{Sp}(T)$. Find a set $R$ so that (1) $R$ has 3 vectors, (2) $R$ is a subset of $T$, and (3) $W = \text{Sp}(R)$.

$$B = \begin{bmatrix} -3 & 1 & -2 & 7 \\ -1 & 2 & 1 & 4 \\ 1 & 1 & 2 & -1 \end{bmatrix}$$

Contributed by Robert Beezer Solution 163

C40 Verify that the set $R' = \{v_1, v_2, v_4\}$ at the end of Example RSC5 152 is linearly independent.

Contributed by Robert Beezer

C50 Consider the set of vectors from $\mathbb{C}^3$, $W$, given below. Find a linearly independent set $T$ that contains three vectors from $W$ and such that $W = \text{Sp}(T)$.

$$W = \text{Sp}\left(\{v_1, v_2, v_3, v_4, v_5\}\right) = \text{Sp}\left(\left\{ \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ -3 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \right)$$

Contributed by Robert Beezer Solution 163

C70 Reprise Example RES 159 by creating a new version of the vector $y$. In other words, form a new, different linear combination of the vectors in $R$ to create a new vector $y$ (but do not simplify the problem too much by choosing any of the five new scalars to be zero). Then express this new $y$ as a combination of the vectors in $P$.

Contributed by Robert Beezer

M10 At the conclusion of Example RSSC4 158 two alternative solutions, sets $T'$ and $T^*$, are proposed. Verify these claims by proving that $\text{Sp}(T) = \text{Sp}(T')$ and $\text{Sp}(T) = \text{Sp}(T^*)$.

Contributed by Robert Beezer
Let \( T = \{ \mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3, \mathbf{w}_4 \} \). The vector \[
\begin{bmatrix}
2 \\
-1 \\
0 \\
1 
\end{bmatrix}
\] is a solution to the homogeneous system with the matrix \( B \) as the coefficient matrix (check this!). By Theorem SLSLC it provides the scalars for a linear combination of the columns of \( B \) (the vectors in \( T \)) that equals the zero vector, a relation of linear dependence on \( T \),

\[
2\mathbf{w}_1 + (-1)\mathbf{w}_2 + (1)\mathbf{w}_4 = \mathbf{0}
\]

We can rearrange this equation by solving for \( \mathbf{w}_4 \),

\[
\mathbf{w}_4 = (-2)\mathbf{w}_1 + \mathbf{w}_2
\]

This equation tells us that the vector \( \mathbf{w}_4 \) is superfluous in the span construction that creates \( W \). So \( W = \text{span}(\{ \mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \}) \). The requested set is \( R = \{ \mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3 \} \).

To apply Theorem RSS, we formulate a matrix \( A \) whose columns are \( \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \mathbf{v}_4, \mathbf{v}_5 \). Then we row-reduce \( A \). After row-reducing, we obtain

\[
\begin{bmatrix}
1 & 0 & 0 & 2 & -1 \\
0 & 1 & 0 & 1 & -2 \\
0 & 0 & 1 & 0 & 0 
\end{bmatrix}
\]

From this we that the pivot columns are \( D = \{ 1, 2, 3 \} \). Thus

\[
T = \{ \mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3 \} = \left\{ \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \right\}
\]

is a linearly independent set and \( \text{span}(T) = W \). Compare this problem with Exercise LI.M50.
Section O
Orthogonality

In this section we define a couple more operations with vectors, and prove a few theorems. These definitions and results are not central to what follows, but we will make use of them frequently throughout the remainder of the course on various occasions. Because we have chosen to use $\mathbb{C}$ as our set of scalars, this subsection is a bit more, uh, . . . complex than it would be for the real numbers. We’ll explain as we go along how things get easier for the real numbers $\mathbb{R}$. If you haven’t already, now would be a good time to review some of the basic properties of arithmetic with complex numbers described in Section CNO.

First, we extend the basics of complex number arithmetic to our study of vectors in $\mathbb{C}^m$.

Subsection CAV
Complex arithmetic and vectors

We know how the addition and multiplication of complex numbers is employed in defining the operations for vectors in $\mathbb{C}^m$ (Definition CVA and Definition CVSM). We can also extend the idea of the conjugate to vectors.

**Definition CCCV**
Complex Conjugate of a Column Vector

Suppose that

$$
\mathbf{u} = \begin{bmatrix}
    u_1 \\
    u_2 \\
    u_3 \\
    \vdots \\
    u_m
\end{bmatrix}
$$

is a vector from $\mathbb{C}^m$. Then the conjugate of the vector is defined as

$$
\overline{\mathbf{u}} = \begin{bmatrix}
    \overline{u_1} \\
    \overline{u_2} \\
    \overline{u_3} \\
    \vdots \\
    \overline{u_m}
\end{bmatrix}
$$

With this definition we can show that the conjugate of a column vector behaves as we would expect with regard to vector addition and scalar multiplication.

**Theorem CRVA**
Conjugation Respects Vector Addition

Suppose $\mathbf{x}$ and $\mathbf{y}$ are two vectors from $\mathbb{C}^m$. Then

$$
\overline{\mathbf{x} + \mathbf{y}} = \overline{\mathbf{x}} + \overline{\mathbf{y}}
$$
Proof Apply the definition of vector addition (Definition CVA 89) and the definition of the conjugate of a vector (Definition CCCV 165), and in each component apply the similar property for complex numbers (Theorem CCRA 640).

Theorem CRSM
Conjugation Respects Vector Scalar Multiplication
Suppose $x$ is a vector from $\mathbb{C}^m$, and $\alpha \in \mathbb{C}$ is a scalar. Then

$$\overline{\alpha x} = \overline{\alpha} \overline{x} \quad \square$$

Proof Apply the definition of scalar multiplication (Theorem CVSM 286) and the definition of the conjugate of a vector (Definition CCCV 165), and in each component apply the similar property for complex numbers (Theorem CCRM 640).

These two theorems together tell us how we can “push” complex conjugation through linear combinations.

Subsection IP
Inner products

Definition IP
Inner Product
Given the vectors

$$u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \quad \quad \quad \quad v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}$$

the inner product of $u$ and $v$ is the scalar quantity in $\mathbb{C}$,

$$\langle u, v \rangle = u_1 \overline{v_1} + u_2 \overline{v_2} + u_3 \overline{v_3} + \cdots + u_m \overline{v_m} = \sum_{i=1}^{m} u_i \overline{v_i} \quad \square$$

This operation is a bit different in that we begin with two vectors but produce a scalar. Computing one is straightforward.

Example CSIP
Computing some inner products
The scalar product of

$$u = \begin{bmatrix} 2 + 3i \\ 5 + 2i \\ -3 + i \end{bmatrix} \quad \quad \quad \quad v = \begin{bmatrix} 1 + 2i \\ -4 + 5i \\ 0 + 5i \end{bmatrix}$$


Version 0.52
is
\[
\langle u, v \rangle = (2 + 3i)(1 + 2i) + (5 + 2i)(-4 + 5i) + (3 + i)(0 + 5i)
\]
\[
= (2 + 3i)(1 - 2i) + (5 + 2i)(-4 - 5i) + (3 + i)(0 - 5i)
\]
\[
= (8 - i) + (-10 - 33i) + (5 + 15i)
\]
\[
= 3 - 19i
\]

The scalar product of
\[
w = \begin{bmatrix} 2 \\ 4 \\ -3 \\ 2 \\ 8 \end{bmatrix} \quad \text{and} \quad x = \begin{bmatrix} 3 \\ 1 \\ 0 \\ -1 \\ -2 \end{bmatrix}
\]
is
\[
\langle w, x \rangle = 2(3) + 4(1) + (-3)(0) + 2(-1) + 8(-2) = 3 + 4(1) + (-3)0 + 2(-1) + 8(-2) = -8.
\]

In the case where the entries of our vectors are all real numbers (as in the second part of Example CSIP [167]), the computation of the inner product may look familiar and be known to you as a dot product or scalar product. So you can view the inner product as a generalization of the scalar product to vectors from \(\mathbb{C}^m\) (rather than \(\mathbb{R}^m\)).

There are several quick theorems we can now prove, and they will each be useful later.

**Theorem IPVA**

**Inner Product and Vector Addition**

Suppose \(u, v, w \in \mathbb{C}^m\). Then

1. \(\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle\)
2. \(\langle u, v + w \rangle = \langle u, v \rangle + \langle u, w \rangle\)

**Proof** The proofs of the two parts are very similar, with the second one requiring just a bit more effort due to the conjugation that occurs. We will prove part 2 and you can prove part 1.

\[
\langle u, v + w \rangle = \sum_{i=1}^{m} u_i(v_i + w_i) \quad \text{Definition IP} \ [166]
\]
\[
= \sum_{i=1}^{m} u_i(v_i + w_i) \quad \text{Theorem CCRA} \ [640]
\]
\[
= \sum_{i=1}^{m} u_i v_i + \sum_{i=1}^{m} u_i w_i \quad \text{Distributivity in } \mathbb{C}
\]
\[
= \sum_{i=1}^{m} u_i v_i + \sum_{i=1}^{m} u_i \bar{w}_i \quad \text{Commutativity in } \mathbb{C}
\]
\[
= \langle u, v \rangle + \langle u, w \rangle \quad \text{Definition IP} \ [166]
\]
Theorem IPSM
Inner Product and Scalar Multiplication
Suppose $u, v \in \mathbb{C}^m$ and $\alpha \in \mathbb{C}$. Then

1. $\langle \alpha u, v \rangle = \alpha \langle u, v \rangle$
2. $\langle u, \alpha v \rangle = \overline{\alpha} \langle u, v \rangle$

Proof The proofs of the two parts are very similar, with the second one requiring just a bit more effort due to the conjugation that occurs. We will prove part 2 and you can prove part 1.

$$\langle u, \alpha v \rangle = \sum_{i=1}^{m} u_i (\overline{\alpha} v_i) \quad \text{Definition IP \ [166]}$$
$$= \sum_{i=1}^{m} u_i (\overline{\alpha} v_i) \quad \text{Theorem CCRM \ [640]}$$
$$= \overline{\alpha} \sum_{i=1}^{m} u_i \overline{v_i} \quad \text{Distributivity in } \mathbb{C}$$
$$= \overline{\alpha} \langle u, v \rangle \quad \text{Definition IP \ [166]}$$

Theorem IPAC
Inner Product is Anti-Commutative
Suppose that $u$ and $v$ are vectors in $\mathbb{C}^m$. Then $\langle u, v \rangle = \overline{\langle v, u \rangle}$.

Proof

$$\langle u, v \rangle = u_1 \overline{v_1} + u_2 \overline{v_2} + u_3 \overline{v_3} + \cdots + u_m \overline{v_m} \quad \text{Definition IP \ [166]}$$
$$= \overline{u_1} v_1 + \overline{u_2} v_2 + \overline{u_3} v_3 + \cdots + \overline{u_m} v_m \quad \text{Theorem CCT \ [640]}$$
$$= \overline{u_1} v_1 + \overline{u_2} v_2 + \overline{u_3} v_3 + \cdots + \overline{u_m} v_m \quad \text{Theorem CCRM \ [640]}$$
$$= \overline{v_1} \overline{u_1} + \overline{v_2} \overline{u_2} + \overline{v_3} \overline{u_3} + \cdots + \overline{v_m} \overline{u_m} \quad \text{Commutativity in } \mathbb{C}$$
$$= \overline{\langle v, u \rangle} \quad \text{Definition IP \ [166]}$$

Subsection N
Norm

If treating linear algebra in a more geometric fashion, the length of a vector occurs naturally, and is what you would expect from its name. With complex numbers, we will define a similar function. Recall that if $c$ is a complex number, then $|c|$ denotes its modulus (Definition MCN \ [641]).
Definition NV
Norm of a Vector
The norm of the vector
\[ u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \]
is the scalar quantity in \( \mathbb{C}^m \)
\[ \|u\| = \sqrt{|u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2} = \sqrt{\sum_{i=1}^{m} |u_i|^2} \]
Computing a norm is also easy to do.

Example CNSV
Computing the norm of some vectors
The norm of
\[ u = \begin{bmatrix} 3 + 2i \\ 1 - 6i \\ 2 + 4i \\ 2 + i \end{bmatrix} \]
is
\[ \|u\| = \sqrt{|3+2i|^2 + |1-6i|^2 + |2+4i|^2 + |2+i|^2} = \sqrt{13 + 37 + 20 + 5} = \sqrt{75} = 5\sqrt{3}. \]
The norm of
\[ v = \begin{bmatrix} 3 \\ -1 \\ 2 \\ 4 \\ -3 \end{bmatrix} \]
is
\[ \|v\| = \sqrt{|3|^2 + |-1|^2 + |2|^2 + |4|^2 + |-3|^2} = \sqrt{3^2 + 1^2 + 2^2 + 4^2 + 3^2} = \sqrt{39}. \]
Notice how the norm of a vector with real number entries is just the length of the vector.

Inner products and norms are related by the following theorem.

Theorem IPN
Inner Products and Norms
Suppose that \( u \) is a vector in \( \mathbb{C}^m \). Then \( \|u\|^2 = \langle u, u \rangle \).

Proof
\[ \|u\|^2 = \left( \sqrt{|u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2} \right)^2 \]
\[ = |u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2 \]
\[ = u_1 \overline{u_1} + u_2 \overline{u_2} + u_3 \overline{u_3} + \cdots + u_m \overline{u_m} \]
\[ = \langle u, u \rangle \]
When our vectors have entries only from the real numbers, Theorem IPN says that the dot product of a vector with itself is equal to the length of the vector squared.

### Theorem PIP
**Positive Inner Products**
Suppose that \( \mathbf{u} \) is a vector in \( \mathbb{C}^m \). Then \( \langle \mathbf{u}, \mathbf{u} \rangle \geq 0 \) with equality if and only if \( \mathbf{u} = \mathbf{0} \).

**Proof** From the proof of Theorem IPN we see that

\[
\langle \mathbf{u}, \mathbf{u} \rangle = |u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2
\]

Since each modulus is squared, every term is positive, and the sum must also be positive. (Notice that in general the inner product is a complex number and cannot be compared with zero, but in the special case of \( \langle \mathbf{u}, \mathbf{u} \rangle \) the result is a real number.) The phrase, “with equality if and only if” means that we want to show that the statement \( \langle \mathbf{u}, \mathbf{u} \rangle = 0 \) (i.e. with equality) is equivalent (“if and only if”) to the statement \( \mathbf{u} = \mathbf{0} \).

If \( \mathbf{u} = \mathbf{0} \), then it is a straightforward computation to see that \( \langle \mathbf{u}, \mathbf{u} \rangle = 0 \). In the other direction, assume that \( \langle \mathbf{u}, \mathbf{u} \rangle = 0 \). As before, \( \langle \mathbf{u}, \mathbf{u} \rangle \) is a sum of moduli. So we have

\[
0 = \langle \mathbf{u}, \mathbf{u} \rangle = |u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2
\]

Now we have a sum of squares equaling zero, so each term must be zero. Then by similar logic, \( |u_i| = 0 \) will imply that \( u_i = 0 \), since \( 0 + 0i \) is the only complex number with zero modulus. Thus every entry of \( \mathbf{u} \) is zero and so \( \mathbf{u} = \mathbf{0} \), as desired.

The conditions of Theorem PIP are summarized by saying “the inner product is positive definite.”

### Subsection OV
**Orthogonal Vectors**

“Orthogonal” is a generalization of “perpendicular.” You may have used mutually perpendicular vectors in a physics class, or you may recall from a calculus class that perpendicular vectors have a zero dot product. We will now extend these ideas into the realm of higher dimensions and complex scalars.

**Definition OV**
**Orthogonal Vectors**
A pair of vectors, \( \mathbf{u} \) and \( \mathbf{v} \), from \( \mathbb{C}^m \) are orthogonal if their inner product is zero, that is, \( \langle \mathbf{u}, \mathbf{v} \rangle = 0 \).

**Example TOV**
**Two orthogonal vectors**
The vectors

\[
\mathbf{u} = \begin{bmatrix} 2 + 3i \\ 4 - 2i \\ 1 + i \\ 1 + i \end{bmatrix} \quad \mathbf{v} = \begin{bmatrix} 1 - i \\ 2 + 3i \\ 2 + 6i \\ 1 \end{bmatrix}
\]
are orthogonal since
\[
\langle u, v \rangle = (2 + 3i)(1 + i) + (4 - 2i)(2 - 3i) + (1 + i)(4 + 6i) + (1 + i)(1)
\]
\[
= (-1 + 5i) + (2 - 16i) + (-2 + 10i) + (1 + i)
\]
\[
= 0 + 0i. \quad \circled{\square}
\]

We extend this definition to whole sets by requiring vectors to be pairwise orthogonal. Despite using the same word, careful thought about what objects you are using will eliminate any source of confusion.

**Definition OSV**
Orthogonal Set of Vectors
Suppose that \( S = \{u_1, u_2, u_3, \ldots, u_n\} \) is a set of vectors from \( \mathbb{C}^m \). Then the set \( S \) is orthogonal if every pair of different vectors from \( S \) is orthogonal, that is \( \langle u_i, u_j \rangle = 0 \) whenever \( i \neq j \).

\[\triangle\]

The next example is trivial in some respects, but is still worthy of discussion since it is the prototypical orthogonal set.

**Example SUVOS**
Standard Unit Vectors are an Orthogonal Set
The standard unit vectors are the columns of the identity matrix (Definition SUV \[210\]).

Computing the inner product of two distinct vectors, \( e_i, e_j, i \neq j \), gives,
\[
\langle e_i, e_j \rangle = 0(0) + 0(0) + \cdots + 1(0) + \cdots + 0(1) + \cdots + 0(0) + 0(0)
\]
\[
= 0 \quad \circled{\square}
\]

**Example AOS**
An orthogonal set
The set
\[\{x_1, x_2, x_3, x_4\} = \left\{ \begin{bmatrix} 1 + i \\ 1 \\ i \end{bmatrix}, \begin{bmatrix} 1 + 5i \\ 6 + 5i \\ 1 - 6i \end{bmatrix}, \begin{bmatrix} -7 + 34i \\ -8 - 23i \\ 30 + 13i \end{bmatrix}, \begin{bmatrix} -2 - 4i \\ 6 + i \\ 6 - i \end{bmatrix} \right\} \]
is an orthogonal set. Since the inner product is anti-commutative (Theorem IPAC \[168\]) we can test pairs of different vectors in any order. If the result is zero, then it will also be zero if the inner product is computed in the opposite order. This means there are six pairs of different vectors to use in an inner product computation. We’ll do two and you can practice your inner products on the other four.

\[
\langle x_1, x_3 \rangle = (1 + i)(-7 - 34i) + (1)(-8 + 23i) + (1 - i)(-10 - 22i) + (i)(30 - 13i)
\]
\[
= (27 - 41i) + (-8 + 23i) + (-32 - 12i) + (13 + 30i)
\]
\[
= 0 + 0i
\]
and
\[
\langle x_2, x_4 \rangle = (1 + 5i)(-2 + 4i) + (6 + 5i)(6 - i) + (-7 - i)(4 - 3i) + (1 - 6i)(6 + i)
\]
\[
= (-22 - 6i) + (41 + 24i) + (-31 + 17i) + (12 - 35i)
\]
\[
= 0 + 0i \quad \circled{\square}
\]
So far, this section has seen lots of definitions, and lots of theorems establishing unsurprising consequences of those definitions. But here is our first theorem that suggests that inner products and orthogonal vectors have some utility. It is also one of our first illustrations of how to arrive at linear independence as the conclusion of a theorem.

**Theorem OSLI**  
**Orthogonal Sets are Linearly Independent**

Suppose that \( S = \{u_1, u_2, u_3, \ldots, u_n\} \) is an orthogonal set of nonzero vectors. Then \( S \) is linearly independent. □

**Proof** To prove linear independence of a set of vectors, we can appeal to the definition (Definition LICV [133]) and begin with a relation of linear dependence (Definition RLDCV [133]),

\[
\alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_n u_n = 0.
\]

Then, for every \( 1 \leq i \leq n \), we have

\[
0 = 0 \langle u_i, u_i \rangle = \langle 0 u_i, u_i \rangle = \langle \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_n u_n, u_i \rangle = \langle \alpha_1 u_1, u_i \rangle + \langle \alpha_2 u_2, u_i \rangle + \langle \alpha_3 u_3, u_i \rangle + \cdots + \langle \alpha_n u_n, u_i \rangle = \alpha_1 \langle u_1, u_i \rangle + \alpha_2 \langle u_2, u_i \rangle + \alpha_3 \langle u_3, u_i \rangle + \cdots + \alpha_n \langle u_n, u_i \rangle = \alpha_1 (0) + \alpha_2 (0) + \alpha_3 (0) + \cdots + \alpha_i (0) + \cdots + \alpha_n (0) = \alpha_i \langle u_i, u_i \rangle
\]

So we have \( 0 = \alpha_i \langle u_i, u_i \rangle \). However, since \( u_i \neq 0 \) (the hypothesis said our vectors were nonzero), [Theorem PIP [170]] says that \( \langle u_i, u_i \rangle > 0 \). So we must conclude that \( \alpha_i = 0 \) for all \( 1 \leq i \leq n \). But this says that \( S \) is a linearly independent set since the only way to form a relation of linear dependence is the trivial way, with all the scalars zero. Boom! ■

**Subsection GSP**  
**Gram-Schmidt Procedure**

**TODO:** Proof technique on induction.

The Gram-Schmidt Procedure is really a theorem. It says that if we begin with a linearly independent set of \( p \) vectors, \( S \), then we can do a number of calculations with these vectors and produce an orthogonal set of \( p \) vectors, \( T \), so that \( Sp(S) = Sp(T) \). Given the large number of computations involved, it is indeed a procedure to do all the necessary computations, and it is best employed on a computer. However, it also has value in proofs where we may on occasion wish to replace a linearly independent set by an orthogonal one.
Theorem GSPCV

Gram-Schmidt Procedure, Column Vectors

Suppose that \( S = \{v_1, v_2, v_3, \ldots, v_p\} \) is a linearly independent set of vectors in \( \mathbb{C}^m \). Define the vectors \( u_i, 1 \leq i \leq p \) by

\[
 u_i = v_i - \frac{\langle v_i, u_1 \rangle}{\langle u_1, u_1 \rangle} u_1 - \frac{\langle v_i, u_2 \rangle}{\langle u_2, u_2 \rangle} u_2 - \frac{\langle v_i, u_3 \rangle}{\langle u_3, u_3 \rangle} u_3 - \cdots - \frac{\langle v_i, u_{i-1} \rangle}{\langle u_{i-1}, u_{i-1} \rangle} u_{i-1}
\]

Then if \( T = \{u_1, u_2, u_3, \ldots, u_p\} \), then \( T \) is an orthogonal set of non-zero vectors, and \( Sp(T) = Sp(S) \).

Proof We will prove the result by using induction on \( p \). To begin, we prove that \( T \) has the desired properties when \( p = 1 \). In this case \( u_1 = v_1 \) and \( T = \{u_1\} = \{v_1\} = S \). Because \( S \) and \( T \) are equal, \( Sp(S) = Sp(T) \). Equally trivial, \( T \) is an orthogonal set. If \( u_1 = \mathbf{0} \), then \( S \) would be a linearly dependent set, a contradiction.

Now suppose that the theorem is true for any set of \( p - 1 \) linearly independent vectors. Let \( S = \{v_1, v_2, v_3, \ldots, v_p\} \) be a linearly independent set of \( p \) vectors. Then \( S' = \{v_1, v_2, v_3, \ldots, v_{p-1}\} \) is also linearly independent. So we can apply the theorem to \( S' \) and construct the vectors \( T' = \{u_1, u_2, u_3, \ldots, u_{p-1}\} \). \( T' \) is therefore an orthogonal set of nonzero vectors and \( Sp(S') = Sp(T') \). Define

\[
 u_p = v_p - \frac{\langle v_p, u_1 \rangle}{\langle u_1, u_1 \rangle} u_1 - \frac{\langle v_p, u_2 \rangle}{\langle u_2, u_2 \rangle} u_2 - \frac{\langle v_p, u_3 \rangle}{\langle u_3, u_3 \rangle} u_3 - \cdots - \frac{\langle v_p, u_{p-1} \rangle}{\langle u_{p-1}, u_{p-1} \rangle} u_{p-1}
\]

and let \( T = T' \cup \{u_p\} \). We need to show now that \( T \) has several properties by building on what we know about \( T' \). But first notice that the above equation has no problems with the denominators \( (\langle u_i, u_i \rangle) \) being zero, since the \( u_i \) are from \( T' \), which is composed of nonzero vectors.

We show that \( Sp(T) = Sp(S) \), by first establishing that \( Sp(T) \subseteq Sp(S) \). Suppose \( x \in Sp(T) \), so

\[
 x = a_1 u_1 + a_2 u_2 + a_3 u_3 + \cdots + a_p u_p
\]

The term \( a_p u_p \) is a linear combination of vectors from \( T' \) and the vector \( v_p \), while the remaining terms are a linear combination of vectors from \( T' \). Since \( Sp(T') = Sp(S') \), any term that is a multiple of a vector from \( T' \) can be rewritten as a linear combination of vectors from \( S' \). The remaining term \( a_p v_p \) is a multiple of a vector in \( S \). So we see that \( x \) can be rewritten as a linear combination of vectors from \( S \), i.e. \( x \in Sp(S) \).

To show that \( Sp(S) \subseteq Sp(T) \), begin with \( y \in Sp(S) \), so

\[
 y = a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_p v_p
\]

Rearrange our defining equation for \( u_p \) by solving for \( v_p \). Then the term \( a_p v_p \) is a multiple of a linear combination of elements of \( T \). The remaining terms are a linear combination of \( v_1, v_2, v_3, \ldots, v_{p-1} \), hence an element of \( Sp(S') = Sp(T') \). Thus these remaining terms can be written as a linear combination of the vectors in \( T' \). So \( y \) is a linear combination of vectors from \( T \), i.e. \( y \in Sp(T) \).

The elements of \( T' \) are nonzero, but what about \( u_p \)? Suppose to the contrary that
We will illustrate the Gram-Schmidt process with three vectors. Begin with the linearly independent set

\[ S = \{ v_1, v_2, v_3 \} \]

Since \( S \) is a linearly independent set (Theorem DLDS [151]), contrary to our lone hypothesis about \( S \). Since \( T \) appear so simple looking. Think about your objects as you work through the following — what is a vector and what is a scalar. Since \( T \) is an orthogonal set by induction, most pairs of elements in \( T \) are orthogonal. We just need to test inner products between \( u_p \) and \( u_i \), for \( 1 \leq i \leq p - 1 \). Here we go, using summation notation,

\[
\langle u_p, u_i \rangle = \left\langle v_p - \sum_{k=1}^{p-1} \frac{\langle v_p, u_k \rangle}{\langle u_k, u_k \rangle} u_k, u_i \right\rangle
\]

\[
= \langle v_p, u_i \rangle - \sum_{k=1}^{p-1} \frac{\langle v_p, u_k \rangle}{\langle u_k, u_k \rangle} \langle u_k, u_i \rangle \quad \text{Theorem IPVA [167]}
\]

\[
= \langle v_p, u_i \rangle - \sum_{k=1}^{p-1} \langle v_p, u_k \rangle \langle u_k, u_i \rangle \quad \text{Theorem IPVA [167]}
\]

\[
= \langle v_p, u_i \rangle - \sum_{k=1}^{p-1} \langle v_p, u_k \rangle \langle u_k, u_i \rangle \quad \text{Theorem IPSM [168]}
\]

\[
= \langle v_p, u_i \rangle - \sum_{k=1}^{p-1} \langle v_p, u_k \rangle \langle u_k, u_i \rangle - \sum_{k \neq i} \frac{\langle v_p, u_k \rangle}{\langle u_k, u_k \rangle} (0)
\]

\[ T' \] orthogonal

\[
= \langle v_p, u_i \rangle - \sum_{k \neq i} 0
\]

\[
= 0
\]

**Example GSTV**

**Gram-Schmidt of three vectors**

We will illustrate the Gram-Schmidt process with three vectors. Begin with the linearly independent (check this!) set

\[
S = \{ v_1, v_2, v_3 \} = \left\{ \begin{bmatrix} 1 & 1+i \\ 1+i & 1 \end{bmatrix}, \begin{bmatrix} -i & i \\ 1 & 1+i \end{bmatrix}, \begin{bmatrix} 0 \\ i \end{bmatrix} \right\}
\]
Then

\[ u_1 = v_1 = \begin{bmatrix} 1 \\ 1 + i \\ 1 \end{bmatrix} \]

\[ u_2 = v_2 - \frac{\langle v_2, u_1 \rangle}{\langle u_1, u_1 \rangle} u_1 = \frac{1}{4} \begin{bmatrix} -2 - 3i \\ 1 - i \\ 2 + 5i \end{bmatrix} \]

\[ u_3 = v_3 - \frac{\langle v_3, u_1 \rangle}{\langle u_1, u_1 \rangle} u_1 - \frac{\langle v_3, u_2 \rangle}{\langle u_2, u_2 \rangle} u_2 = \frac{1}{11} \begin{bmatrix} -3 - i \\ 1 + 3i \\ -1 - i \end{bmatrix} \]

and

\[ T = \{ u_1, u_2, u_3 \} = \left\{ \begin{bmatrix} 1 \\ 1 + i \\ 1 \end{bmatrix}, \frac{1}{4} \begin{bmatrix} -2 - 3i \\ 1 - i \\ 2 + 5i \end{bmatrix}, \frac{1}{11} \begin{bmatrix} -3 - i \\ 1 + 3i \\ -1 - i \end{bmatrix} \right\} \]

is an orthogonal set (which you can check) of nonzero vectors and \( S_p(T) = S_p(S) \) (all by Theorem GSPCV [173]). Of course, as a by-product of orthogonality, the set \( T \) is also linearly independent (Theorem OSLI [172]).

One final definition related to orthogonal vectors.

**Definition ONS**

**Orthonormal Set**

Suppose \( S = \{ u_1, u_2, u_3, \ldots, u_n \} \) is an orthogonal set of vectors such that \( \| u_i \| = 1 \) for all \( 1 \leq i \leq n \). Then \( S \) is an **orthonormal** set of vectors.

Once you have an orthogonal set, it is easy to convert it to an orthonormal set — multiply each vector by the reciprocal of its norm, and the resulting vector will have norm 1. This scaling of each vector will not affect the orthogonality properties (apply Theorem IPSM [168]).

**Example ONTV**

**Orthonormal set, three vectors**

The set

\[ T = \{ u_1, u_2, u_3 \} = \left\{ \begin{bmatrix} 1 \\ 1 + i \\ 1 \end{bmatrix}, \frac{1}{4} \begin{bmatrix} -2 - 3i \\ 1 - i \\ 2 + 5i \end{bmatrix}, \frac{1}{11} \begin{bmatrix} -3 - i \\ 1 + 3i \\ -1 - i \end{bmatrix} \right\} \]

from Example GSTV [174] is an orthogonal set. We compute the norm of each vector,

\[ \| u_1 \| = 2 \quad \| u_2 \| = \frac{1}{2} \sqrt{11} \quad \| u_3 \| = \frac{\sqrt{2}}{\sqrt{11}} \]
Converting each vector to a norm of 1, yields an orthonormal set,

\[ w_1 = \frac{1}{2} \begin{bmatrix} 1 + i \\ 1 \end{bmatrix} \]

\[ w_2 = \frac{1}{\sqrt{11}} \begin{bmatrix} -2 - 3i \\ 1 - i \\ 2 + 5i \end{bmatrix} = \frac{1}{2\sqrt{11}} \begin{bmatrix} -2 - 3i \\ 1 - i \\ 2 + 5i \end{bmatrix} \]

\[ w_3 = \frac{1}{\sqrt{11}} \begin{bmatrix} -3 - i \\ 1 + 3i \\ -1 - i \end{bmatrix} = \frac{1}{\sqrt{22}} \begin{bmatrix} -3 - i \\ 1 + 3i \\ -1 - i \end{bmatrix} \]

Example ONFV
Orthonormal set, four vectors
As an exercise convert the linearly independent set

\[ S = \left\{ \begin{bmatrix} 1 + i \\ 1 \\ 1 - i \end{bmatrix}, \begin{bmatrix} i \\ 1 + i \\ -i \end{bmatrix}, \begin{bmatrix} i \\ -1 + i \\ 1 \end{bmatrix}, \begin{bmatrix} -1 - i \\ i \\ -1 \end{bmatrix} \right\} \]

to an orthogonal set via the Gram-Schmidt Process (Theorem GSPCV [173]) and then scale the vectors to norm 1 to create an orthonormal set. You should get the same set you would if you scaled the orthogonal set of Example AOS [171] to become an orthonormal set.

Over the course of the next couple of chapters we will discover that orthonormal sets have some very nice properties (in addition to being linearly independent).

Subsection READ
Reading Questions

1. Is the set

\[ \left\{ \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 5 \\ 3 \\ -1 \end{bmatrix}, \begin{bmatrix} 8 \\ 4 \\ -2 \end{bmatrix} \right\} \]

an orthogonal set? Why?

2. What is the distinction between an orthogonal set and an orthonormal set?

3. What is nice about the output of the Gram-Schmidt process?
Subsection EXC
Exercises

C20  Complete Example AOS [171] by verifying that the four remaining inner products are zero.

Contributed by Robert Beezer

C21  Verify that the set $T$ created in Example GSTV [174] by the Gram-Schmidt Procedure is an orthogonal set.

Contributed by Robert Beezer

C22  Work Example ONFV [176].

Contributed by Robert Beezer
We have made frequent use of matrices for solving systems of equations, and we have begun to investigate a few of their properties, such as the null space and nonsingularity. In this chapter, we will take a more systematic approach to the study of matrices, and in this section we will backup and start simple. We begin with the definition of an important set.

Definition VSM
Vector Space of $m \times n$ Matrices
The vector space $M_{mn}$ is the set of all $m \times n$ matrices with entries from the set of complex numbers.

Subsection MEASM
Matrix equality, addition, scalar multiplication

Just as we made, and used, a careful definition of equality for column vectors, so too, we have precise definitions for matrices.

Definition ME
Matrix Equality
The $m \times n$ matrices $A$ and $B$ are equal, written $A = B$ provided $[A]_{ij} = [B]_{ij}$ for all $1 \leq i \leq m, 1 \leq j \leq n$.

So equality of matrices translates to the equality of complex numbers, on an entry-by-entry basis. Notice that we now have our fourth definition that uses the symbol ‘$=$’ for shorthand. Whenever a theorem has a conclusion saying two matrices are equal (think about your objects), we will consider appealing to this definition as a way of formulating the top-level structure of the proof. We will now define two operations on the set $M_{mn}$. Again, we will overload a symbol (‘$+$’) and a convention (juxtaposition for scalar multiplication).
**Definition MA**  
**Matrix Addition**  
Given the $m \times n$ matrices $A$ and $B$, define the **sum** of $A$ and $B$ as an $m \times n$ matrix, written $A + B$, according to

$$[A + B]_{ij} = [A]_{ij} + [B]_{ij} \quad 1 \leq i \leq m, 1 \leq j \leq n$$

So matrix addition takes two matrices of the same size and combines them (in a natural way!) to create a new matrix of the same size. Perhaps this is the “obvious” thing to do, but it doesn’t relieve us from the obligation to state it carefully.

**Example MA**  
**Addition of two matrices in $M_{23}$**  
If

$$A = \begin{bmatrix} 2 & -3 & 4 \\ 1 & 0 & -7 \end{bmatrix} \quad B = \begin{bmatrix} 6 & 2 & -4 \\ 3 & 5 & 2 \end{bmatrix}$$

then

$$A + B = \begin{bmatrix} 2 & -3 & 4 \\ 1 & 0 & -7 \end{bmatrix} + \begin{bmatrix} 6 & 2 & -4 \\ 3 & 5 & 2 \end{bmatrix} = \begin{bmatrix} 2 + 6 & -3 + 2 & 4 + (-4) \\ 1 + 3 & 0 + 5 & -7 + 2 \end{bmatrix} = \begin{bmatrix} 8 & -1 & 0 \\ 4 & 5 & -5 \end{bmatrix}$$

Our second operation takes two objects of different types, specifically a number and a matrix, and combines them to create another matrix. As with vectors, in this context we call a number a **scalar** in order to emphasize that it is not a matrix.

**Definition MSM**  
**Matrix Scalar Multiplication**  
Given the $m \times n$ matrix $A$ and the scalar $\alpha \in \mathbb{C}$, the **scalar multiple** of $A$ is an $m \times n$ matrix, written $\alpha A$ and defined according to

$$[\alpha A]_{ij} = \alpha [A]_{ij} \quad 1 \leq i \leq m, 1 \leq j \leq n$$

Notice again that we have yet another kind of multiplication, and it is again written putting two symbols side-by-side. Computationally, scalar matrix multiplication is very easy.

**Example MSM**  
**Scalar multiplication in $M_{32}$**  
If

$$A = \begin{bmatrix} 2 & 8 \\ -3 & 5 \\ 0 & 1 \end{bmatrix}$$

and $\alpha = 7$, then

$$\alpha A = 7 \begin{bmatrix} 2 & 8 \\ -3 & 5 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7(2) & 7(8) \\ 7(-3) & 7(5) \\ 7(0) & 7(1) \end{bmatrix} = \begin{bmatrix} 14 & 56 \\ -21 & 35 \\ 0 & 7 \end{bmatrix}$$

Its usually straightforward to have a calculator do these computations.
Subsection VSP
Vector Space Properties

With definitions of matrix addition and scalar multiplication we can now state, and prove, several properties of each operation, and some properties that involve their interplay. We now collect ten of them here for later reference.

Theorem VSPM
Vector Space Properties of Matrices
Suppose that $M_{mn}$ is the set of all $m \times n$ matrices (Definition VSM 179) with addition and scalar multiplication as defined in Definition MA 180 and Definition MSM 180. Then

- **ACM** Additive Closure, Matrices
  If $A, B \in M_{mn}$, then $A + B \in M_{mn}$.

- **SCM** Scalar Closure, Matrices
  If $\alpha \in \mathbb{C}$ and $A \in M_{mn}$, then $\alpha A \in M_{mn}$.

- **CM** Commutativity, Matrices
  If $A, B \in M_{mn}$, then $A + B = B + A$.

- **AAM** Additive Associativity, Matrices
  If $A, B, C \in M_{mn}$, then $A + (B + C) = (A + B) + C$.

- **ZM** Zero Vector, Matrices
  There is a matrix, $O$, called the zero matrix, such that $A + O = A$ for all $A \in M_{mn}$.

- **AIM** Additive Inverses, Matrices
  If $A \in M_{mn}$, then there exists a matrix $-A \in M_{mn}$ so that $A + (-A) = O$.

- **SMAM** Scalar Multiplication Associativity, Matrices
  If $\alpha, \beta \in \mathbb{C}$ and $A \in M_{mn}$, then $\alpha(\beta A) = (\alpha \beta)A$.

- **DMAM** Distributivity across Matrix Addition, Matrices
  If $\alpha \in \mathbb{C}$ and $A, B \in M_{mn}$, then $\alpha(A + B) = \alpha A + \alpha B$.

- **DSAM** Distributivity across Scalar Addition, Matrices
  If $\alpha, \beta \in \mathbb{C}$ and $A \in M_{mn}$, then $(\alpha + \beta)A = \alpha A + \beta A$.

- **OM** One, Matrices
  If $A \in M_{mn}$, then $1A = A$.

**Proof** While some of these properties seem very obvious, they all require proof. However, the proofs are not very interesting, and border on tedious. We’ll prove one version of distributivity very carefully, and you can test your proof-building skills on some of the others. We’ll give our new notation for matrix entries a workout here. Compare the style of the proofs here with those given for vectors in Theorem VSPCV 92 — while the objects here are more complicated, our notation makes the proofs cleaner.
To prove that \((\alpha + \beta)A = \alpha A + \beta A\), we need to establish the equality of two matrices (see [Technique GS 23]). [Definition ME 179] says we need to establish the equality of their entries, one-by-one. How do we do this, when we do not even know how many entries the two matrices might have? This is where [Notation ME 29] comes into play. Ready? Here we go.

For any \(i\) and \(j\), \(1 \leq i \leq m\), \(1 \leq j \leq n\),

\[
[(\alpha + \beta)A]_{ij} = (\alpha + \beta) [A]_{ij} = \alpha [A]_{ij} + \beta [A]_{ij} = [\alpha A]_{ij} + [\beta A]_{ij} = [\alpha A + \beta A]_{ij}
\]

There are several things to notice here. (1) Each equals sign is an equality of numbers. (2) The two ends of the equation, being true for any \(i\) and \(j\), allow us to conclude the equality of the matrices by [Definition ME 179]. (3) There are several plus signs, and several instances of juxtaposition. Identify each one, and state exactly what operation is being represented by each. □

For now, note the similarities between [Theorem VSPM 181] about matrices and [Theorem VSPCV 92] about vectors.

The zero matrix described in this theorem, \(O\), is what you would expect — a matrix full of zeros.

[Definition ZM] Zero Matrix
The \(m \times n\) zero matrix is written as \(O = O_{m \times n}\) and defined by 
\([O]_{ij} = 0\), for all \(1 \leq i \leq m\), \(1 \leq j \leq n\). □

Subsection TSM
Transposes and Symmetric Matrices

We describe one more common operation we can perform on matrices. Informally, to transpose a matrix is to build a new matrix by swapping its rows and columns.

[Definition TM] Transpose of a Matrix
Given an \(m \times n\) matrix \(A\), its transpose is the \(n \times m\) matrix \(A^t\) given by

\[
[A^t]_{ij} = [A]_{ji}, \quad 1 \leq i \leq n, \ 1 \leq j \leq m.
\]

Example TM
Transpose of a \(3 \times 4\) matrix
Suppose

\[
D = \begin{bmatrix}
3 & 7 & 2 & -3 \\
-1 & 4 & 2 & 8 \\
0 & 3 & -2 & 5
\end{bmatrix}.
\]
We could formulate the transpose, entry-by-entry, using the definition. But it is easier to just systematically rewrite rows as columns (or vice-versa). The form of the definition given will be more useful in proofs. So we have

\[ D^t = \begin{bmatrix} 3 & -1 & 0 \\ 7 & 4 & 3 \\ 2 & 2 & -2 \\ -3 & 8 & 5 \end{bmatrix} \]

It will sometimes happen that a matrix is equal to its transpose. In this case, we will call a matrix symmetric. These matrices occur naturally in certain situations, and also have some nice properties, so it is worth stating the definition carefully. Informally a matrix is symmetric if we can “flip” it about the main diagonal (upper-left corner, running down to the lower-right corner) and have it look unchanged.

**Definition SYM**

**Symmetric Matrix**

The matrix \( A \) is **symmetric** if \( A = A^t \).

**Example SYM**

**A symmetric 5 \times 5 matrix**

The matrix

\[ E = \begin{bmatrix} 2 & 3 & -9 & 5 & 7 \\ 3 & 1 & 6 & -2 & -3 \\ -9 & 6 & 0 & -1 & 9 \\ 5 & -2 & -1 & 4 & -8 \\ 7 & -3 & 9 & -8 & -3 \end{bmatrix} \]

is symmetric.

You might have noticed that **Definition SYM** did not specify the size of the matrix \( A \), as has been our custom. That’s because it wasn’t necessary. An alternative would have been to state the definition just for square matrices, but this is the substance of the next proof. But first, a bit more advice about constructing proofs.

**Proof Technique P**

**Practice**

Here is a technique used by many practicing mathematicians when they are teaching themselves new mathematics. As they read a textbook, monograph or research article, they attempt to prove each new theorem themselves, before reading the proof. Often the proofs can be very difficult, so it is wise not to spend too much time on each. Maybe limit your losses and try each proof for 10 or 15 minutes. Even if the proof is not found, it is time well-spent. You become more familiar with the definitions involved, and the hypothesis and conclusion of the theorem. When you do work through the proof, it might make more sense, and you will gain added insight about just how to construct a proof.

The next theorem is a great place to try this technique.

**Theorem SMS**

**Symmetric Matrices are Square**

Suppose that \( A \) is a symmetric matrix. Then \( A \) is square.
Proof We start by specifying $A$’s size, without assuming it is square, since we are trying to prove that, so we can’t also assume it. Suppose $A$ is an $m \times n$ matrix. Because $A$ is symmetric, we know by Definition SM \[361\] that $A = A^t$. So, in particular, $A$ and $A^t$ have the same size. The size of $A^t$ is $n \times m$, so from $m \times n = n \times m$, we conclude that $m = n$, and hence $A$ must be square. □

We finish this section with two easy theorems, but they illustrate the interplay of our three new operations, our new notation, and the techniques used to prove matrix equalities.

Theorem TMA

Transpose and Matrix Addition

Suppose that $A$ and $B$ are $m \times n$ matrices. Then $(A + B)^t = A^t + B^t$. □

Proof The statement to be proved is an equality of matrices, so we work entry-by-entry and use Definition ME \[179\]. Think carefully about the objects involved here, and the many uses of the plus sign.

\[
\left[(A + B)^t\right]_{ij} = [A + B]_{ji} \quad \text{Definition TM} \quad 182
\]
\[
= [A]_{ji} + [B]_{ji} \quad \text{Definition MA} \quad 180
\]
\[
= [A^t]_{ij} + [B^t]_{ij} \quad \text{Definition TM} \quad 182
\]
\[
= [A^t + B^t]_{ij} \quad \text{Definition MA} \quad 180
\]

Since the matrices $(A + B)^t$ and $A^t + B^t$ agree at each entry, Theorem ME \[406\] tells us the two matrices are equal. □

Theorem TMSM

Transpose and Matrix Scalar Multiplication

Suppose that $\alpha \in \mathbb{C}$ and $A$ is an $m \times n$ matrix. Then $(\alpha A)^t = \alpha A^t$. □

Proof The statement to be proved is an equality of matrices, so we work entry-by-entry and use Definition ME \[179\]. Think carefully about the objects involved here, the many uses of juxtaposition.

\[
\left[(\alpha A)^t\right]_{ij} = [\alpha A]_{ji} \quad \text{Definition TM} \quad 182
\]
\[
= \alpha [A]_{ji} \quad \text{Definition MSM} \quad 180
\]
\[
= \alpha [A^t]_{ij} \quad \text{Definition TM} \quad 182
\]
\[
= [\alpha A^t]_{ij} \quad \text{Definition MSM} \quad 180
\]

Since the matrices $(\alpha A)^t$ and $\alpha A^t$ agree at each entry, Theorem ME \[406\] tells us the two matrices are equal. □

Theorem TT

Transpose of a Transpose

Suppose that $A$ is an $m \times n$ matrix. Then $(A^t)^t = A$. □

Proof We again want to prove an equality of matrices, so we work entry-by-entry and use Definition ME \[179\].

\[
\left[(A^t)^t\right]_{ij} = [A^t]_{ji} \quad \text{Definition TM} \quad 182
\]
\[
= [A]_{ij} \quad \text{Definition TM} \quad 182
\]
It's usually pretty straightforward to coax the transpose of a matrix out of a calculator.

**Computation Note** TM.MMA

**Transpose of a Matrix** (Mathematica)

Contributed by Robert Beezer

Suppose `a` is the name of a matrix stored in Mathematica. Then `Transpose[a]` will create the transpose of `a`.

**Computation Note** TM.TI86

**Transpose of a Matrix** (TI-86)

Contributed by Eric Fickenscher

Suppose `A` is the name of a matrix stored in the TI-86. Use the command `A^T` to transpose `A`. This command can be found by pressing the `MATRX` key, then F3 for `MATH`, then F2 for `T`.

**Subsection MCC**

**Matrices and Complex Conjugation**

As we did with vectors (Definition CCCV [165]), we can define what it means to take the conjugate of a matrix.

**Definition CCM**

**Complex Conjugate of a Matrix**

Suppose `A` is an `m` × `n` matrix. Then the conjugate of `A`, written `\overline{A}` is an `m` × `n` matrix defined by

\[
[\overline{A}]_{ij} = \overline{[A]_{ij}}
\]

**Example CCM**

**Complex conjugate of a matrix**

If

\[
A = \begin{bmatrix} 2 - i & 3 & 5 + 4i \\ -3 + 6i & 2 - 3i & 0 \end{bmatrix}
\]

then

\[
\overline{A} = \begin{bmatrix} 2 + i & 3 & 5 - 4i \\ -3 - 6i & 2 + 3i & 0 \end{bmatrix}
\]

The interplay between the conjugate of a matrix and the two operations on matrices is what you might expect.

**Theorem CRMA**

**Conjugation Respects Matrix Addition**

Suppose that `A` and `B` are `m` × `n` matrices. Then `\overline{A + B} = \overline{A} + \overline{B}`.
Proof

\[
\begin{align*}
[A + B]_{ij} &= [A + B]_{ij} \\
&= [A]_{ij} + [B]_{ij} \quad \text{Definition CCM 185} \\
&= [A]_{ij} + [B]_{ij} \quad \text{Definition MA 180} \\
&= [\bar{A}]_{ij} + [\bar{B}]_{ij} \quad \text{Theorem CCRA 640} \\
&= [\bar{A} + \bar{B}]_{ij} \quad \text{Definition CCM 185} \\
&= [\bar{A} + \bar{B}]_{ij} \quad \text{Definition MA 180}
\end{align*}
\]

Since the matrices \( \bar{A} + \bar{B} \) and \( \bar{A} + \bar{B} \) are equal in each entry, Definition ME 179 says that \( \bar{A} + \bar{B} = \bar{A} + \bar{B} \).

\[\square\]

**Theorem CRMSM**

Conjugation Respects Matrix Scalar Multiplication

Suppose that \( \alpha \in \mathbb{C} \) and \( A \) is an \( m \times n \) matrix. Then \( \bar{\alpha A} = \bar{\alpha} \bar{A} \).

\[\square\]

**Proof**

\[
\begin{align*}
[\alpha A]_{ij} &= [\alpha A]_{ij} \\
&= \alpha [A]_{ij} \quad \text{Definition CCM 185} \\
&= \alpha [A]_{ij} \quad \text{Definition MSM 180} \\
&= \alpha [\bar{A}]_{ij} \quad \text{Theorem CCRM 640} \\
&= \alpha [\bar{A}]_{ij} \quad \text{Definition CCM 185} \\
&= [\bar{\alpha A}]_{ij} \quad \text{Definition MSM 180}
\end{align*}
\]

Since the matrices \( \bar{\alpha A} \) and \( \bar{\alpha} \bar{A} \) are equal in each entry, Definition ME 179 says that \( \bar{\alpha A} = \bar{\alpha} \bar{A} \).

\[\square\]

**Subsection READ**

**Reading Questions**

1. Perform the following matrix computation.

\[
(6) \begin{bmatrix} 2 & -2 & 8 & 1 \\ 4 & 5 & -1 & 3 \\ 7 & -3 & 0 & 2 \end{bmatrix} + (-2) \begin{bmatrix} 2 & 7 & 1 & 2 \\ 3 & -1 & 0 & 5 \\ 1 & 7 & 3 & 3 \end{bmatrix}
\]

2. **Theorem VSPM 181** reminds you of what previous theorem? How strong is the similarity?

3. Compute the transpose of the matrix below.

\[
\begin{bmatrix} 6 & 8 & 4 \\ -2 & 1 & 0 \\ 9 & -5 & 6 \end{bmatrix}
\]
Section MM
Matrix Multiplication

We know how to add vectors and how to multiply them by scalars. Together, these operations give us the possibility of making linear combinations. Similarly, we know how to add matrices and how to multiply matrices by scalars. In this section we mix all these ideas together and produce an operation known as matrix multiplication. This will lead to some results that are both surprising and central. We begin with a definition of how to multiply a vector by a matrix.

Subsection MVP
Matrix-Vector Product

We have repeatedly seen the importance of forming linear combinations of the columns of a matrix. As one example of this, [Theorem SLSLC][103] said that every solution to a system of linear equations gives rise to a linear combination of the column vectors of the coefficient matrix that equals the vector of constants. This theorem, and others, motivates the following central definition.

**Definition MVP**
Matrix-Vector Product
Suppose $A$ is an $m \times n$ matrix with columns $A_1, A_2, A_3, \ldots, A_n$ and $u$ is a vector of size $n$. Then the **matrix-vector product** of $A$ with $u$ is

$$Au = [A_1|A_2|A_3|\ldots|A_n] = u_1A_1 + u_2A_2 + u_3A_3 + \cdots + u_nA_n$$

So, the matrix-vector product is yet another version of “multiplication,” at least in the sense that we have yet again overloaded juxtaposition of two symbols. Remember your objects, an $m \times n$ matrix times a vector of size $n$ will create a vector of size $m$. So if $A$ is rectangular, then the size of the vector changes. With all the linear combinations we have performed so far, this computation should now seem second nature.

**Example MTV**
A matrix times a vector
Consider

$$A = \begin{bmatrix} 1 & 4 & 2 & 3 & 4 \\ -3 & 2 & 0 & 1 & -2 \\ 1 & 6 & -3 & -1 & 5 \end{bmatrix} \quad u = \begin{bmatrix} 2 \\ 1 \\ -2 \\ 3 \\ -1 \end{bmatrix}$$
Then
\[
A \mathbf{u} = 2 \begin{bmatrix} 1 \\ -3 \\ 1 \end{bmatrix} + 1 \begin{bmatrix} 4 \\ 2 \\ 6 \end{bmatrix} + (-2) \begin{bmatrix} 2 \\ 0 \\ -3 \end{bmatrix} + 3 \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} + (-1) \begin{bmatrix} 4 \\ -2 \\ 5 \end{bmatrix} = \begin{bmatrix} 7 \\ 1 \end{bmatrix}.
\]

This definition now makes it possible to represent systems of linear equations compactly in terms of an operation.

**Theorem SLEMM**

**Systems of Linear Equations as Matrix Multiplication**

Solutions to the linear system \( \mathcal{L} \mathbf{S}(A, \mathbf{b}) \) are the solutions for \( \mathbf{x} \) in the vector equation \( A \mathbf{x} = \mathbf{b} \).

**Proof** This theorem says (not very clearly) that two sets (of solutions) are equal. So we need to show that one set of solutions is a subset of the other, and vice versa (recall [Technique SE][17]). Both of these inclusions are easy with the following chain of equivalences,

\[
\begin{align*}
\mathbf{x} &= \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_i \end{bmatrix} \text{ is a solution to } \mathcal{L} \mathbf{S}(A, \mathbf{b}) \\
\iff x_1 \mathbf{A}_1 + x_2 \mathbf{A}_2 + x_3 \mathbf{A}_3 + \cdots + x_n \mathbf{A}_n = \mathbf{b} & \quad \text{Theorem SLSLC[103]} \\
\iff \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_i \end{bmatrix} \text{ is a solution to } A \mathbf{x} = \mathbf{b} & \quad \text{Definition MVP[187]}.
\end{align*}
\]

**Example MNSLE**

**Matrix notation for systems of linear equations**

Consider the system of linear equations from [Example NSLE][68].

\[
\begin{align*}
2x_1 + 4x_2 - 3x_3 + 5x_4 + x_5 &= 9 \\
3x_1 + x_2 + x_4 - 3x_5 &= 0 \\
-2x_1 + 7x_2 - 5x_3 + 2x_4 + 2x_5 &= -3
\end{align*}
\]

has coefficient matrix

\[
A = \begin{bmatrix} 2 & 4 & -3 & 5 & 1 \\ 3 & 1 & 0 & 1 & -3 \\ -2 & 7 & -5 & 2 & 2 \end{bmatrix}
\]

and vector of constants

\[
\mathbf{b} = \begin{bmatrix} 9 \\ 0 \\ -3 \end{bmatrix}
\]

and so will be described compactly by the equation \( A \mathbf{x} = \mathbf{b} \).
The matrix-vector product is a very natural computation. We have motivated it by its connections with systems of equations, but here is another example.

**Example MBC**

**Money’s best cities**

Every year *Money* magazine selects several cities in the United States as the “best” cities to live in, based on a wide array of statistics about each city. This is an example of how the editors of *Money* might arrive at a single number that consolidates the statistics about a city. We will analyze Los Angeles, Chicago and New York City, based on four criteria: average high temperature in July (Fahrenheit), number of colleges and universities in a 30-mile radius, number of toxic waste sites in the Superfund clean-up program and a personal crime index based on FBI statistics (average = 100, smaller is safer). It should be apparent how to generalize the example to a greater number of cities and a greater number of statistics.

We begin by building a table of statistics. The rows will be labeled with the cities, and the columns with statistical categories. These values are from *Money*’s website in early 2005.

<table>
<thead>
<tr>
<th>City</th>
<th>Temp</th>
<th>Colleges</th>
<th>Superfund</th>
<th>Crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles</td>
<td>77</td>
<td>28</td>
<td>93</td>
<td>254</td>
</tr>
<tr>
<td>Chicago</td>
<td>84</td>
<td>38</td>
<td>85</td>
<td>363</td>
</tr>
<tr>
<td>New York</td>
<td>84</td>
<td>99</td>
<td>1</td>
<td>193</td>
</tr>
</tbody>
</table>

Conceivably these data might reside in a spreadsheet. Now we must combine the statistics for each city. We could accomplish this by weighting each category, scaling the values and summing them. The sizes of the weights would depend upon the numerical size of each statistic generally, but more importantly, they would reflect the editors opinions or beliefs about which statistics were most important to their readers. Is the crime index more important than the number of colleges and universities? Of course, there is no right answer to this question.

Suppose the editors finally decide on the following weights to employ: temperature, 0.23; colleges, 0.46; Superfund, −0.05; crime, −0.20. Notice how negative weights are used for undesirable statistics. Then, for example, the editors would compute for Los Angeles,

\[(0.23)(77) + (0.46)(28) + (-0.05)(93) + (-0.20)(254) = -24.86\]

This computation might remind you of an inner product, but we will produce the computations for all of the cities as a matrix-vector product. Write the table of raw statistics as a matrix

\[
T = \begin{bmatrix}
77 & 28 & 93 & 254 \\
84 & 38 & 85 & 363 \\
84 & 99 & 1 & 193 \\
\end{bmatrix}
\]

and the weights as a vector

\[
w = \begin{bmatrix}
0.23 \\
0.46 \\
-0.05 \\
-0.20 \\
\end{bmatrix}
\]
then the matrix-vector product (Definition MVP [187]) yields

\[
T \mathbf{w} = (0.23) \begin{bmatrix} 77 \\ 84 \\ 84 \end{bmatrix} + (0.46) \begin{bmatrix} 28 \\ 38 \\ 99 \end{bmatrix} + (-0.05) \begin{bmatrix} 93 \\ 85 \\ 1 \end{bmatrix} + (-0.20) \begin{bmatrix} 254 \\ 363 \\ 193 \end{bmatrix} = \begin{bmatrix} -24.86 \\ -40.05 \\ 26.21 \end{bmatrix}
\]

This vector contains a single number for each of the cities being studied, so the editors would rank New York best, Los Angeles next, and Chicago third. Of course, Chicago and Los Angeles are free to counter with a different set of weights that cause it to be ranked best. These alternative weights would play to each cities’ strengths and minimize their problem areas.

If a spreadsheet were used to make these computations, a row of weights would be entered somewhere near the table of data and the formulas in the spreadsheet would effect a matrix-vector product. This example is meant to illustrate how “linear” computations (addition, multiplication) can be organized as a matrix-vector product.

Later (much later) we will need the following theorem. Since we are in a position to prove it now, we will. But you can safely skip it now, if you promise to come back later to study the proof when the theorem is employed.

**Theorem EMMVP**

**Equal Matrices and Matrix-Vector Products**

Suppose that \( A \) and \( B \) are \( m \times n \) matrices such that \( Ax = Bx \) for every \( x \in \mathbb{C}^n \). Then \( A = B \).

**Proof** Since \( Ax = Bx \) for all \( x \in \mathbb{C}^n \), choose \( x \) to be a vector of all zeros, with a lone 1 in the \( i \)-th slot. Then

\[
Ax = [A_1 | A_2 | A_3 | \ldots | A_n] \begin{bmatrix} 0 \\ 0 \\ \ldots \\ 0 \\ 1 \\ \ldots \\ 0 \end{bmatrix} = 0A_1 + 0A_2 + 0A_3 + \cdots + 0A_{i-1} + 1A_i + 0A_{i+1} + \cdots + 0A_n \quad \text{Definition MVP [187]}
\]

Similarly, \( Bx = B_1 \), so \( A_i = B_i, 1 \leq i \leq n \) and so all the columns of \( A \) and \( B \) are equal. Then our definition of column vector equality (Definition CVE [88]) establishes that the individual entries of \( A \) and \( B \) in each column are equal. So by Definition ME [179] the matrices \( A \) and \( B \) are equal.

The hypotheses of this theorem could be weakened to suppose only the equality of the matrix-vector products for just the standard unit vectors (Definition SUV [210]) or any other basis (Definition B [317]) of \( \mathbb{C}^n \). However, when we apply this theorem we will only need this weaker form.
We now define how to multiply two matrices together. Stop for a minute and think about how you might define this new operation.

Many books would present this definition much earlier in the course. However, we have taken great care to delay it as long as possible and to present as many ideas as practical based mostly on the notion of linear combinations. Towards the conclusion of the course, or when you perhaps take a second course in linear algebra, you may be in a position to appreciate the reasons for this. For now, understand that matrix multiplication is a central definition and perhaps you will appreciate its importance more by having saved it for later.

**Definition MM**

Matrix Multiplication

Suppose $A$ is an $m \times n$ matrix and $B$ is an $n \times p$ matrix with columns $B_1$, $B_2$, $B_3$, ..., $B_p$. Then the **matrix product** of $A$ with $B$ is the $m \times p$ matrix where column $i$ is the matrix-vector product $AB_i$. Symbolically,

$$AB = A \left[ B_1 | B_2 | B_3 | \ldots | B_p \right] = \left[ AB_1 | AB_2 | AB_3 | \ldots | AB_p \right].$$

**Example PTM**

Product of two matrices

Set

$$A = \begin{bmatrix} 1 & 2 & -1 & 4 & 6 \\ 0 & -4 & 1 & 2 & 3 \\ -5 & 1 & 2 & -3 & 4 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 6 & 2 & 1 \\ -1 & 4 & 3 & 2 \\ 1 & 1 & 2 & 3 \\ 6 & 4 & -1 & 2 \\ 1 & -2 & 3 & 0 \end{bmatrix}$$

Then

$$AB = \begin{bmatrix} 1 & 6 & 2 & 1 \\ -1 & 4 & 3 & 2 \\ 1 & 1 & 2 & 3 \\ 6 & 4 & -1 & 2 \\ 1 & -2 & 3 & 0 \end{bmatrix} = \begin{bmatrix} 28 & 17 & 20 & 10 \\ -13 & -3 & -1 \\ 20 & -13 & -3 & -1 \\ -18 & -44 & 12 & -3 \end{bmatrix}.$$ 

Is this the definition of matrix multiplication you expected? Perhaps our previous operations for matrices caused you to think that we might multiply two matrices of the *same* size, *entry-by-entry*? Notice that our current definition uses matrices of different sizes (though the number of columns in the first must equal the number of rows in the second), and the result is of a third size. Notice too in the previous example that we cannot even consider the product $BA$, since the sizes of the two matrices in this order aren’t right.

But it gets weirder than that. Many of your old ideas about “multiplication” won’t apply to matrix multiplication, but some still will. So make no assumptions, and don’t do anything until you have a theorem that says you can. Even if the sizes are right, matrix multiplication is not commutative — order matters.
Example MMNC
Matrix Multiplication is not commutative
Set
\[
A = \begin{bmatrix} 1 & 3 \\ -1 & 2 \end{bmatrix}, \quad B = \begin{bmatrix} 4 & 0 \\ 5 & 1 \end{bmatrix}.
\]

Then we have two square, 2 × 2 matrices, so Definition MM allows us to multiply them in either order. We find
\[
AB = \begin{bmatrix} 19 & 3 \\ 6 & 2 \end{bmatrix}, \quad BA = \begin{bmatrix} 4 & 12 \\ 4 & 17 \end{bmatrix}
\]
and \(AB \neq BA\). Not even close. It should not be hard for you to construct other pairs of matrices that do not commute (try a couple of 3 × 3’s). Can you find a pair of non-identical matrices that do commute?

Computation Note MM.MMA
Matrix Multiplication (Mathematica)
If \(A\) and \(B\) are matrices defined in Mathematica, then \(A.B\) will return the product of the two matrices (notice the dot between the matrices). If \(A\) is a matrix and \(v\) is a vector, then \(A.v\) will return the vector that is the matrix-vector product of \(A\) and \(v\). In every case the sizes of the matrices and vectors need to be correct.

Some examples:
\[
\{\{1, 2\}, \{3, 4\}\}.\{\{5, 6, 7\}, \{8, 9, 10\}\} = \{\{21, 24, 27\}, \{47, 54, 61\}\}
\]
\[
\{\{1, 2\}, \{3, 4\}\}.\{\{5\}, \{6\}\} = \{\{17\}, \{39\}\}
\]
\[
\{\{1, 2\}, \{3, 4\}\}.\{5, 6\} = \{17, 39\}
\]

Understanding the difference between the last two examples will go a long way to explaining how some Mathematica constructs work.

Subsection MMEE
Matrix Multiplication, Entry-by-Entry

While certain “natural” properties of multiplication don’t hold, many more do. In the next subsection, we’ll state and prove the relevant theorems. But first, we need a theorem that provides an alternate means of multiplying two matrices. In many texts, this would be given as the definition of matrix multiplication. We prefer to turn it around and have the following formula as a consequence of the definition. It will prove useful for proofs of matrix equality, where we need to examine products of matrices, entry-by-entry.

Theorem EMP
Entries of Matrix Products
Suppose \(A\) is an \(m \times n\) matrix and \(B = \) is an \(n \times p\) matrix. Then the entries of \(AB\) are given by
\[
[AB]_{ij} = [A]_{i1} [B]_{1j} + [A]_{i2} [B]_{2j} + [A]_{i3} [B]_{3j} + \cdots + [A]_{in} [B]_{nj} = \sum_{k=1}^{n} [A]_{ik} [B]_{kj}
\]
Proof The value of \([AB]_{ij}\) lies in column \(j\) of the product of \(A\) and \(B\), and so by Definition MM [191] is the value in location \(i\) of the matrix-vector product \(AB_j\). By Definition MVP [187] this matrix-vector product is a linear combination

\[
AB_j = [B]_{1j}A_1 + [B]_{2j}A_2 + [B]_{3j}A_3 + \cdots + [B]_{nj}A_n
\]

This can be written as

\[
= [B]_{1j} \begin{bmatrix} [A]_{i1} \\ [A]_{i2} \\ \vdots \\ [A]_{im} \end{bmatrix} + [B]_{2j} \begin{bmatrix} [A]_{i1} \\ [A]_{i2} \\ \vdots \\ [A]_{im} \end{bmatrix} + [B]_{3j} \begin{bmatrix} [A]_{i1} \\ [A]_{i2} \\ \vdots \\ [A]_{im} \end{bmatrix} + \cdots + [B]_{nj} \begin{bmatrix} [A]_{i1} \\ [A]_{i2} \\ \vdots \\ [A]_{im} \end{bmatrix}
\]

We are after the value in location \(i\) of this linear combination. Using Definition CVA [89] and Definition CVSM [90] we course through this linear combination in location \(i\) to find

\[
[AB]_{ij} = [B]_{1j} [A]_{i1} + [B]_{2j} [A]_{i2} + [B]_{3j} [A]_{i3} + \cdots + [B]_{nj} [A]_{in}
\]

\[
= [A]_{i1} [B]_{1j} + [A]_{i2} [B]_{2j} + [A]_{i3} [B]_{3j} + \cdots + [A]_{in} [B]_{nj}
\]

\[
= \sum_{k=1}^{n} [A]_{ik} [B]_{kj}
\]

\[
\boxdot
\]

Example PTMEE

Product of two matrices, entry-by-entry

Consider again the two matrices from Example PTM [191]

\[
A = \begin{bmatrix} 1 & 2 & -1 & 4 & 6 \\ 0 & -4 & 1 & 2 & 3 \\ -5 & 1 & 2 & -3 & 4 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 6 & 2 & 1 \\ -1 & 4 & 3 & 2 \\ 1 & 1 & 2 & 3 \\ 6 & 4 & -1 & 2 \\ 1 & -2 & 3 & 0 \end{bmatrix}
\]

Then suppose we just wanted the entry of \(AB\) in the second row, third column:

\[
[AB]_{23} = [A]_{21} [B]_{13} + [A]_{22} [B]_{23} + [A]_{23} [B]_{33} + [A]_{24} [B]_{43} + [A]_{25} [B]_{53}
\]

\[
= (0)(2) + (-4)(3) + (1)(2) + (2)(-1) + (3)(3) = -3
\]

Notice how there are 5 terms in the sum, since 5 is the common dimension of the two matrices (column count for \(A\), row count for \(B\)). In the conclusion of Theorem EMP [193], it would be the index \(k\) that would run from 1 to 5 in this computation. Here’s a bit more practice.

The entry of third row, first column:

\[
[AB]_{31} = [A]_{31} [B]_{11} + [A]_{32} [B]_{21} + [A]_{33} [B]_{31} + [A]_{34} [B]_{41} + [A]_{35} [B]_{51}
\]

\[
= (-5)(1) + (1)(-1) + (2)(1) + (-3)(6) + (4)(1) = -18
\]

To get some more practice on your own, complete the computation of the other 10 entries of this product. Construct some other pairs of matrices (of compatible sizes) and compute their product two ways. First use Definition MM [191]. Since linear combinations are straightforward for you now, this should be easy to do and to do correctly. Then do it again, using Theorem EMP [193]. Since this process may take some practice, use your first computation to check your work.
Theorem EMP \[193\] is the way most people compute matrix products by hand. It will also be very useful for the theorems we are going to prove shortly. However, the definition (Definition MM \[191\]) is frequently the most useful for its connections with deeper ideas like the null space and the upcoming column space.

Subsection PMM
Properties of Matrix Multiplication

In this subsection, we collect properties of matrix multiplication and its interaction with the zero matrix (Definition ZM \[182\]), the identity matrix (Definition IM \[76\]), matrix addition (Definition MA \[180\]), scalar matrix multiplication (Definition MSM \[180\]), the inner product (Definition IP \[166\]), conjugation (Theorem MMCC \[197\]), and the transpose (Definition TM \[182\]). Whew! Here we go. These are great proofs to practice with, so try to concoct the proofs before reading them, they’ll get progressively more complicated as we go.

Theorem MMZM
Matrix Multiplication and the Zero Matrix
Suppose \(A\) is an \(m \times n\) matrix. Then
1. \(AO_{n \times p} = O_{m \times p}\)
2. \(O_{p \times m}A = O_{p \times n}\)

Proof We’ll prove (1) and leave (2) to you. Entry-by-entry,

\[
[AO_{n \times p}]_{ij} = \sum_{k=1}^{n} [A]_{ik} [O_{n \times p}]_{kj}
\]

\[
= \sum_{k=1}^{n} [A]_{ik} 0
\]

\[
= \sum_{k=1}^{n} 0 = 0.
\]

So every entry of the product is the scalar zero, i.e. the result is the zero matrix.

Theorem MMIM
Matrix Multiplication and Identity Matrix
Suppose \(A\) is an \(m \times n\) matrix. Then
1. \(AI_{n} = A\)
2. \(I_{m}A = A\)
Proof Again, we’ll prove (1) and leave (2) to you. Entry-by-entry,

\[ [AI_n]_{ij} = \sum_{k=1}^{n} [A]_{ik} [I_n]_{kj} \]

\[ = [A]_{ij} [I_n]_{jj} + \sum_{k=1,k\neq j}^{n} [A]_{ik} [I_n]_{kj} \]

\[ = [A]_{ij} (1) + \sum_{k=1,k\neq j}^{n} [A]_{ik} (0) \]

\[ = [A]_{ij} + \sum_{k=1,k\neq j}^{n} 0 \]

\[ = [A]_{ij} \]

So the matrices \( A \) and \( AI_n \) are equal, entry-by-entry, and by the definition of matrix equality (Definition ME 179) we can say they are equal matrices.

\[ ■ \]

It is this theorem that gives the identity matrix its name. It is a matrix that behaves with matrix multiplication like the scalar 1 does with scalar multiplication. To multiply by the identity matrix is to have no effect on the other matrix.

**Theorem MMDAA**
**Matrix Multiplication Distributes Across Addition**

Suppose \( A \) is an \( m \times n \) matrix and \( B \) and \( C \) are \( n \times p \) matrices and \( D \) is a \( p \times s \) matrix. Then

1. \( A(B + C) = AB + AC \)
2. \( (B + C)D = BD + CD \)

**Proof** We’ll do (1), you do (2). Entry-by-entry,

\[ [A(B + C)]_{ij} = \sum_{k=1}^{n} [A]_{ik} [B + C]_{kj} \]

\[ = \sum_{k=1}^{n} [A]_{ik} ([B]_{kj} + [C]_{kj}) \]

\[ = \sum_{k=1}^{n} [A]_{ik} [B]_{kj} + \sum_{k=1}^{n} [A]_{ik} [C]_{kj} \]

\[ = [AB]_{ij} + [AC]_{ij} \]

\[ = [AB + AC]_{ij} \]

So the matrices \( A(B + C) \) and \( AB + AC \) are equal, entry-by-entry, and by the definition of matrix equality (Definition ME 179) we can say they are equal matrices.

\[ ■ \]

**Theorem MMSMM**
**Matrix Multiplication and Scalar Matrix Multiplication**

Suppose \( A \) is an \( m \times n \) matrix and \( B \) is an \( n \times p \) matrix. Let \( \alpha \) be a scalar. Then

\( \alpha(AB) = (\alpha A)B = A(\alpha B) \).
Proof These are equalities of matrices. We’ll do the first one, the second is similar and will be good practice for you.

\[
\alpha (AB)_{ij} = \alpha [AB]_{ij} \quad \text{Definition MSM 180}
\]

\[
= \alpha \sum_{k=1}^{n} [A]_{ik} [B]_{kj} \quad \text{Theorem EMP 193}
\]

\[
= \sum_{k=1}^{n} \alpha [A]_{ik} [B]_{kj} \quad \text{Distributivity in } \mathbb{C}
\]

\[
= \sum_{k=1}^{n} [\alpha A]_{ik} [B]_{kj} \quad \text{Definition MSM 180}
\]

\[
= \alpha [AB]_{ij} \quad \text{Theorem EMP 193}
\]

So the matrices \( \alpha (AB) \) and \( (\alpha A)B \) are equal, entry-by-entry, and by the definition of matrix equality (Definition ME 179) we can say they are equal matrices.

Theorem MMA
Matrix Multiplication is Associative
Suppose \( A \) is an \( m \times n \) matrix, \( B \) is an \( n \times p \) matrix and \( D \) is a \( p \times s \) matrix. Then \( A(BD) = (AB)D \).

Proof A matrix equality, so we’ll go entry-by-entry, no surprise there.

\[
(A(BD))_{ij} = \sum_{k=1}^{n} [A]_{ik} [BD]_{kj} \quad \text{Theorem EMP 193}
\]

\[
= \sum_{k=1}^{n} [A]_{ik} \left( \sum_{\ell=1}^{p} [B]_{k\ell} [D]_{\ell j} \right) \quad \text{Theorem EMP 193}
\]

\[
= \sum_{k=1}^{n} \sum_{\ell=1}^{p} [A]_{ik} [B]_{k\ell} [D]_{\ell j} \quad \text{Distributivity in } \mathbb{C}
\]

We can switch the order of the summation since these are finite sums,

\[
= \sum_{\ell=1}^{p} \sum_{k=1}^{n} [A]_{ik} [B]_{k\ell} [D]_{\ell j} \quad \text{Commutativity in } \mathbb{C}
\]

As \([D]_{\ell j}\) does not depend on the index \( k \), we can factor it out of the inner sum,

\[
= \sum_{\ell=1}^{p} [D]_{\ell j} \left( \sum_{k=1}^{n} [A]_{ik} [B]_{k\ell} \right) \quad \text{Commutativity in } \mathbb{C}
\]

\[
= \sum_{\ell=1}^{p} [D]_{\ell j} [AB]_{i\ell} \quad \text{Theorem EMP 193}
\]

\[
= \sum_{\ell=1}^{p} [AB]_{i\ell} [D]_{\ell j} \quad \text{Commutativity in } \mathbb{C}
\]

\[
= [(AB)D]_{ij} \quad \text{Theorem EMP 193}
\]

So the matrices \((AB)D\) and \((A(BD))\) are equal, entry-by-entry, and by the definition of matrix equality (Definition ME 179) we can say they are equal matrices.

\[\blacksquare\]
Theorem MMIP
Matrix Multiplication and Inner Products
If we consider the vectors \( u, v \in \mathbb{C}^m \) as \( m \times 1 \) matrices then
\[
\langle u, v \rangle = u^t v
\]
\[\square\]

Proof Write \( u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \) and \( v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix} \). Then
\[
\langle u, v \rangle = \sum_{k=1}^{m} u_k \overline{v_k} \quad \text{Definition IP [166]}
\]
\[
= \sum_{k=1}^{m} [u]_{1k} [v]_{k1} \quad \text{Column vectors as matrices}
\]
\[
= \sum_{k=1}^{m} [u^t]_{1k} [v]_{k1} \quad \text{Definition TM [182]}
\]
\[
= \sum_{k=1}^{m} [u^t]_{1k} [\overline{v}]_{k1} \quad \text{Definition CCCV [165]}
\]
\[
= [u^t \overline{v}]_{11} \quad \text{Theorem EMP [193]}
\]

To finish we just blur the distinction between a \( 1 \times 1 \) matrix \((u^t \overline{v})\) and its lone entry. \(\square\)

Theorem MMCC
Matrix Multiplication and Complex Conjugation
Suppose \( A \) is an \( m \times n \) matrix and \( B \) is an \( n \times p \) matrix. Then \( \overline{AB} = \overline{A \overline{B}} \).
\[\square\]

Proof To obtain this matrix equality, we will work entry-by-entry,
\[
[\overline{AB}]_{ij} = \overline{[AB]_{ij}} \quad \text{Definition CM [66]}
\]
\[
= \sum_{k=1}^{n} [A]_{ik} [B]_{kj} \quad \text{Theorem EMP [193]}
\]
\[
= \sum_{k=1}^{n} [A]_{ik} [\overline{B}]_{kj} \quad \text{Theorem CCRA [640]}
\]
\[
= \sum_{k=1}^{n} [\overline{A}]_{ik} [\overline{B}]_{kj} \quad \text{Theorem CCRM [640]}
\]
\[
= \sum_{k=1}^{n} [\overline{A}]_{ik} [\overline{B}]_{kj} \quad \text{Definition CCM [185]}
\]
\[
= [\overline{A \overline{B}}]_{ij} \quad \text{Theorem EMP [193]}
\]

So the matrices \( \overline{AB} \) and \( \overline{A \overline{B}} \) are equal, entry-by-entry, and by the definition of matrix equality (Definition ME [179]) we can say they are equal matrices. \(\square\)
One more theorem in this style, and its a good one. If you’ve been practicing with the previous proofs you should be able to do this one yourself.

**Theorem MMT**  
Matrix Multiplication and Transposes

Suppose $A$ is an $m \times n$ matrix and $B$ is an $n \times p$ matrix. Then $(AB)^t = B^tA^t$. □

**Proof**  
This theorem may be surprising but if we check the sizes of the matrices involved, then maybe it will not seem so far-fetched. First, $AB$ has size $m \times p$, so its transpose has size $p \times m$. The product of $B^t$ with $A^t$ is a $p \times n$ matrix times an $n \times m$ matrix, also resulting in a $p \times m$ matrix. So at least our objects are compatible for equality (and would not be, in general, if we didn’t reverse the order of the operation).

Here we go again, entry-by-entry,

$$[(AB)^t]_{ij} = [AB]_{ji}$$

$$= \sum_{k=1}^{n} [A]_{jk} [B]_{ki}$$

$$= \sum_{k=1}^{n} [B]_{ki} [A]_{jk}$$

Commutativity in $\mathbb{C}$

$$= \sum_{k=1}^{n} [B^t]_{ik} [A^t]_{kj}$$

$$= [B^tA^t]_{ij}$$

So the matrices $(AB)^t$ and $B^tA^t$ are equal, entry-by-entry, and by the definition of matrix equality (Definition ME 179) we can say they are equal matrices. □

This theorem seems odd at first glance, since we have to switch the order of $A$ and $B$. But if we simply consider the sizes of the matrices involved, we can see that the switch is necessary for this reason alone. That the individual entries of the products then come along is a bonus.

Notice how none of these proofs above relied on writing out huge general matrices with lots of ellipses (“...”) and trying to formulate the equalities a whole matrix at a time. This messy business is a “proof technique” to be avoided at all costs.

These theorems, along with Theorem VSP (189), give you the “rules” for how matrices interact with the various operations we have defined. Use them and use them often. But don’t try to do anything with a matrix that you don’t have a rule for. Together, we would informally call all these operations, and the attendant theorems, “the algebra of matrices.” Notice, too, that every column vector is just a $n \times 1$ matrix, so these theorems apply to column vectors also. Finally, these results may make us feel that the definition of matrix multiplication is not so unnatural.

**Subsection PSHS**  
Particular Solutions, Homogeneous Solutions

Having delayed presenting matrix multiplication, we have one theorem we could have stated long ago, but its proof is much easier now that we know how to represent a system
of linear equations with matrix multiplication and how to mix matrix multiplication with other operations.

The next theorem tells us that in order to find all of the solutions to a linear system of equations, it is sufficient to find just one solution, and then find all of the solutions to the corresponding homogeneous system. This explains part of our interest in the null space, the set of all solutions to a homogeneous system.

**Theorem PSPHS**

**Particular Solution Plus Homogeneous Solutions**

Suppose that \( z \) is one solution to the linear system of equations \( \mathcal{L}S(A, b) \). Then \( y \) is a solution to \( \mathcal{L}S(A, b) \) if and only if \( y = z + w \) for some vector \( w \in N(A) \).

**Proof** We will work with the vector equality representations of the relevant systems of equations, as described by Theorem SLEMM \[188\].

\((\Leftarrow)\) Suppose \( y = z + w \) and \( w \in N(A) \). Then

\[
A y = A(z + w) = A z + A w = b + 0 \text{ w } w \in N(A) = b \text{ Property ZC [92]}
\]

demonstrating that \( y \) is a solution.

\((\Rightarrow)\) Suppose \( y \) is a solution to \( \mathcal{L}S(A, b) \). Then

\[
A(y - z) = A y - A z = b - b = 0 \text{ Property AIC [92]}
\]

which says that \( y - z \in N(A) \). In other words, \( y - z = w \) for some vector \( w \in N(A) \).

Rewritten, this is \( y = z + w \), as desired. \(\blacksquare\)

After proving Theorem NSMUS \[79\] we commented (insufficiently) on the negation of one half of the theorem. Nonsingular coefficient matrices lead to unique solutions for every choice of the vector of constants. What does this say about singular matrices? A singular matrix \( A \) has a nontrivial null space (Theorem NSTNS \[78\]). For a given vector of constants, \( b \), the system \( \mathcal{L}S(A, b) \) could be inconsistent, meaning there are no solutions. But if there is at least one solution (\( z \)), then Theorem PSPHS \[199\] tells us there will be infinitely many solutions because of the role of the infinite null space for a singular matrix. So a system of equations with a singular coefficient matrix never has a unique solution. Either there are no solutions, or infinitely many solutions.

**Example PSNS**

**Particular solutions, homogeneous solutions, Archetype D**

Archetype D \[577\] is a consistent system of equations with a nontrivial null space. The write-up for this system begins with three solutions,

\[
y_1 = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 1 \end{bmatrix} \quad y_2 = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad y_3 = \begin{bmatrix} 7 \\ 8 \\ 1 \\ 3 \end{bmatrix}
\]
We will choose to have $y_1$ play the role of $z$ in the statement of Theorem PSPHS [199], any one of the three vectors listed here (or others) could have been chosen. To illustrate the theorem, we should be able to write each of these three solutions as the vector $z$ plus a solution to the corresponding homogeneous system of equations. Since $0$ is always a solution to a homogeneous system we can easily write

$$y_1 = z = z + 0.$$ 

The vectors $y_2$ and $y_3$ will require a bit more effort. Solutions to the homogeneous system are exactly the elements of the null space of the coefficient matrix, which is

$$S_p \left\{ \begin{bmatrix} \begin{array}{c} -3 \\ -1 \\ 1 \\ 0 \end{array} \end{bmatrix}, \begin{bmatrix} \begin{array}{c} 2 \\ 3 \\ 0 \\ 1 \end{array} \end{bmatrix} \right\}.$$ 

Then

$$y_2 = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 4 \\ -1 \\ -2 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 1 \end{bmatrix} + \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix} = z + w_2$$

where

$$w_2 = \begin{bmatrix} 4 \\ -1 \\ -2 \\ -1 \end{bmatrix} = \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix}.$$ 

is obviously a solution of the homogeneous system since it is written as a linear combination of the vectors describing the null space of the coefficient matrix as a span (or as a check, you could just evaluate the equations in the homogeneous system with $w_2$).

Again

$$y_3 = \begin{bmatrix} 7 \\ 8 \\ 1 \\ 3 \end{bmatrix} + \begin{bmatrix} 7 \\ -1 \\ -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 1 \end{bmatrix} + \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix} = z + w_3$$

where

$$w_3 = \begin{bmatrix} 7 \\ -1 \\ 1 \\ 2 \end{bmatrix} = \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix} + 2 \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix}.$$ 

is obviously a solution of the homogeneous system since it is written as a linear combination of the vectors describing the null space of the coefficient matrix as a span (or as a check, you could just evaluate the equations in the homogeneous system with $w_2$).

Here’s another view of this theorem, in the context of this example. Grab two new solutions of the original system of equations, say

$$y_4 = \begin{bmatrix} 11 \\ 0 \\ -3 \\ -1 \end{bmatrix} \quad y_5 = \begin{bmatrix} -4 \\ 2 \\ 4 \\ 2 \end{bmatrix}.$$
and form their difference,

\[
\mathbf{u} = \begin{bmatrix} 11 \\ 0 \\ -3 \\ -1 \end{bmatrix} - \begin{bmatrix} -4 \\ 2 \\ 4 \\ 2 \end{bmatrix} = \begin{bmatrix} 15 \\ -2 \\ -7 \\ -3 \end{bmatrix}.
\]

It is no accident that \( \mathbf{u} \) is a solution to the homogeneous system (check this!). In other words, the difference between any two solutions to a linear system of equations is an element of the null space of the coefficient matrix. This is an equivalent way to state Theorem PSPHS [199]. If we let \( D \) denote the coefficient matrix then we can use the following application of Theorem PSPHS [199] as the basis of a formal proof of this assertion,

\[
D(\mathbf{y}_4 - \mathbf{y}_5) = D((z + \mathbf{w}_4) - (z + \mathbf{w}_5))
= D(\mathbf{w}_4 - \mathbf{w}_5)
= D\mathbf{w}_4 - D\mathbf{w}_5
= 0 - 0 = 0.
\]

It would be very instructive to formulate the precise statement of a theorem and fill in the details and justifications of the proof (see Exercise MM.T50 [203]). ☀

The ideas of this subsection will be appear again in Chapter LT [429] when we discuss pre-images of linear transformations (Definition PT [442]).

**Subsection READ**

**Reading Questions**

1. Form the matrix vector product of

\[
\begin{bmatrix} 2 & 3 & -1 & 0 \\ 1 & -2 & 7 & 3 \\ 1 & 5 & 3 & 2 \end{bmatrix}
\]

with

\[
\begin{bmatrix} 2 \\ -3 \\ 0 \\ 5 \end{bmatrix}
\]

2. Multiply together the two matrices below (in the order given).

\[
\begin{bmatrix} 2 & 3 & -1 & 0 \\ 1 & -2 & 7 & 3 \\ 1 & 5 & 3 & 2 \end{bmatrix} \begin{bmatrix} 2 & 6 \\ -3 & -4 \\ 0 & 2 \\ 3 & -1 \end{bmatrix}
\]

3. Rewrite the system of linear equations below as a vector equality and using a matrix-vector product. (This question does not ask for a solution to the system. But it does ask you to express the system of equations in a new form using tools from this section.)

\[
2x_1 + 3x_2 - x_3 = 0 \\
x_1 + 2x_2 + x_3 = 3 \\
x_1 + 3x_2 + 3x_3 = 7
\]
Subsection EXC
Exercises

C20 Compute the product of the two matrices below, \( AB \). Do this using the definitions of the matrix-vector product (Definition MVP [187]) and the definition of matrix multiplication (Definition MM [191]).

\[
A = \begin{bmatrix}
2 & 5 \\
-1 & 3 \\
2 & -2
\end{bmatrix} \quad B = \begin{bmatrix}
1 & 5 & -3 & 4 \\
2 & 0 & 2 & -3
\end{bmatrix}
\]

Contributed by Robert Beezer  Solution [205]

T10 Suppose that \( A \) is a square matrix and there is a vector, \( b \), such that \( \mathcal{L}S(A, b) \) has a unique solution. Prove that \( A \) is nonsingular. Give a direct proof (perhaps appealing to Theorem PSPHS [199]) rather than just negating a sentence from the text discussing a similar situation.

Contributed by Robert Beezer  Solution [205]

T20 Prove the second part of Theorem MMZM [194].

Contributed by Robert Beezer

T21 Prove the second part of Theorem MMIM [195].

Contributed by Robert Beezer

T22 Prove the second part of Theorem MMDAA [195].

Contributed by Robert Beezer

T23 Prove the second part of Theorem MMSMM [196].

Contributed by Robert Beezer

T40 Suppose that \( A \) is an \( m \times n \) matrix and \( B \) is an \( n \times p \) matrix. Prove that the null space of \( B \) is a subset of the null space of \( AB \), that is \( \mathcal{N}(B) \subseteq \mathcal{N}(AB) \). Provide an example where the opposite is false, in other words give an example where \( \mathcal{N}(AB) \nsubseteq \mathcal{N}(B) \).

Contributed by Robert Beezer  Solution [205]

TODO: Converse with \( A \) nonsingular, or four parter, prove or disprove?

T50 Suppose \( u \) and \( v \) are any two solutions of the linear system \( \mathcal{L}S(A, b) \). Prove that \( u - v \) is an element of the null space of \( A \), that is, \( u - v \in \mathcal{N}(A) \).

Contributed by Robert Beezer
Subsection SOL
Solutions

C20 Contributed by Robert Beezer  Statement 203
By Definition MM [191],
\[
AB = \begin{bmatrix}
2 & 5 \\
-1 & 3 \\
2 & -2 \\
\end{bmatrix}
\begin{bmatrix}
1 \\
2 \\
\end{bmatrix} = \begin{bmatrix}
2 & 5 \\
-1 & 3 \\
2 & -2 \\
\end{bmatrix}
\begin{bmatrix}
5 \\
0 \\
-3 \\
\end{bmatrix} = \begin{bmatrix}
2 & 5 \\
-1 & 3 \\
2 & -2 \\
\end{bmatrix}
\begin{bmatrix}
4 \\
-2 \\
\end{bmatrix}
\]
Repeated applications of Definition MVP [187] give
\[
= \begin{bmatrix}
12 & 10 & 4 \\
-7 & -5 & 9 \\
10 & -10 & 14 \\
\end{bmatrix}
\]

T10 Contributed by Robert Beezer  Statement 203
Since $LS(A, b)$ has at least one solution, we can apply Theorem PSPHS [199]. Because the solution is assumed to be unique, the null space of $A$ must be trivial. Then Theorem NSTNS [78] implies that $A$ is nonsingular.

The converse of this statement is a trivial application of Theorem NSMUS [79]. That said, we could extend our NSMxx series of theorems with an added equivalence for nonsingularity, “Given a single vector of constants, $b$, the system $LS(A, b)$ has a unique solution.”

T40 Contributed by Robert Beezer  Statement 203
To prove that one set is a subset of another, we start with an element of the smaller set and see if we can determine that it is a member of the larger set (Technique SE [17]). Suppose $x \in \mathcal{N}(B)$. Then we know that $Bx = 0$ by Definition NSM [68]. Consider
\[
(AB)x = A(Bx) = A0 = 0
\]
To show that the inclusion does not hold in the opposite direction, choose $B$ to be any nonsingular matrix of size $n$. Then $\mathcal{N}(B) = \{0\}$ by Theorem NSTNS [78]. Let $A$ be the square zero matrix, $O$, of the same size. Then $AB = OB = O$ by Theorem MMZM [194] and therefore $\mathcal{N}(AB) = \mathbb{C}^n$, and is not a subset of $\mathcal{N}(B) = \{0\}$. 

Version 0.52
Section MISLE
Matrix Inverses and Systems of Linear Equations

We begin with a familiar example, performed in a novel way.

Example SABMI
Solutions to Archetype B with a matrix inverse
Archetype B \([568]\) is the system of \(m = 3\) linear equations in \(n = 3\) variables,
\[
\begin{align*}
-7x_1 - 6x_2 - 12x_3 &= -33 \\
5x_1 + 5x_2 + 7x_3 &= 24 \\
x_1 + 4x_3 &= 5
\end{align*}
\]
By Theorem SLEMM \([188]\) we can represent this system of equations as
\[
Ax = b
\]
where
\[
A = \begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{bmatrix} \quad x = \begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix} \quad b = \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix}
\]
We’ll pull a rabbit out of our hat and present the \(3 \times 3\) matrix \(B\),
\[
B = \begin{bmatrix}
-10 & -12 & -9 \\
\frac{13}{2} & 8 & \frac{11}{2} \\
3 & \frac{13}{2} & \frac{11}{2}
\end{bmatrix}
\]
and note that
\[
BA = \begin{bmatrix}
-10 & -12 & -9 \\
\frac{13}{2} & 8 & \frac{11}{2} \\
3 & \frac{13}{2} & \frac{11}{2}
\end{bmatrix} \begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}.
\]
Now apply this computation to the problem of solving the system of equations,
\[
x = I_3x \quad \text{Theorem MMIM \([195]\)}
\]
\[
= (BA)x \quad \text{Substitution}
\]
\[
= B(Ax) \quad \text{Theorem MMA \([196]\)}
\]
\[
= Bb \quad \text{Substitution}
\]
So we have
\[
x = Bb = \begin{bmatrix}
-10 & -12 & -9 \\
\frac{13}{2} & 8 & \frac{11}{2} \\
3 & \frac{13}{2} & \frac{11}{2}
\end{bmatrix} \begin{bmatrix}
-33 \\
24 \\
5
\end{bmatrix} = \begin{bmatrix}
-3 \\
5 \\
2
\end{bmatrix}
\]
So with the help and assistance of \(B\) we have been able to determine a solution to the system represented by \(Ax = b\) through judicious use of matrix multiplication. We know
by Theorem NSMUS [79] that since the coefficient matrix in this example is nonsingular, there would be a unique solution, no matter what the choice of \( b \). The derivation above amplifies this result, since we were forced to conclude that \( x = Bb \) and the solution couldn’t be anything else. You should notice that this argument would hold for any particular value of \( b \).

The matrix \( B \) of the previous example is called the inverse of \( A \). When \( A \) and \( B \) are combined via matrix multiplication, the result is the identity matrix, which can be inserted “in front” of \( x \) as the first step in finding the solution. This is entirely analogous to how we might solve a single linear equation like \( 3x = 12 \).

\[
x = 1x = \left( \frac{1}{3} (3) \right) x = \frac{1}{3} (3x) = \frac{1}{3} (12) = 4
\]

Here we have obtained a solution by employing the “multiplicative inverse” of 3, \( 3^{-1} = \frac{1}{3} \). This works fine for any scalar multiple of \( x \), except for zero, since zero does not have a multiplicative inverse. For matrices, it is more complicated. Some matrices have inverses, some do not. And when a matrix does have an inverse, just how would we compute it? In other words, just where did that matrix \( B \) in the last example come from? Are there other matrices that might have worked just as well?

Subsection IM
Inverse of a Matrix

Definition MI
Matrix Inverse
Suppose \( A \) and \( B \) are square matrices of size \( n \) such that \( AB = I_n \) and \( BA = I_n \). Then \( A \) is invertible and \( B \) is the inverse of \( A \). In this situation, we write \( B = A^{-1} \).

Notice that if \( B \) is the inverse of \( A \), then we can just as easily say \( A \) is the inverse of \( B \), or \( A \) and \( B \) are inverses of each other.

Not every square matrix has an inverse. In Example SABMI [207] the matrix \( B \) is the inverse the coefficient matrix of Archetype B [568]. To see this it only remains to check that \( AB = I_3 \). What about Archetype A [563]? It is an example of a square matrix without an inverse.

Example MWIAA
A matrix without an inverse, Archetype A
Consider the coefficient matrix from Archetype A [563],

\[
A = \begin{bmatrix} 1 & -1 & 2 \\ 2 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}
\]

Suppose that \( A \) is invertible and does have an inverse, say \( B \). Choose the vector of constants

\[
b = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}
\]
and consider the system of equations \( \mathbf{L} \mathbf{S}(A, \mathbf{b}) \). Just as in Example SABMI 207, this vector equation would have the unique solution \( \mathbf{x} = B\mathbf{b} \).

However, this system is inconsistent. Form the augmented matrix \([A | \mathbf{b}]\) and row-reduce to
\[
\begin{bmatrix}
1 & 0 & 1 & 0 \\
0 & 1 & -1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]
which allows to recognize the inconsistency by Theorem RCLS 53.

So the assumption of \( A \)'s inverse leads to a logical inconsistency (the system can’t be both consistent and inconsistent), so our assumption is false. \( A \) is not invertible.

It's possible this example is less than satisfying. Just where did that particular choice of the vector \( \mathbf{b} \) come from anyway? Stay tuned for an application of the future Theorem CSCS 236 in Example CSAA 240.

Let’s look at one more matrix inverse before we embark on a more systematic study.

**Example MIAK**

**Matrix Inverse, Archetype K**

Consider the matrix defined as Archetype K 609,
\[
K = \begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20
\end{bmatrix}
\]
And the matrix
\[
L = \begin{bmatrix}
1 & -\left(\frac{2}{7}\right) & -\left(\frac{3}{7}\right) & 3 & -6 \\
\frac{21}{7} & \frac{43}{7} & \frac{21}{7} & 9 & -9 \\
-15 & -\left(\frac{24}{7}\right) & -11 & -15 & \frac{39}{2} \\
\frac{9}{2} & \frac{13}{4} & \frac{9}{2} & 10 & -15 \\
\frac{6}{2} & \frac{13}{4} & \frac{6}{2} & 6 & -\left(\frac{19}{2}\right)
\end{bmatrix}
\]
Then
\[
KL = \begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20
\end{bmatrix}
\begin{bmatrix}
1 & -\left(\frac{2}{7}\right) & -\left(\frac{3}{7}\right) & 3 & -6 \\
\frac{21}{7} & \frac{43}{7} & \frac{21}{7} & 9 & -9 \\
-15 & -\left(\frac{24}{7}\right) & -11 & -15 & \frac{39}{2} \\
\frac{9}{2} & \frac{13}{4} & \frac{9}{2} & 10 & -15 \\
\frac{6}{2} & \frac{13}{4} & \frac{6}{2} & 6 & -\left(\frac{19}{2}\right)
\end{bmatrix}
= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]
and
\[
LK = \begin{bmatrix}
1 & -\left(\frac{2}{7}\right) & -\left(\frac{3}{7}\right) & 3 & -6 \\
\frac{21}{7} & \frac{43}{7} & \frac{21}{7} & 9 & -9 \\
-15 & -\left(\frac{24}{7}\right) & -11 & -15 & \frac{39}{2} \\
\frac{9}{2} & \frac{13}{4} & \frac{9}{2} & 10 & -15 \\
\frac{6}{2} & \frac{13}{4} & \frac{6}{2} & 6 & -\left(\frac{19}{2}\right)
\end{bmatrix}
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20
\end{bmatrix}
= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]
so by Definition MI 208, we can say that \( K \) is invertible and write \( L = K^{-1} \).

We will now concern ourselves less with whether or not an inverse of a matrix exists, but instead with how you can find one when it does exist. In Section MINSM 223 we will have some theorems that allow us to more quickly and easily determine when a matrix is invertible.
Subsection CIM
Computing the Inverse of a Matrix

We will have occasion in this subsection (and later) to reference the following frequently used vectors, so we will make a useful definition now.

**Definition SUV**
**Standard Unit Vectors**
Let \( e_i \in \mathbb{C}^m \) denote the column vector that is column \( i \) of the \( m \times m \) identity matrix \( I_m \). Then the set
\[
\{ e_1, e_2, e_3, \ldots, e_m \} = \{ e_i \mid 1 \leq i \leq m \}
\]
is the set of **standard unit vectors** in \( \mathbb{C}^m \).

Notice that \( e_i \) is a column vector full of zeros, with a lone 1 in the \( i \)-th position. We will make reference to these vectors often.

We’ve seen that the matrices from **Archetype B** [568] and **Archetype K** [609] both have inverses, but these inverse matrices have just dropped from the sky. How would we compute an inverse? And just when is a matrix invertible, and when is it not? Writing a putative inverse with \( n^2 \) unknowns and solving the resultant \( n^2 \) equations is one approach. Applying this approach to \( 2 \times 2 \) matrices can get us somewhere, so just for fun, let’s do it.

**Theorem TTMI**
**Two-by-Two Matrix Inverse**
Suppose
\[
A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}
\]
Then \( A \) is invertible if and only if \( ad - bc \neq 0 \). When \( A \) is invertible, we have
\[
A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}.
\]

**Proof** \((\Leftarrow)\) If \( ad - bc \neq 0 \) then the displayed formula is legitimate (we are not dividing by zero), and it is a simple matter to actually check that \( A^{-1}A = AA^{-1} = I_2 \).

\((\Rightarrow)\) Assume that \( A \) is invertible, and proceed with a proof by contradiction, by assuming also that \( ad - bc = 0 \). This means that \( ad = bc \). Let
\[
B = \begin{bmatrix} e & f \\ g & h \end{bmatrix}
\]
be a putative inverse of \( A \). This means that
\[
I_2 = AB = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} e & f \\ g & h \end{bmatrix} = \begin{bmatrix} ae + bg & af + bh \\ ce + dg & cf + dh \end{bmatrix}
\]
Working on the matrices on both ends of this equation, we will multiply the top row by \( c \) and the bottom row by \( a \).
\[
\begin{bmatrix} c & 0 \\ 0 & a \end{bmatrix} = \begin{bmatrix} ace + bg & acf + bch \\ ace + adg & acf + adh \end{bmatrix}
\]
We are assuming that $ad = bc$, so we can replace two occurrences of $ad$ by $bc$ in the bottom row of the right matrix.

$$\begin{bmatrix} c & 0 \\ 0 & a \end{bmatrix} = \begin{bmatrix} ace + bch & acf + bch \\ ace + bch & acf + bch \end{bmatrix}$$

The matrix on the right now has two rows that are identical, and therefore the same must be true of the matrix on the left. Given the form of the matrix on the left, identical rows implies that $a = 0$ and $c = 0$.

With this information, the product $AB$ becomes

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I_2 = AB = \begin{bmatrix} ae + bg & af + bh \\ ce + dg & cf + dh \end{bmatrix} = \begin{bmatrix} bg & bh \\ dg & dh \end{bmatrix}$$

So $bg = dh = 1$ and thus $b, g, d, h$ are all nonzero. But then $bh$ and $dg$ (the “other corners”) must also be nonzero, so this is (finally) a contradiction. So our assumption was false and we see that $ad - bc \neq 0$ whenever $A$ has an inverse.

There are several ways one could try to prove this theorem, but there is a continual temptation to divide by one of the eight entries involved ($a$ through $f$), but we can never be sure if these numbers are zero or not. This could lead to an analysis by cases, which is messy, messy, messy. Note how the above proof never divides, but always multiplies, and how zero/nonzero considerations are handled. Pay attention to the expression $ad - bc$, we will see it again in a while.

This theorem is cute, and it is nice to have a formula for the inverse, and a condition that tells us when we can use it. However, this approach becomes impractical for larger matrices, even though it is possible to demonstrate that, in theory, there is a general formula. (Think for a minute about extending this result to just $3 \times 3$ matrices. For starters, we need 18 letters!) Instead, we will work column-by-column. Let’s first work an example that will motivate the main theorem and remove some of the previous mystery.

**Example CMIAK**

**Computing a Matrix Inverse, Archetype K**

Consider the matrix defined as Archetype K [609],

$$A = \begin{bmatrix} 10 & 18 & 24 & 24 & -12 \\ 12 & -2 & -6 & 0 & -18 \\ -30 & -21 & -23 & -30 & 39 \\ 27 & 30 & 36 & 37 & -30 \\ 18 & 24 & 30 & 30 & -20 \end{bmatrix}.$$  

For its inverse, we desire a matrix $B$ so that $AB = I_5$. Emphasizing the structure of the columns and employing the definition of matrix multiplication [Definition MM 191],

$$AB = I_5$$

$$A|B_1|B_2|B_3|B_4|B_5] = [e_1|e_2|e_3|e_4|e_5]$$

$$[AB_1|AB_2|AB_3|AB_4|AB_5] = [e_1|e_2|e_3|e_4|e_5].$$

Equating the matrices column-by-column we have

$$AB_1 = e_1, \quad AB_2 = e_2, \quad AB_3 = e_3, \quad AB_4 = e_4, \quad AB_5 = e_5.$$
Since the matrix $B$ is what we are trying to compute, we can view each column, $B_i$, as a column vector of unknowns. Then we have five systems of equations to solve, each with 5 equations in 5 variables. Notice that all 5 of these systems have the same coefficient matrix. We’ll now solve each system in turn,

Row-reduce the augmented matrix of the linear system $LS(A, e_1)$,

$$
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 & 1 \\
12 & -2 & -6 & 0 & -18 & 0 \\
-30 & -21 & -23 & -30 & 39 & 0 \\
27 & 30 & 36 & 37 & -30 & 0 \\
18 & 24 & 30 & 30 & -20 & 0
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 21/2 \\
0 & 0 & 1 & 0 & 0 & -15 \\
0 & 0 & 0 & 1 & 0 & 9 \\
0 & 0 & 0 & 0 & 1 & 9/2
\end{bmatrix}
\rightarrow
B_1 = \begin{bmatrix}
1/2 \\
9/2 \\
-15 \\
9 \\
9/2
\end{bmatrix}
$$

Row-reduce the augmented matrix of the linear system $LS(A, e_2)$,

$$
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 & 0 \\
12 & -2 & -6 & 0 & -18 & 1 \\
-30 & -21 & -23 & -30 & 39 & 0 \\
27 & 30 & 36 & 37 & -30 & 0 \\
18 & 24 & 30 & 30 & -20 & 0
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & -9/4 \\
0 & 1 & 0 & 0 & 0 & 43/4 \\
0 & 0 & 1 & 0 & 0 & -21/4 \\
0 & 0 & 0 & 1 & 0 & 15/4 \\
0 & 0 & 0 & 0 & 1 & 3/4
\end{bmatrix}
\rightarrow
B_2 = \begin{bmatrix}
-9/4 \\
-21/4 \\
15/4 \\
15/4 \\
3/4
\end{bmatrix}
$$

Row-reduce the augmented matrix of the linear system $LS(A, e_3)$,

$$
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 & 0 \\
12 & -2 & -6 & 0 & -18 & 0 \\
-30 & -21 & -23 & -30 & 39 & 1 \\
27 & 30 & 36 & 37 & -30 & 0 \\
18 & 24 & 30 & 30 & -20 & 0
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & -3/4 \\
0 & 1 & 0 & 0 & 0 & 21/4 \\
0 & 0 & 1 & 0 & 0 & -11 \\
0 & 0 & 0 & 1 & 0 & 9/4 \\
0 & 0 & 0 & 0 & 1 & 9/4
\end{bmatrix}
\rightarrow
B_3 = \begin{bmatrix}
-3/4 \\
-21/4 \\
-11 \\
-9/4 \\
9/4
\end{bmatrix}
$$

Row-reduce the augmented matrix of the linear system $LS(A, e_4)$,

$$
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 & 0 \\
12 & -2 & -6 & 0 & -18 & 0 \\
-30 & -21 & -23 & -30 & 39 & 0 \\
27 & 30 & 36 & 37 & -30 & 1 \\
18 & 24 & 30 & 30 & -20 & 0
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 3 \\
0 & 1 & 0 & 0 & 0 & 9 \\
0 & 0 & 1 & 0 & 0 & -15 \\
0 & 0 & 0 & 1 & 0 & 10 \\
0 & 0 & 0 & 0 & 1 & 6
\end{bmatrix}
\rightarrow
B_4 = \begin{bmatrix}
3 \\
9 \\
-15 \\
10 \\
6
\end{bmatrix}
$$

Row-reduce the augmented matrix of the linear system $LS(A, e_5)$,

$$
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 & 0 \\
12 & -2 & -6 & 0 & -18 & 0 \\
-30 & -21 & -23 & -30 & 39 & 0 \\
27 & 30 & 36 & 37 & -30 & 0 \\
18 & 24 & 30 & 30 & -20 & 1
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & -6 \\
0 & 1 & 0 & 0 & 0 & 9 \\
0 & 0 & 1 & 0 & 0 & 39/2 \\
0 & 0 & 0 & 1 & 0 & -15 \\
0 & 0 & 0 & 0 & 1 & 19/2
\end{bmatrix}
\rightarrow
B_5 = \begin{bmatrix}
-6 \\
-9 \\
39/2 \\
-15 \\
-19/2
\end{bmatrix}
$$
We can now collect our 5 solution vectors into the matrix $B$,

$$B = [B_1 | B_2 | B_3 | B_4 | B_5]$$

$$= \begin{bmatrix}
\frac{21}{2} & -\frac{9}{2} & \frac{43}{2} & \frac{21}{2} & \frac{21}{2} \\
-15 & -11 & -9 & 9 & -9 \\
9 & \frac{12}{3} & 10 & 9 & 10 \\
9 & \frac{3}{4} & 6 & \frac{3}{2} & \frac{3}{2} \\
\end{bmatrix} \begin{bmatrix}
3 \\
-6 \\
-9 \\
-15 \\
-19 \\
\end{bmatrix} = \begin{bmatrix}
1 & -\frac{9}{2} & \frac{43}{2} & \frac{21}{2} & 3 & -6 \\
-15 & -\frac{21}{2} & -11 & 9 & 10 & -15 \\
9 & \frac{12}{3} & 10 & \frac{3}{2} & \frac{3}{2} & 6 & -\left(\frac{19}{2}\right)
\end{bmatrix}$$

By this method, we know that $AB = I_5$. Check that $BA = I_5$, and then we will know that we have the inverse of $A$.

Notice how the five systems of equations in the preceding example were all solved by exactly the same sequence of row operations. Wouldn’t it be nice to avoid this obvious duplication of effort? Our main theorem for this section follows, and it mimics this previous example, while also avoiding all the overhead.

**Theorem CINSN**

**Computing the Inverse of a NonSingular Matrix**

Suppose $A$ is a nonsingular square matrix of size $n$. Create the $n \times 2n$ matrix $M$ by placing the $n \times n$ identity matrix $I_n$ to the right of the matrix $A$. Let $N$ be a matrix that is row-equivalent to $M$ and in reduced row-echelon form. Finally, let $J$ be the matrix formed from the final $n$ columns of $N$. Then $AJ = I_n$.

**Proof** $A$ is nonsingular, so by Theorem NSRRI there is a sequence of row operations that will convert $A$ into $I_n$. It is this same sequence of row operations that will convert $M$ into $N$, since having the identity matrix in the first $n$ columns of $N$ is sufficient to guarantee that $N$ is in reduced row-echelon form.

If we consider the systems of linear equations, $LS(A, e_i)$, $1 \leq i \leq n$, we see that the aforementioned sequence of row operations will also bring the augmented matrix of each system into reduced row-echelon form. Furthermore, the unique solution to each of these systems appears in column $n + 1$ of the row-reduced augmented matrix and is equal to column $n + i$ of $N$. Let $N_1$, $N_2$, $N_3$, $\ldots$, $N_{2n}$ denote the columns of $N$. So we find,

$$AJ = A[N_{n+1}|N_{n+2}|N_{n+3}|\ldots|N_{n+n}]$$

$$= [AN_{n+1}|AN_{n+2}|AN_{n+3}|\ldots|AN_{n+n}]$$

$$= [e_1|e_2|e_3|\ldots|e_n]$$

$$= I_n$$

as desired.

We have to be just a bit careful here. This theorem only guarantees that $AB = I_n$, while the definition requires that $BA = I_n$ also. However, we’ll soon see that this is always the case, in Theorem OSIS, so the title of this theorem is not inaccurate.

We’ll finish by computing the inverse for the coefficient matrix of Archetype B, the one we just pulled from a hat in Example SABMI. There are more examples in the Archetypes (Chapter A) to practice with, though notice that it is silly to ask for the inverse of a rectangular matrix (the sizes aren’t right) and not every square matrix has an inverse (remember Example MWIAA).
Example CMIAB

Computing a Matrix Inverse, Archetype B

Archetype B has a coefficient matrix given as

\[
B = \begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{bmatrix}
\]

Exercising Theorem CINSM we set

\[
M = \begin{bmatrix}
-7 & -6 & -12 & 1 & 0 & 0 \\
5 & 5 & 7 & 0 & 1 & 0 \\
1 & 0 & 4 & 0 & 0 & 1
\end{bmatrix}
\]

which row reduces to

\[
N = \begin{bmatrix}
1 & 0 & 0 & -10 & -12 & -9 \\
0 & 1 & 0 & \frac{13}{2} & 8 & \frac{11}{2} \\
0 & 0 & 1 & \frac{3}{2} & 3 & \frac{5}{2}
\end{bmatrix}
\]

So

\[
B^{-1} = \begin{bmatrix}
-10 & -12 & -9 \\
\frac{13}{2} & 8 & \frac{11}{2} \\
\frac{3}{2} & 3 & \frac{5}{2}
\end{bmatrix}
\]

once we check that \(B^{-1}B = I_3\) (the product in the opposite order is a consequence of the theorem).

While we can use a row-reducing procedure to compute an inverse, many computational devices have a built-in procedure.

Computation Note MI.MMA

Matrix Inverses (Mathematica)

If \(A\) is a matrix defined in Mathematica, then \texttt{Inverse[A]} will return the inverse of \(A\), should it exist. In the case where \(A\) does not have an inverse Mathematica will tell you the matrix is singular (see Theorem NSI).

Subsection PMI

Properties of Matrix Inverses

The inverse of a matrix enjoys some nice properties. We collect a few here. First, a matrix can have but one inverse.

Theorem MIU

Matrix Inverse is Unique

Suppose the square matrix \(A\) has an inverse. Then \(A^{-1}\) is unique.
As described in Technique U [78], we will assume that $A$ has two inverses. The hypothesis tells there is at least one. Suppose then that $B$ and $C$ are both inverses for $A$. Then, repeated use of Definition MI [208] and Theorem MMIM [195] plus one application of Theorem MMA [196] gives

\[
B = BI_n = B(AC) = (BA)C = I_nC = C
\]

So we conclude that $B$ and $C$ are the same, and cannot be different. So any matrix that acts like an inverse, must be the inverse. ■

When most of dress in the morning, we put on our socks first, followed by our shoes. In the evening we must then first remove our shoes, followed by our socks. Try to connect the conclusion of the following theorem with this everyday example.

**Theorem SS**

**Socks and Shoes**

Suppose $A$ and $B$ are invertible matrices of size $n$. Then $(AB)^{-1} = B^{-1}A^{-1}$ and $AB$ is an invertible matrix. □

**Proof** At the risk of carrying our everyday analogies too far, the proof of this theorem is quite easy when we compare it to the workings of a dating service. We have a statement about the inverse of the matrix $AB$, which for all we know right now might not even exist. Suppose $AB$ was to sign up for a dating service with two requirements for a compatible date. Upon multiplication on the left, and on the right, the result should be the identity matrix. In other words, $AB$’s ideal date would be its inverse.

Now along comes the matrix $B^{-1}A^{-1}$ (which we know exists because our hypothesis says both $A$ and $B$ are invertible and we can form the product of these two matrices), also looking for a date. Let’s see if $B^{-1}A^{-1}$ is a good match for $AB$. First they meet at a non-committal neutral location, say a coffee shop, for quiet conversation:

\[
(B^{-1}A^{-1})(AB) = B^{-1}(A^{-1}A)B = B^{-1}I_nB = B^{-1}B = I_n
\]

The first date having gone smoothly, a second, more serious, date is arranged, say dinner and a show:

\[
(AB)(B^{-1}A^{-1}) = A(AB^{-1})A^{-1} = AI_nA^{-1} = AA^{-1} = I_n
\]

So the matrix $B^{-1}A^{-1}$ has met all of the requirements to be $AB$’s inverse (date) and with the ensuing marriage proposal we can announce that $(AB)^{-1} = B^{-1}A^{-1}$. ■
**Theorem MIMI**  
**Matrix Inverse of a Matrix Inverse**  
Suppose \( A \) is an invertible matrix. Then \( (A^{-1})^{-1} = A \) and \( A^{-1} \) is invertible. \( \square \)

**Proof** As with the proof of Theorem SS [215], we examine if \( A \) is a suitable inverse for \( A^{-1} \) (by definition, the opposite is true).

\[
AA^{-1} = I_n \quad \text{Definition MI 208}
\]

and

\[
A^{-1}A = I_n \quad \text{Definition MI 208}
\]

The matrix \( A \) has met all the requirements to be the inverse of \( A^{-1} \), so we can write \( A = (A^{-1})^{-1} \). \( \blacksquare \)

**Theorem MIT**  
**Matrix Inverse of a Transpose**  
Suppose \( A \) is an invertible matrix. Then \( (A^t)^{-1} = (A^{-1})^t \) and \( A^t \) is invertible. \( \square \)

**Proof** As with the proof of Theorem SS [215], we see if \( (A^{-1})^t \) is a suitable inverse for \( A^t \). Apply Theorem MMT [198] to see that

\[
(A^{-1})^t A^t = (AA^{-1})^t \quad \text{Theorem MMT 198}
\]

\[
= I_n^t \quad \text{Definition MI 208}
\]

\[
= I_n \quad \text{\( I_n \) is symmetric}
\]

and

\[
A^t (A^{-1})^t = (A^{-1}A)^t \quad \text{Theorem MMT 198}
\]

\[
= I_n^t \quad \text{Definition MI 208}
\]

\[
= I_n \quad \text{\( I_n \) is symmetric}
\]

The matrix \( (A^{-1})^t \) has met all the requirements to be the inverse of \( A^t \), so we can write \( (A^t)^{-1} = (A^{-1})^t \). \( \blacksquare \)

**Theorem MISM**  
**Matrix Inverse of a Scalar Multiple**  
Suppose \( A \) is an invertible matrix and \( \alpha \) is a nonzero scalar. Then \( (\alpha A)^{-1} = \frac{1}{\alpha} A^{-1} \) and \( \alpha A \) is invertible. \( \square \)

**Proof** As with the proof of Theorem SS [215], we see if \( \frac{1}{\alpha} A^{-1} \) is a suitable inverse for \( \alpha A \).

\[
\left( \frac{1}{\alpha} A^{-1} \right) (\alpha A) = \left( \frac{1}{\alpha} \right) (AA^{-1}) \quad \text{Theorem MMSMM 196}
\]

\[
= I_n \quad \text{Scalar multiplicative inverses}
\]

\[
= I_n \quad \text{Property OM 181}
\]
and
\[(\alpha A) \left( \frac{1}{\alpha} A^{-1} \right) = \left( \frac{1}{\alpha} \right) (A^{-1} A) \]
\[= 1I_n \quad \text{Theorem MMSMM 196} \]
\[= I_n \quad \text{Scalar multiplicative inverses} \]
\[= I_n \quad \text{Property OM 181} \]

The matrix \( \frac{1}{\alpha} A^{-1} \) has met all the requirements to be the inverse of \( \alpha A \), so we can write \((\alpha A)^{-1} = \frac{1}{\alpha} A^{-1}\). ■

Notice that there are some likely theorems that are missing here. For example, it would be tempting to think that \((A + B)^{-1} = A^{-1} + B^{-1}\), but this is false. Can you find a counterexample?

**Subsection READ**

**Reading Questions**

1. Compute the inverse of the matrix below.
\[
\begin{bmatrix}
4 & 10 \\
2 & 6
\end{bmatrix}
\]

2. Compute the inverse of the matrix below.
\[
\begin{bmatrix}
2 & 3 & 1 \\
1 & -2 & -3 \\
-2 & 4 & 6
\end{bmatrix}
\]

3. Explain why Theorem SS has the title it does. (Do not just state the theorem, explain the choice of the title making reference to the theorem itself.)
Subsection EXC
Exercises

C21 Verify that $B$ is the inverse of $A$.

$$A = \begin{bmatrix} 1 & 1 & -1 & 2 \\ -2 & -1 & 2 & -3 \\ 1 & 1 & 0 & 2 \\ -1 & 2 & 0 & 2 \end{bmatrix}, \quad B = \begin{bmatrix} 4 & 2 & 0 & -1 \\ 8 & 4 & -1 & -1 \\ -1 & 0 & 1 & 0 \\ -6 & -3 & 1 & 1 \end{bmatrix}$$

Contributed by Robert Beezer   Solution 221

C22 Recycle the matrix $A$ from Exercise MISLE.C21 219 and set

$$c = \begin{bmatrix} 2 \\ 1 \\ -3 \\ 2 \end{bmatrix}, \quad d = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

Employ the matrix $B$ from Exercise MISLE.C21 219 to solve the two linear systems $\mathcal{L}S(A, c)$ and $\mathcal{L}S(A, d)$.

Contributed by Robert Beezer   Solution 221

C23 If it exists, find the inverse of the $2 \times 2$ matrix

$$A = \begin{bmatrix} 7 & 3 \\ 5 & 2 \end{bmatrix}$$

and check your answer. (See Theorem TTMI 210.)

Contributed by Robert Beezer

C24 If it exists, find the inverse of the $2 \times 2$ matrix

$$A = \begin{bmatrix} 6 & 3 \\ 4 & 2 \end{bmatrix}$$

and check your answer. (See Theorem TTMI 210.)

Contributed by Robert Beezer

C25 At the conclusion of Example CMIAK 211, verify that $BA = I_5$ by computing the matrix product.

Contributed by Robert Beezer

C26 Let

$$D = \begin{bmatrix} 1 & -1 & 3 & -2 & 1 \\ -2 & 3 & -5 & 3 & 0 \\ 1 & -1 & 4 & -2 & 2 \\ -1 & 4 & -1 & 0 & 4 \\ 1 & 0 & 5 & -2 & 5 \end{bmatrix}$$

Compute the inverse of $D$, $D^{-1}$, by forming the $5 \times 10$ matrix $[D \mid I_5]$ and row-reducing (Theorem CINSM 213). Then use a calculator to compute $D^{-1}$ directly.

Contributed by Robert Beezer   Solution 221

Version 0.52
C27  Let

\[
E = \begin{bmatrix}
1 & -1 & 3 & -2 & 1 \\
-2 & 3 & -5 & 3 & -1 \\
1 & -1 & 4 & -2 & 2 \\
-1 & 4 & -1 & 0 & 2 \\
1 & 0 & 5 & -2 & 4
\end{bmatrix}
\]

Compute the inverse of \(E, E^{-1}\), by forming the \(5 \times 10\) matrix \([E \mid I_5]\) and row-reducing (Theorem CINSM 213). Then use a calculator to compute \(E^{-1}\) directly.

Contributed by Robert Beezer  Solution 221

C28  Let

\[
C = \begin{bmatrix}
1 & 1 & 3 & 1 \\
-2 & -1 & -4 & -1 \\
1 & 4 & 10 & 2 \\
-2 & 0 & -4 & 5
\end{bmatrix}
\]

Compute the inverse of \(C, C^{-1}\), by forming the \(4 \times 8\) matrix \([C \mid I_4]\) and row-reducing (Theorem CINSM 213). Then use a calculator to compute \(C^{-1}\) directly.

Contributed by Robert Beezer  Solution 221

C40  Find all solutions to the system of equations below, making use of the matrix inverse found in Exercise MISLE.C28 220.

\[
\begin{align*}
x_1 + x_2 + 3x_3 + x_4 &= -4 \\
-2x_1 - x_2 - 4x_3 - x_4 &= 4 \\
x_1 + 4x_2 + 10x_3 + 2x_4 &= -20 \\
-2x_1 - 4x_3 + 5x_4 &= 9
\end{align*}
\]

Contributed by Robert Beezer  Solution 222

T10  Construct an example to demonstrate that \((A + B)^{-1} = A^{-1} + B^{-1}\) is not true for all square matrices \(A\) and \(B\) of the same size.

Contributed by Robert Beezer  Solution 222
Subsection SOL
Solutions

C21 Contributed by Robert Beezer Statement [219]
Check that both matrix products (Definition MM [191]) \(AB\) and \(BA\) equal the 4 \(\times\) 4 identity matrix \(I_4\) (Definition IM [76]).

C22 Contributed by Robert Beezer Statement [219]
Represent each of the two systems by a vector equality, \(Ax = c\) and \(Ay = d\). Then in the spirit of Example SABMI [207], solutions are given by

\[
\begin{align*}
x &= Bc = \begin{bmatrix} 8 \\ 21 \\ -5 \\ -16 \end{bmatrix} \\
y &= Bd = \begin{bmatrix} 5 \\ 10 \\ 0 \\ -7 \end{bmatrix}
\end{align*}
\]

Notice how we could solve many more systems having \(A\) as the coefficient matrix, and how each such system has a unique solution. You might check your work by substituting the solutions back into the systems of equations, or forming the linear combinations of the columns of \(A\) suggested by Theorem SLSLC [103].

C26 Contributed by Robert Beezer Statement [219]
The inverse of \(D\) is

\[
D^{-1} = \begin{bmatrix} -7 & -6 & -3 & 2 & 1 \\ -7 & -4 & 2 & 2 & -1 \\ -5 & -2 & 3 & 1 & -1 \\ -6 & -3 & 1 & 1 & 0 \\ 4 & 2 & -2 & -1 & 1 \end{bmatrix}
\]

C27 Contributed by Robert Beezer Statement [220]
The matrix \(E\) has no inverse. When row-reducing the matrix \([E \mid I_5]\), the first 5 columns will not row-reduce to the 5 \(\times\) 5 identity matrix. When requesting that your calculator compute \(E^{-1}\), it should give some indication that \(E\) does not have an inverse.

C28 Contributed by Robert Beezer Statement [220]
Employ Theorem CINSM [213],

\[
\begin{pmatrix}
1 & 1 & 3 & 1 & 1 & 0 & 0 & 0 \\
-2 & -1 & -4 & -1 & 0 & 1 & 0 & 0 \\
1 & 4 & 10 & 2 & 0 & 0 & 1 & 0 \\
-2 & 0 & -4 & 5 & 0 & 0 & 0 & 1
\end{pmatrix} \xrightarrow{\text{REF}}
\begin{pmatrix}
1 & 0 & 0 & 0 & 38 & 18 & -5 & -2 \\
0 & 1 & 0 & 0 & 96 & 47 & -12 & -5 \\
0 & 0 & 1 & 0 & -39 & -19 & 5 & 2 \\
0 & 0 & 0 & 1 & -16 & -8 & 2 & 1
\end{pmatrix}
\]

And therefore we see that \(C\) is nonsingular (\(C\) row-reduces to the identity matrix, Theorem NSRRI [77]) and by Theorem CINSM [213],

\[
C^{-1} = \begin{bmatrix} 38 & 18 & -5 & -2 \\ 96 & 47 & -12 & -5 \\ -39 & -19 & 5 & 2 \\ -16 & -8 & 2 & 1 \end{bmatrix}
\]
View this system as \( \mathbf{L} \mathbf{S}(\mathbf{C}, \mathbf{b}) \), where \( \mathbf{C} \) is the \( 4 \times 4 \) matrix from Exercise MISLE.C28 and \( \mathbf{b} = \begin{bmatrix} -4 \\ 4 \\ -20 \\ 9 \end{bmatrix} \). Since \( \mathbf{C} \) was seen to be nonsingular in Exercise MISLE.C28, Theorem SNSCM says the solution, which is unique by Theorem NSMUS, is given by

\[
\mathbf{C}^{-1} \mathbf{b} = \begin{bmatrix} 38 & 18 & -5 & -2 \\ 96 & 47 & -12 & -5 \\ -39 & -19 & 5 & 2 \\ -16 & -8 & 2 & 1 \end{bmatrix} \begin{bmatrix} -4 \\ 4 \\ -20 \\ 9 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ -2 \\ 1 \end{bmatrix}
\]

Notice that this solution can be easily checked in the original system of equations.

Let \( \mathbf{D} \) be any \( 2 \times 2 \) matrix that has an inverse (Theorem TTMI can help you construct such a matrix, \( \mathbf{I}_2 \) is a simple choice). Set \( \mathbf{A} = \mathbf{D} \) and \( \mathbf{B} = (-1)\mathbf{D} \). While \( \mathbf{A}^{-1} \) and \( \mathbf{B}^{-1} \) both exist, what is \( \mathbf{A} + \mathbf{B}^{-1} \)? Can the proposed statement be a theorem?
Section MINSM
Matrix Inverses and NonSingular Matrices

We saw in Theorem CINSM [213] that if a square matrix $A$ is nonsingular, then there is a matrix $B$ so that $AB = I_n$. In other words, $B$ is halfway to being an inverse of $A$. We will see in this section that $B$ automatically fulfills the second condition $(BA = I_n)$.

Example MWIAA [208] showed us that the coefficient matrix from Archetype A [563] had no inverse. Not coincidentally, this coefficient matrix is singular. We’ll make all these connections precise now. Not many examples or definitions in this section, just theorems.

Subsection NSMI
NonSingular Matrices are Invertible

We need a couple of technical results for starters. Some books would call these minor, but essential, results “lemmas.” We’ll just call ’em theorems.

Theorem PWSMS
Product With a Singular Matrix is Singular
Suppose that $A$ or $B$ are matrices of size $n$, and one, or both, is singular. Then their product, $AB$, is singular.

Proof We’ll do the proof in two cases, and its interesting to notice exactly how we break down the cases.

Case 1. Suppose $B$ is singular. Then there is a nonzero vector $z$ that is a solution to $LS(B, 0)$. Then

$$(AB)z = A(Bz) = A0 = 0$$

by Theorem MMA [196], Theorem SLEMM [188], and Theorem MMZM [194].

Because $z$ is a nonzero solution to $LS(AB, 0)$, we can conclude that $AB$ is singular by Definition NM [75].

Case 2. Suppose $B$ is nonsingular and $A$ is singular. This is probably not the second case you were expecting. Why not just state the second case as “$A$ is singular”? The best answer is that the proof is easier with the more restrictive assumption that $A$ is singular and $B$ is nonsingular. But before we see why, convince yourself that the two cases, as stated, will cover all three of the possibilities (out of four formed by the combinations $A$ singular/nonsingular and $B$ singular/nonsingular) that are allowed by our hypothesis.

Since $A$ is singular, there is a nonzero vector $y$ that is a solution to $LS(A, 0)$. Now use this vector $y$ and consider the linear system $LS(B, y)$. Since $B$ is nonsingular, the system has a unique solution, which we will call $w$. We claim $w$ is not the zero vector.
either. Assuming the opposite, suppose that $w = 0$. Then

\[
y = Bw \quad \text{w solution to } \mathcal{L}S(B, y)\quad \text{Theorem SLEMM 188}
\]
\[
= B0 \quad \text{Substitution, } w = 0
\]
\[
= 0 \quad \text{Theorem MMZM 194}
\]

contrary to $y$ being nonzero. So $w \neq 0$. The pieces are in place, so here we go,

\[
(AB)w = A(Bw) \quad \text{Theorem MMA 196}
\]
\[
= Ay \quad \text{w solution to } \mathcal{L}S(B, y)\quad \text{Theorem SLEMM 188}
\]
\[
= 0 \quad \text{y solution to } \mathcal{L}S(A, 0)\quad \text{Theorem SLEMM 188}
\]

So $w$ is a nonzero solution to $\mathcal{L}S(AB, 0)$, and this is convincing evidence that that $AB$ is singular (Definition NM 75). ■

**Theorem OSIS**

**One-Sided Inverse is Sufficient**

Suppose $A$ and $B$ are square matrices of size $n$ such that $AB = I_n$. Then $BA = I_n$. □

**Proof** The matrix $I_n$ is nonsingular (since it row-reduces easily to $I_n$, Theorem NSRRI 77). If $B$ is singular, then Theorem PWSMS 223 would imply that $I_n$ is singular, a contradiction. So $B$ must be nonsingular also. Now that we know that $B$ is nonsingular, we can apply Theorem CINSM 213 to assert the existence of a matrix $C$ so that $BC = I_n$.

This application of Theorem CINSM 213 could be a bit confusing, mostly because of the names of the matrices involved. $B$ is nonsingular, so there must be a “right-inverse” for $B$, and we’re calling it $C$.

Now

\[
C = I_nC \quad \text{Theorem MMIM 195}
\]
\[
= (AB)C \quad \text{Hypothesis, Substitution}
\]
\[
= A(BC) \quad \text{Theorem MMA 196}
\]
\[
= AI_n \quad \text{C “right-inverse” of $B$}
\]
\[
= A \quad \text{Theorem MMIM 195}
\]

So it happens that the matrix $C$ we just found is really $A$ in disguise. So we can write

\[
I_n = BC \quad \text{C “right-inverse” of $B$}
\]
\[
= BA \quad \text{Substitution}
\]

which is the desired conclusion. ■

So Theorem OSIS 224 tells us that if $A$ is nonsingular, then the matrix $B$ guaranteed by Theorem CINSM 213 will be both a “right-inverse” and a “left-inverse” for $A$, so $A$ is invertible and $A^{-1} = B$.

So if you have a nonsingular matrix, $A$, you can use the procedure described in Theorem CINSM 213 to find an inverse for $A$. If $A$ is singular, then the procedure in Theorem CINSM 213 will fail as the first $n$ columns of $M$ will not row-reduce to the identity matrix.

This may feel like we are splitting hairs, but its important that we do not make unfounded assumptions. These observations form the next theorem.
Theorem NSI
NonSingularity is Invertibility
Suppose that $A$ is a square matrix. Then $A$ is nonsingular if and only if $A$ is invertible. □

Proof ($\Leftarrow$) Suppose $A$ is invertible, and suppose that $x$ is any solution to the homogeneous system $LS(A, 0)$. Then

\[
x = I_n x = (A^{-1}A)x = A^{-1}(Ax) = A^{-1}0 = 0
\]

So the only solution to $LS(A, 0)$ is the zero vector, so by Definition NM 75, $A$ is nonsingular.

($\Rightarrow$) Suppose now that $A$ is nonsingular. By Theorem CINSM 213 we find $B$ so that $AB = I_n$. Then Theorem OSIS 224 tells us that $BA = I_n$. So $B$ is $A$'s inverse, and by construction, $A$ is invertible. □

So for a square matrix, the properties of having an inverse and of having a trivial null space are one and the same. Can’t have one without the other. Now we can update our list of equivalences for nonsingular matrices (Theorem NSME2 140).

Theorem NSME3
NonSingular Matrix Equivalences, Round 3
Suppose that $A$ is a square matrix of size $n$. The following are equivalent.

1. $A$ is nonsingular.
2. $A$ row-reduces to the identity matrix.
3. The null space of $A$ contains only the zero vector, $\mathcal{N}(A) = \{0\}$.
4. The linear system $LS(A, b)$ has a unique solution for every possible choice of $b$.
5. The columns of $A$ are a linearly independent set.
6. $A$ is invertible. □

In the case that $A$ is a nonsingular coefficient matrix of a system of equations, the inverse allows us to very quickly compute the unique solution, for any vector of constants.

Theorem SNSSCM
Solution with NonSingular Coefficient Matrix
Suppose that $A$ is nonsingular. Then the unique solution to $LS(A, b)$ is $A^{-1}b$. □

Proof By Theorem NSMUS 79 we know already that $LS(A, b)$ has a unique solution for every choice of $b$. We need to show that the expression stated is indeed a solution (the solution). That’s easy, just “plug it in” to the corresponding vector equation representation,

\[
A (A^{-1}b) = (AA^{-1}) b = I_n b = b
\]

Version 0.52
Since $Ax = b$ is true when we substitute $A^{-1}b$ for $x$, $A^{-1}b$ is a (the) solution to $LS(A, b)$. ■

Subsection OM
Orthogonal Matrices

Definition OM
Orthogonal Matrices
Suppose that $Q$ is a square matrix of size $n$ such that $(Q)^t Q = I_n$. Then we say $Q$ is orthogonal. △

This condition may seem rather far-fetched at first glance. Would there be any matrix that behaved this way? Well, yes, here’s one.

Example OM3
Orthogonal matrix of size 3

\[
Q = \begin{bmatrix}
\frac{1+i}{\sqrt{2}} & \frac{3+2i}{\sqrt{5}} & \frac{2+2i}{\sqrt{22}} \\
\frac{1-i}{\sqrt{2}} & \frac{2+2i}{\sqrt{5}} & \frac{2+2i}{\sqrt{22}} \\
\frac{1}{\sqrt{2}} & \frac{3-2i}{\sqrt{5}} & \frac{-3+i}{\sqrt{22}} \\
\end{bmatrix}
\]

The computations get a bit tiresome, but if you work your way through $(Q)^t Q$, you will arrive at the $3 \times 3$ identity matrix $I_3$. ⊚

Orthogonal matrices do not have to look quite so gruesome. Here’s a larger one that is a bit more pleasing.

Example OPM
Orthogonal permutation matrix

The matrix

\[
P = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 \\
\end{bmatrix}
\]

is orthogonal as can be easily checked. Notice that it is just a rearrangement of the columns of the $5 \times 5$ identity matrix, $I_5$. [Definition IM 76].

An interesting exercise is to build another $5 \times 5$ orthogonal matrix, $R$, using a different rearrangement of the columns of $I_5$. Then form the product $PR$. This will be another orthogonal matrix (reference exercise here). If you were to build all $5! = 5 \times 4 \times 3 \times 2 \times 1 = 120$ matrices of this type you would have a set that remains closed under matrix multiplication. It is an example of another algebraic structure known as a group since together the set and the one operation (matrix multiplication here) is closed, associative, has an identity ($I_5$), and inverses [Theorem OMI 227]. Notice though that the operation in this group is not commutative! ⊚

Orthogonal matrices have easily computed inverses. They also have columns that form orthonormal sets. Here are the theorems that show us that orthogonal matrices are not as strange as they might initially appear.
Theorem OMI
Orthogonal Matrices are Invertible
Suppose that \( Q \) is an orthogonal matrix of size \( n \). Then \( Q \) is nonsingular, and \( Q^{-1} = (Q)^t \).

Proof By Definition OM [226], we know that \((Q)^t Q = I_n\). If either \((Q)^t\) or \( Q \) were singular, then this equation, together with Theorem PWSMS [223], would have us conclude that \( I_n \) is singular. This is a contradiction, since \( I_n \) row-reduces to the identity matrix (Theorem NSRRI [77]). So \( Q \), and \((Q)^t\), are both nonsingular.

The equation \((Q)^t Q = I_n\) gets us halfway to an inverse of \( Q \), and since we now know that \((Q)^t\) is nonsingular, Theorem OSIS [224] tells us that \( Q (Q)^t = I_n \) also. So \( Q \) and \((Q)^t\) are inverses of each other (Definition MI [208]). ■

Theorem COMOS
Columns of Orthogonal Matrices are Orthonormal Sets
Suppose that \( A \) is a square matrix of size \( n \) with columns \( S = \{A_1, A_2, A_3, \ldots, A_n\} \). Then \( A \) is an orthogonal matrix if and only if \( S \) is an orthonormal set.

Proof The proof revolves around recognizing that a typical entry of the product \((\overline{A})^t A\) is an inner product of columns of \( A \). Here are the details to support this claim.

\[
\left[(\overline{A})^t A\right]_{ij} = \sum_{k=1}^{n} [(\overline{A})^t]_{ik} [A]_{kj} \quad \text{Theorem EMP [193]}
\]

\[
= \sum_{k=1}^{n} [\overline{A}]_{ki} [A]_{kj} \quad \text{Definition TM [182]}
\]

\[
= \sum_{k=1}^{n} [A]_{kj} [\overline{A}]_{ki} \quad \text{Definition CCM [185]}
\]

\[
= [\overline{A}]_{kj} [A]_{ki} \quad \text{Commutativity in } \mathbb{C}
\]

\[
= \langle A_j, A_i \rangle \quad \text{Definition IP [166]}
\]

We now employ this equality in a chain of equivalences,

\[
S = \{A_1, A_2, A_3, \ldots, A_n\} \text{ is an orthonormal set}
\]

\[
\iff \langle A_j, A_i \rangle = \begin{cases} 
0 & \text{if } i \neq j \\
1 & \text{if } i = j 
\end{cases} \quad \text{Definition ONS [175]}
\]

\[
\iff \left[(\overline{A})^t A\right]_{ij} = \begin{cases} 
0 & \text{if } i \neq j \\
1 & \text{if } i = j 
\end{cases} \quad \text{Substitution}
\]

\[
\iff \left[(\overline{A})^t A\right]_{ij} = [I_n]_{ij}, \ 1 \leq i \leq n, \ 1 \leq j \leq n \quad \text{Definition IM [76]}
\]

\[
\iff \overline{A}^t A = I_n \quad \text{Definition ME [179]}
\]

\[
\iff A \text{ is an orthogonal matrix} \quad \text{Definition OM [226]}
\]

■
Example OSMC
Orthonormal Set from Matrix Columns

The matrix

$$Q = \begin{bmatrix}
\frac{1+i}{\sqrt{5}} & \frac{3+2i}{\sqrt{11}} & \frac{2+2i}{\sqrt{23}} \\
\frac{1}{\sqrt{5}} & \frac{\sqrt{5}i}{2} & \frac{-2}{\sqrt{11}} \\
\frac{\sqrt{2}+2i}{\sqrt{23}} & \frac{-3+2i}{\sqrt{55}} & \frac{2+i}{\sqrt{55}} \\
\frac{1+i}{\sqrt{5}} & \frac{1+i}{\sqrt{5}} & \frac{1+i}{\sqrt{5}} \\
\end{bmatrix}$$

from Example OM3 [226] is an orthogonal matrix. By Theorem COMOS [227] its columns

$$\begin{bmatrix}
[1+i]/\sqrt{5} & 3+2i/\sqrt{11} & 2+2i/\sqrt{23} \\
1/\sqrt{5} & \sqrt{5}i/2 & -2/\sqrt{11} \\
\sqrt{2}+2i/\sqrt{23} & -3+2i/\sqrt{55} & 2+i/\sqrt{55} \\
1+i/\sqrt{5} & 1+i/\sqrt{5} & 1+i/\sqrt{5} \\
\end{bmatrix}$$

form an orthonormal set. You might find checking the six inner products of pairs of these vectors easier than doing the matrix product $Q^t Q$.

When using vectors and matrices that only have real number entries, orthogonal matrices are those matrices with inverses that equal their transpose. Similarly, the inner product is the familiar dot product. Keep this special case in mind as you read the next theorem.

Theorem OMPIP
Orthogonal Matrices Preserve Inner Products

Suppose that $Q$ is an orthogonal matrix of size $n$ and $u$ and $v$ are two vectors from $\mathbb{C}^n$. Then

$$\langle Qu, Qv \rangle = \langle u, v \rangle \quad \text{and} \quad \|Qv\| = \|v\|$$

**Proof** We will be a bit fast and loose with the interplay of conjugates and transposes here, but you should be able to supply some of the missing theorems.

$$\langle Qu, Qv \rangle = (Qu)^T Qv \quad \text{Definition IP [166]}$$

$$= u^T Q^T Qv \quad \text{Theorem MMT [198]}$$

$$= u^T Q^T Qv \quad \text{Theorem MMCC [197]}$$

$$= u^T \overline{Q^T} Qv \quad \text{Conjugation twice}$$

$$= u^T \overline{Q^T} Qv$$

$$= u^T \overline{Q^T} Qv \quad \text{Theorem MMCC [197]}$$

$$= u^T \overline{Q} Qv \quad \text{Definition OM [226]}$$

$$= u^T \overline{I_n} v \quad I_n \text{ has real entries}$$

$$= u^T \overline{v} \quad \text{Theorem MMIM [195]}$$

$$= \langle u, v \rangle \quad \text{Definition IP [166]}$$

The second conclusion is just a specialization.

$$\|Qv\|^2 = \langle Qv, Qv \rangle \quad \text{Theorem IPN [170]}$$

$$= \langle v, v \rangle \quad \text{Previous conclusion}$$

$$= \|v\|^2 \quad \text{Theorem IPN [170]}$$
Now take a square root on both sides to get the result.

**Definition A**

**Adjoint**

If $A$ is a square matrix, then its **adjoint** is $A^H = (\overline{A})^t$.

Sometimes a matrix is equal to its adjoint. A simple example would be any symmetric matrix with real entries.

**Definition HM**

**Hermitian Matrix**

The square matrix $A$ is **Hermitian** (or self-adjoint) if $A = (\overline{A})^t$.

**Subsection READ**

**Reading Questions**

1. Show how to use the inverse of a matrix to solve the system of equations below.
   
   \[
   \begin{align*}
   4x_1 + 10x_2 &= 12 \\
   2x_1 + 6x_2 &= 4
   \end{align*}
   \]

2. In the reading questions for Section MISLE 207, you were asked to find the inverse of the $3 \times 3$ matrix below.

   \[
   \begin{bmatrix}
   2 & 3 & 1 \\
   1 & -2 & -3 \\
   -2 & 4 & 6 \\
   \end{bmatrix}
   \]

   Because the matrix was not nonsingular, you had no theorems at that point that would allow you to compute the inverse. Explain why you now know that the inverse does not exist (which is different than not being able to compute it) by quoting the relevant theorem’s acronym.

3. Is the matrix $A$ orthogonal? Why?

   \[
   A = \begin{bmatrix}
   \frac{1}{\sqrt{7}} (4 + 2i) & \frac{1}{\sqrt{7}} (5 + 3i) \\
   \frac{1}{\sqrt{2}} (-1 - i) & \frac{1}{\sqrt{2}} (12 + 14i)
   \end{bmatrix}
   \]
Subsection EXC
Exercises

C40  Solve the system of equations below using the inverse of a matrix.

\[
\begin{align*}
x_1 + x_2 + 3x_3 + x_4 &= 5 \\
-2x_1 - x_2 - 4x_3 - x_4 &= -7 \\
x_1 + 4x_2 + 10x_3 + 2x_4 &= 9 \\
-2x_1 - 4x_3 + 5x_4 &= 9
\end{align*}
\]

Contributed by Robert Beezer  Solution 233

M20  Construct an example of a 4 \times 4 orthogonal matrix.
Contributed by Robert Beezer  Solution 233

T10  Suppose that \( Q \) and \( P \) are orthogonal matrices of size \( n \). Prove that \( QP \) is an orthogonal matrix.
Contributed by Robert Beezer

T11  Prove that Hermitian matrices (Definition HM 229) have real entries on the diagonal. More precisely, suppose that \( A \) is a Hermitian matrix of size \( n \). Then \([A]_{ii} \in \mathbb{R}, 1 \leq i \leq n\).
Contributed by Robert Beezer
C40 Contributed by Robert Beezer Statement 231
The coefficient matrix and vector of constants for the system are
\[
\begin{pmatrix}
1 & 1 & 3 & 1 \\
-2 & -1 & -4 & -1 \\
1 & 4 & 10 & 2 \\
-2 & 0 & -4 & 5
\end{pmatrix}
\begin{pmatrix}
b \end{pmatrix}
\begin{pmatrix}
5 \\
-7 \\
9 \\
9
\end{pmatrix}
\]

\(A^{-1}\) can be computed by using a calculator, or by the method of Theorem CINS. Then Theorem SNSCM says the unique solution is
\[
A^{-1}b = \begin{pmatrix}
38 & 18 & -5 & -2 \\
96 & 47 & -12 & -5 \\
-39 & -19 & 5 & 2 \\
-16 & -8 & 2 & 1
\end{pmatrix}
\begin{pmatrix}
5 \\
-7 \\
9 \\
9
\end{pmatrix}
= \begin{pmatrix}
1 \\
-2 \\
1 \\
3
\end{pmatrix}
\]

M20 Contributed by Robert Beezer Statement 231
The 4 \times 4 identity matrix, \(I_4\), would be one example (Definition IM). Any of the 23 other rearrangements of the columns of \(I_4\) would be a simple, but less trivial, example. See Example OPM. 
Section CRS
Column and Row Spaces

**Theorem SLSLC** showed us that there is a natural correspondence between solutions to linear systems and linear combinations of the columns of the coefficient matrix. This idea motivates the following important definition.

**Definition CSM**

**Column Space of a Matrix**

Suppose that \( A \) is an \( m \times n \) matrix with columns \( \{A_1, A_2, A_3, \ldots, A_n\} \). Then the **column space** of \( A \), written \( \mathcal{C}(A) \), is the subset of \( \mathbb{C}^m \) containing all linear combinations of the columns of \( A \),

\[
\mathcal{C}(A) = \text{Sp}(\{A_1, A_2, A_3, \ldots, A_n\})
\]

Some authors refer to the column space of a matrix as the **range**, but we will reserve this term for use with linear transformations (Definition RLT).

**Subsection CSSE**

**Column spaces and systems of equations**

Upon encountering any new set, the first question we ask is what objects are in the set, and which objects are not? Here’s an example of one way to answer this question, and it will motivate a theorem that will then answer the question precisely.

**Example CSMCS**

**Column space of a matrix and consistent systems**

Archetype D \([577]\) and Archetype E \([581]\) are linear systems of equations, with an identical \(3 \times 4\) coefficient matrix, which we call \( A \) here. However, Archetype D \([577]\) is consistent, while Archetype E \([581]\) is not. We can explain this difference by employing the column space of the matrix \( A \).

The column vector of constants, \( b \), in Archetype D \([577]\) is

\[
b = \begin{bmatrix} 8 \\ -12 \\ 4 \end{bmatrix}
\]

One solution to \( \mathcal{L}S(A, b) \), as listed, is

\[
x = \begin{bmatrix} 7 \\ 8 \\ 1 \\ 3 \end{bmatrix}
\]
By Theorem SLSLC [103], we can summarize this solution as a linear combination of the columns of \( A \) that equals \( b \),

\[
7 \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix} + 8 \begin{bmatrix} 1 \\ 4 \\ 1 \end{bmatrix} + 1 \begin{bmatrix} 7 \\ -5 \\ 4 \end{bmatrix} + 3 \begin{bmatrix} -7 \\ -6 \\ -5 \end{bmatrix} = \begin{bmatrix} 8 \\ -12 \\ 4 \end{bmatrix} = b.
\]

This equation says that \( b \) is a linear combination of the columns of \( A \), and then by Definition CSM [235], we can say that \( b \in \mathcal{C}(A) \).

On the other hand, Archetype E [581] is the linear system \( \mathcal{L}(A, c) \), where the vector of constants is

\[
c = \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}
\]

and this system of equations is inconsistent. This means \( c \not\in \mathcal{C}(A) \), for if it were, then it would equal a linear combination of the columns of \( A \) and Theorem SLSLC [103] would lead us to a solution of the system \( \mathcal{L}(A, c) \).

So if we fix the coefficient matrix, and vary the vector of constants, we can sometimes find consistent systems, and sometimes inconsistent systems. The vectors of constants that lead to consistent systems are exactly the elements of the column space. This is the content of the next theorem, and since it is an equivalence, it provides an alternate view of the column space.

**Theorem CSCS**

**Column Spaces and Consistent Systems**

Suppose \( A \) is an \( m \times n \) matrix and \( b \) is a vector of size \( m \). Then \( b \in \mathcal{C}(A) \) if and only if \( \mathcal{L}(A, b) \) is consistent.

**Proof** (\( \Rightarrow \)) Suppose \( b \in \mathcal{C}(A) \). Then we can write \( b \) as some linear combination of the columns of \( A \). By Theorem SLSLC [103], we can use the scalars from this linear combination to form a solution to \( \mathcal{L}(A, b) \), so this system is consistent.

(\( \Leftarrow \)) If \( \mathcal{L}(A, b) \) is consistent, there is a solution that may be used with Theorem SLSLC [103] to write \( b \) as a linear combination of the columns of \( A \). This qualifies \( b \) for membership in \( \mathcal{C}(A) \).

This theorem tells us that asking if the system \( \mathcal{L}(A, b) \) is consistent is exactly the same question as asking if \( b \) is in the column space of \( A \). Or equivalently, it tells us that the column space of the matrix \( A \) is precisely those vectors of constants, \( b \), that can be paired with \( A \) to create a system of linear equations \( \mathcal{L}(A, b) \) that is consistent.

An alternative (and popular) definition of the column space of an \( m \times n \) matrix \( A \) would then be

\[
\mathcal{C}(A) = \{Ax \mid x \in \mathbb{C}^n \}.
\]

We recognize this as saying take all the matrix vector products possible with the matrix \( A \). By Definition MVP [187] we see that this means take all possible linear combinations of the columns of \( A \) — precisely the definition of the column space (Definition CSM [235]) we have chosen.

Given a vector \( b \) and a matrix \( A \) it is now very mechanical to test if \( b \in \mathcal{C}(A) \). Form the linear system \( \mathcal{L}(A, b) \), row-reduce the augmented matrix, \([A \mid b]\), and test for consistency with Theorem RCLS [53]. Here’s an example of this procedure.
Example MCSM
Membership in the column space of a matrix
Consider the column space of the $3 \times 4$ matrix $A$,

$$A = \begin{bmatrix} 3 & 2 & 1 & -4 \\ -1 & 1 & -2 & 3 \\ 2 & -4 & 6 & -8 \end{bmatrix}$$

We first show that $v = \begin{bmatrix} 18 \\ -6 \\ 12 \end{bmatrix}$ is in the column space of $A$, $v \in \mathcal{C}(A)$. Theorem CSCS \[236\] says we need only check the consistency of $\mathcal{LS}(A, v)$. Form the augmented matrix and row-reduce,

$$\begin{bmatrix} 3 & 2 & 1 & -4 & 18 \\ -1 & 1 & -2 & 3 & -6 \\ 2 & -4 & 6 & -8 & 12 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 1 & -2 & 6 \\ 0 & 1 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Without a leading 1 in the final column, Theorem RCLS \[53\] tells us the system is consistent and therefore by Theorem CSCS \[236\], $v \in \mathcal{C}(A)$.

If we wished to demonstrate explicitly that $v$ is a linear combination of the columns of $A$, we can find a solution (any solution) of $\mathcal{LS}(A, v)$ and use Theorem SLSLC \[103\] to construct the desired linear combination. For example, set the free variables to $x_3 = 2$ and $x_4 = 1$. Then a solution has $x_2 = 1$ and $x_1 = 6$. Then by Theorem SLSLC \[103\],

$$v = \begin{bmatrix} 18 \\ -6 \\ 12 \end{bmatrix} = 6 \begin{bmatrix} 3 \\ -1 \\ 2 \end{bmatrix} + 1 \begin{bmatrix} 2 \\ -4 \\ -6 \end{bmatrix} + 2 \begin{bmatrix} 1 \\ 1 \\ 6 \end{bmatrix} + 1 \begin{bmatrix} -4 \\ 3 \\ -8 \end{bmatrix}$$

Now we show that $w = \begin{bmatrix} 2 \\ 1 \\ -3 \end{bmatrix}$ is not in the column space of $A$, $w \notin \mathcal{C}(A)$. Theorem CSCS \[236\] says we need only check the consistency of $\mathcal{LS}(A, w)$. Form the augmented matrix and row-reduce,

$$\begin{bmatrix} 3 & 2 & 1 & -4 & 2 \\ -1 & 1 & -2 & 3 & 1 \\ 2 & -4 & 6 & -8 & -3 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 1 & -2 & 0 \\ 0 & 1 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

With a leading 1 in the final column, Theorem RCLS \[53\] tells us the system is inconsistent and therefore by Theorem CSCS \[236\], $w \notin \mathcal{C}(A)$.
Example CSTW
Column space, two ways
Consider the $5 \times 7$ matrix $A$,

$$
\begin{pmatrix}
2 & 4 & 1 & -1 & 1 & 4 & 4 \\
1 & 2 & 1 & 0 & 2 & 4 & 7 \\
0 & 0 & 1 & 4 & 1 & 8 & 7 \\
1 & 2 & -1 & 2 & 1 & 9 & 6 \\
-2 & -4 & 1 & 3 & -1 & -2 & -2
\end{pmatrix}
$$

According to the definition (Definition CSM [235]), the column space of $A$ is

$$
C(A) = S_p \left\{ \begin{pmatrix} 2 \\ 1 \\ 0 \\ 1 \\ -2 \end{pmatrix}, \begin{pmatrix} 4 \\ 2 \\ 0 \\ 2 \\ -4 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \\ 4 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 2 \\ 4 \\ 2 \end{pmatrix} \right\}
$$

While this is a concise description of an infinite set, we might be able to describe the span with fewer than seven vectors. This is the substance of Theorem RSS [157]. So we take these seven vectors and make them the columns of matrix, which is simply the original matrix $A$ again. Now we row-reduce,

$$
\begin{pmatrix}
2 & 4 & 1 & -1 & 1 & 4 & 4 \\
1 & 2 & 1 & 0 & 2 & 4 & 7 \\
0 & 0 & 1 & 4 & 1 & 8 & 7 \\
1 & 2 & -1 & 2 & 1 & 9 & 6 \\
-2 & -4 & 1 & 3 & -1 & -2 & -2
\end{pmatrix} \xrightarrow{\text{RREF}} \begin{pmatrix}
1 & 2 & 0 & 0 & 0 & 3 & 1 \\
0 & 0 & 1 & 0 & 0 & -1 & 0 \\
0 & 0 & 0 & 1 & 0 & 2 & 1 \\
0 & 0 & 0 & 0 & 1 & 1 & 3 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
$$

The pivot columns are $D = \{1, 3, 4, 5\}$, so we can create the set

$$
T = \left\{ \begin{pmatrix} 2 \\ 1 \\ 0 \\ 1 \\ -2 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ -1 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ 0 \\ 4 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 2 \\ 1 \\ -1 \end{pmatrix} \right\}
$$

and know that $C(A) = S_p(T)$ and $T$ is a linearly independent set of columns from the set of columns of $A$.

We will now formalize the previous example, which will make it trivial to determine a linearly independent set of vectors that will span the column space of a matrix, and is constituted of just columns of $A$.

Theorem BCSOC
Basis of the Column Space with Original Columns
Suppose that $A$ is an $m \times n$ matrix with columns $A_1, A_2, A_3, \ldots, A_n$, and $B$ is a row-equivalent matrix in reduced row-echelon form with $r$ nonzero rows. Let $D = \{d_1, d_2, d_3, \ldots, d_r\}$ be the set of column indices where $B$ has leading 1’s. Let $T = \{A_{d_1}, A_{d_2}, A_{d_3}, \ldots, A_{d_r}\}$. Then

1. $T$ is a linearly independent set.
2. $\mathcal{C}(A) = \mathcal{S}p(T)$.

**Proof** [Definition CSM 235] describes the column space as the span of the set of columns of $A$. [Theorem RSS 157] tells us that we can reduce the set of vectors used in a span. If we apply [Theorem RSS 157] to $\mathcal{C}(A)$, we would collect the columns of $A$ into a matrix (which would just be $A$ again) and bring the matrix to reduced row-echelon form, which is the matrix $B$ in the statement of the theorem. In this case, the conclusions of [Theorem RSS 157] applied to $A$, $B$ and $\mathcal{C}(A)$ are exactly the conclusions we desire. □

This is a nice result since it gives us a handful of vectors that describe the entire column space (through the span), and we believe this set is as small as possible because we cannot create any more relations of linear dependence to trim it down further. Furthermore, we defined the column space (Definition CSM 235) as all linear combinations of the columns of the matrix, and the elements of the set $S$ are still columns of the matrix (we won’t be so lucky in the next two constructions of the column space).

Procedurally this theorem is extremely easy to apply. Row-reduce the original matrix, identify $r$ columns with leading 1’s in this reduced matrix, and grab the corresponding columns of the original matrix. But it is still important to study the proof of [Theorem RSS 157] and its motivation in [Example COV 154] which lie at the root of this theorem. We’ll trot through an example all the same.

**Example ROCD**

**Range with original columns, Archetype D**

Let’s determine a compact expression for the entire column space of the coefficient matrix of the system of equations that is [Archetype D 577]. Notice that in [Example CSMCS 235] we were only determining if individual vectors were in the column space or not, now we are describing the entire column space.

To start with the application of [Theorem BCSOC 238], call the coefficient matrix $A$

$$A = \begin{bmatrix} 2 & 1 & 7 & -7 \\ -3 & 4 & -5 & -6 \\ 1 & 1 & 4 & -5 \end{bmatrix}.$$  

and row-reduce it to reduced row-echelon form,

$$B = \begin{bmatrix} 1 & 0 & 3 & -2 \\ 0 & 1 & 1 & -3 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$  

There are leading 1’s in columns 1 and 2, so $D = \{1, 2\}$. To construct a set that spans $\mathcal{C}(A)$, just grab the columns of $A$ indicated by the set $D$, so

$$\mathcal{C}(A) = \mathcal{S}p\left( \left\{ \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 1 \end{bmatrix} \right\} \right).$$  

That’s it.

In [Example CSMCS 235] we determined that the vector

$$c = \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}$$  

Version 0.52
was not in the column space of \( A \). Try to write \( \mathbf{c} \) as a linear combination of the first two columns of \( A \). What happens?

Also in Example CSMCS 235 we determined that the vector

\[
\mathbf{b} = \begin{bmatrix} 8 \\ -12 \\ 4 \end{bmatrix}
\]

was in the column space of \( A \). Try to write \( \mathbf{b} \) as a linear combination of the first two columns of \( A \). What happens? Did you find a unique solution to this question? Hmmmm.

Subsection CSNSM
Column Space of a Nonsingular Matrix

Let’s specialize to square matrices and contrast the column spaces of the coefficient matrices in Archetype A 563 and Archetype B 568.

Example CSAA
Column space of Archetype A

The coefficient matrix in Archetype A 563 is

\[
A = \begin{bmatrix} 1 & -1 & 2 \\ 2 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}
\]

which row-reduces to

\[
\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{bmatrix}.
\]

Columns 1 and 2 have leading 1’s, so by Theorem BCSOC 238 we can write

\[
\mathcal{C}(A) = Sp(\{ A_1, A_2 \}) = Sp \left( \left\{ \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \right\} \right).
\]

We want to show in this example that \( \mathcal{C}(A) \neq \mathbb{C}^3 \). So take, for example, the vector

\[
\mathbf{b} = \begin{bmatrix} 3 \\ 2 \end{bmatrix}.
\]

Then there is no solution to the system \( \mathcal{L}S(A, \mathbf{b}) \), or equivalently, it is not possible to write \( \mathbf{b} \) as a linear combination of \( A_1 \) and \( A_2 \). Try one of these two computations yourself. (Or try both!). Since \( \mathbf{b} \not\in \mathcal{C}(A) \), the column space of \( A \) cannot be all of \( \mathbb{C}^3 \). So by varying the vector of constants, it is possible to create inconsistent systems of equations with this coefficient matrix (the vector \( \mathbf{b} \) being one such example).

In Example MWIAA 208 we wished to show that the coefficient matrix from Archetype A 563 was not invertible as a first example of a matrix without an inverse. Our device there was to find an inconsistent linear system with \( A \) as the coefficient matrix. The vector of constants in that example was \( \mathbf{b} \), deliberately chosen outside the column space of \( A \).
Example CSAB
Column space of Archetype B

The coefficient matrix in Archetype B, call it $B$, here, is known to be nonsingular (see Example NS [76]). By Theorem NSMUS [79], the linear system $\mathcal{L}S(B, b)$ has a (unique) solution for every choice of $b$. Theorem CSCS [236] then says that $b \in \mathcal{C}(B)$ for all $b \in \mathbb{C}^3$. Stated differently, there is no way to build an inconsistent system with the coefficient matrix $B$, but then we knew that already from Theorem NSMUS [79]. ⊚

Example CSAA [240] and Example CSAB [241] together motivate the following equivalence, which says that nonsingular matrices have column spaces that are as big as possible.

Theorem CSNSM
Column Space of a NonSingular Matrix

Suppose $A$ is a square matrix of size $n$. Then $A$ is nonsingular if and only if $\mathcal{C}(A) = \mathbb{C}^n$. □

Proof ($\Leftarrow$) Suppose $A$ is nonsingular. By Theorem NSMUS [79], the linear system $\mathcal{L}S(A, b)$ has a (unique) solution for every choice of $b$. Theorem CSCS [236] then says that $b \in \mathcal{C}(A)$ for all $b \in \mathbb{C}^n$. In other words, $\mathcal{C}(A) = \mathbb{C}^n$.

($\Rightarrow$) If $e_i$ is column $i$ of the $n \times n$ identity matrix (Definition SUV [210]) and by hypothesis $\mathcal{C}(A) = \mathbb{C}^n$, then $e_i \in \mathcal{C}(A)$ for $1 \leq i \leq n$. By Theorem CSCS [236], the system $\mathcal{L}S(A, e_i)$ is consistent for $1 \leq i \leq n$. Let $b_i$ denote a single solution to $\mathcal{L}S(A, e_i)$, $1 \leq i \leq n$.

Define the $n \times n$ matrix $B = [b_1|b_2|b_3|\ldots|b_n]$. Then

\[
AB = A[b_1|b_2|b_3|\ldots|b_n] \\
= [Ab_1|Ab_2|Ab_3|\ldots|Ab_n] \\
= [e_1|e_2|e_3|\ldots|e_n] \\
= I_n
\]

Definition MM [191] Definition SUV [210]

So the matrix $B$ is a “right-inverse” for $A$. By Theorem OSIS [224], this is enough to conclude that $A$ is invertible. Then Theorem NSI [225] implies that $A$ is nonsingular. □

With this equivalence for nonsingular matrices we can update our list, Theorem NSME3 [225].

Theorem NSME4
NonSingular Matrix Equivalences, Round 4

Suppose that $A$ is a square matrix of size $n$. The following are equivalent.

1. $A$ is nonsingular.
2. $A$ row-reduces to the identity matrix.
3. The null space of $A$ contains only the zero vector, $\mathcal{N}(A) = \{0\}$.
4. The linear system $\mathcal{L}S(A, b)$ has a unique solution for every possible choice of $b$.
5. The columns of $A$ are a linearly independent set.
6. $A$ is invertible.

7. The column space of $A$ is $\mathbb{C}^n$, $\mathcal{C}(A) = \mathbb{C}^n$. □

**Proof** Since Theorem CSNSM [241] is an equivalence, we can add it to the list in Theorem NSME3 [225].

**Subsection RSM**

**Row Space of a Matrix**

The rows of a matrix can be viewed as vectors, since they are just lists of numbers, arranged horizontally. So we will transpose a matrix, turning rows into columns, so we can then manipulate rows as column vectors. As a result we will be able to make some new connections between row operations and solutions to systems of equations. OK, here is the second primary definition of this section.

**Definition RSM**

**Row Space of a Matrix**

Suppose $A$ is an $m \times n$ matrix. Then the **row space** of $A$, $\mathcal{R}(A)$, is the column space of $A^t$, i.e. $\mathcal{R}(A) = \mathcal{C}(A^t)$. △

Informally, the row space is the set of all linear combinations of the rows of $A$. However, we write the rows as column vectors, thus the necessity of using the transpose to make the rows into columns. Additionally, with the row space defined in terms of the column space, all of the previous results of this section can be applied to row spaces.

Notice that if $A$ is a rectangular $m \times n$ matrix, then $\mathcal{C}(A) \subseteq \mathbb{C}^m$, while $\mathcal{R}(A) \subseteq \mathbb{C}^n$ and the two sets are not comparable since they do not even hold objects of the same type. However, when $A$ is square of size $n$, both $\mathcal{C}(A)$ and $\mathcal{R}(A)$ are subsets of $\mathbb{C}^n$, though usually the sets will not be equal (but see Exercise CRS.M20 [251]).

**Example RSAI**

**Row space of Archetype I**

The coefficient matrix in Archetype I [599] is

\[
I = \begin{bmatrix}
1 & 4 & 0 & -1 & 0 & 7 & -9 \\
2 & 8 & -1 & 3 & 9 & -13 & 7 \\
0 & 0 & 2 & -3 & -4 & 12 & -8 \\
-1 & -4 & 2 & 4 & 8 & -31 & 37
\end{bmatrix}.
\]

To build the row space, we transpose the matrix,

\[
I^t = \begin{bmatrix}
1 & 2 & 0 & -1 \\
4 & 8 & 0 & -4 \\
0 & -1 & 2 & 2 \\
-1 & 3 & -3 & 4 \\
0 & 9 & -4 & 8 \\
7 & -13 & 12 & -31 \\
-9 & 7 & -8 & 37
\end{bmatrix}.
\]
Then the columns of this matrix are used in a span to build the row space,

\[
\mathcal{R}(I) = \mathcal{C}(I^t) = Sp
\begin{bmatrix}
\begin{bmatrix}
1 & 2 & 0 & -1 \\
4 & 8 & 0 & -4 \\
0 & -1 & 2 & 2 \\
-1 & 3 & -3 & 4 \\
0 & 9 & -4 & 8 \\
7 & -13 & 12 & -31 \\
-9 & 7 & -8 & 37
\end{bmatrix}
\end{bmatrix}.
\]

However, we can use Theorem BCSOC \[238\] to get a slightly better description. First, row-reduce \(I^t\),

\[
\begin{bmatrix}
1 & 0 & 0 & -\frac{31}{7} \\
0 & 1 & 0 & \frac{12}{7} \\
0 & 0 & 1 & \frac{13}{7} \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}.
\]

Since there are leading 1’s in columns with indices \(D = \{1, 2, 3\}\), the column space of \(I^t\) can be spanned by just the first three columns of \(I^t\),

\[
\mathcal{R}(I) = \mathcal{C}(I^t) = Sp
\begin{bmatrix}
\begin{bmatrix}
1 & 2 & 0 \\
4 & 8 & 0 \\
0 & -1 & 2 \\
-1 & 3 & -3 \\
0 & 9 & -4 \\
7 & -13 & 12 \\
-9 & 7 & -8
\end{bmatrix}
\end{bmatrix}.
\]

The row space would not be too interesting if it was simply the column space of the transpose. However, when we do row operations on a matrix we have no effect on the many linear combinations that can be formed with the rows of the matrix. This is stated more carefully in the following theorem.

**Theorem REMRS**

**Row-Equivalent Matrices have equal Row Spaces**

Suppose \(A\) and \(B\) are row-equivalent matrices. Then \(\mathcal{R}(A) = \mathcal{R}(B)\).

**Proof** Two matrices are row-equivalent (Definition REM \[32\]) if one can be obtained from another by a sequence of (possibly many) row operations. We will prove the theorem for two matrices that differ by a single row operation, and then this result can be applied repeatedly to get the full statement of the theorem. The row spaces of \(A\) and \(B\) are spans of the columns of their transposes. For each row operation we perform on a matrix, we can define an analogous operation on the columns. Perhaps we should call these column operations. Instead, we will still call them row operations, but we will apply them to the columns of the transposes.

Refer to the columns of \(A^t\) and \(B^t\) as \(A_i\) and \(B_i\), \(1 \leq i \leq m\). The row operation that switches rows will just switch columns of the transposed matrices. This will have no effect on the possible linear combinations formed by the columns.
Suppose that $B'$ is formed from $A'$ by multiplying column $A_t$ by $\alpha \neq 0$. In other words, $B_t = \alpha A_t$, and $B_i = A_i$ for all $i \neq t$. We need to establish that two sets are equal, $C(A') = C(B')$. We will take a generic element of one and show that it is contained in the other.

\[
\beta_1 B_1 + \beta_2 B_2 + \beta_3 B_3 + \cdots + \beta_i B_i + \cdots + \beta_m B_m = \\
\beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \cdots + \beta_i (\alpha A_t) + \cdots + \beta_m A_m = \\
\beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \cdots + (\alpha \beta_t) A_i + \cdots + \beta_m A_m
\]
says that $C(B') \subseteq C(A')$. Similarly,

\[
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + \gamma_t A_t + \cdots + \gamma_m A_m = \\
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + \left(\frac{\gamma_t}{\alpha}\right) A_t + \cdots + \gamma_m A_m = \\
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + \frac{\gamma_t}{\alpha} (\alpha A_t) + \cdots + \gamma_m A_m = \\
\gamma_1 B_1 + \gamma_2 B_2 + \gamma_3 B_3 + \cdots + \frac{\gamma_t}{\alpha} B_t + \cdots + \gamma_m B_m
\]
says that $C(A') \subseteq C(B')$. So $R(A) = C(A') = C(B') = R(B)$ when a single row operation of the second type is performed.

Suppose now that $B'$ is formed from $A'$ by replacing $A_t$ with $\alpha A_s + A_i$ for some $\alpha \in \mathbb{C}$ and $s \neq t$. In other words, $B_t = \alpha A_s + A_t$, and $B_i = A_i$ for $i \neq t$.

\[
\beta_1 B_1 + \beta_2 B_2 + \beta_3 B_3 + \cdots + \beta_i B_i + \cdots + \beta_m B_m = \\
\beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \cdots + \beta_s A_s + \cdots + \beta_i (\alpha A_s + A_t) + \cdots + \beta_m A_m = \\
\beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \cdots + \beta_s A_s + \cdots + (\beta t) A_s + \beta_i A_t + \cdots + \beta_m A_m = \\
\beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \cdots + (\beta s + \beta t \alpha) A_s + \cdots + \beta_i A_t + \cdots + \beta_m A_m
\]
says that $C(B') \subseteq C(A')$. Similarly,

\[
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + \gamma_s A_s + \cdots + \gamma_t A_t + \cdots + \gamma_m A_m = \\
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + \gamma_s A_s + \cdots + (\gamma_t \alpha) A_s + \gamma_s A_s + \cdots + (\gamma_t A_t) A_t + \cdots + \gamma_m A_m = \\
\gamma_1 A_1 + \gamma_2 A_2 + \gamma_3 A_3 + \cdots + (\gamma_t A_t + \gamma_s A_s) A_s + \cdots + \gamma_t A_t A_t + \cdots + \gamma_m A_m = \\
\gamma_1 B_1 + \gamma_2 B_2 + \gamma_3 B_3 + \cdots + (\gamma_t A_t + \gamma_s A_s) B_s + \cdots + \gamma_t B_t + \cdots + \gamma_m B_m
\]
says that $C(A') \subseteq C(B')$. So $R(A) = C(A') = C(B') = R(B)$ when a single row operation of the third type is performed.

So the row space of a matrix is preserved by each row operation, and hence row spaces of row-equivalent matrices are equal sets.

Example RSREM
Row spaces of two row-equivalent matrices
In Example TREM\[32\] we saw that the matrices

\[
A = \begin{bmatrix}
2 & -1 & 3 & 4 \\
5 & 2 & -2 & 3 \\
1 & 1 & 0 & 6
\end{bmatrix} \hspace{1cm} B = \begin{bmatrix}
1 & 1 & 0 & 6 \\
3 & 0 & -2 & -9 \\
2 & -1 & 3 & 4
\end{bmatrix}
\]

Version 0.52
are row-equivalent by demonstrating a sequence of two row operations that converted $A$ into $B$. Applying Theorem REMRS we can say

$$R(A) = Sp \left( \begin{bmatrix} 2 & 5 & 1 \\ -1 & 2 & 1 \\ 3 & -2 & -2 \\ 4 & 3 & -1 \end{bmatrix} \right) = Sp \left( \begin{bmatrix} 1 & 3 & 2 \\ 1 & 0 & -1 \\ 0 & -2 & 3 \\ 1 & -9 & 4 \end{bmatrix} \right) = R(B) \Circle$$

Theorem REMRS is at its best when one of the row-equivalent matrices is in reduced row-echelon form. The vectors that correspond to the zero rows can be ignored (who needs the zero vector when building a span?, see Exercise LI.T10). The echelon pattern insures that the nonzero rows yield vectors that are linearly independent. Here’s the theorem.

**Theorem BRS**

**Basis for the Row Space**

Suppose that $A$ is a matrix and $B$ is a row-equivalent matrix in reduced row-echelon form. Let $S$ be the set of nonzero columns of $B^t$. Then

1. $R(A) = Sp(S)$.
2. $S$ is a linearly independent set. □

**Proof** From Theorem REMRS we know that $R(A) = R(B)$. If $B$ has any zero rows, these correspond to columns of $B^t$ that are the zero vector. We can safely toss out the zero vector in the span construction, since it can be recreated from the nonzero vectors by a linear combination where all the scalars are zero. So $R(A) = Sp(S)$.

Suppose $B$ has $r$ nonzero rows and let $D = \{d_1, d_2, d_3, \ldots, d_r\}$ denote the column indices of $B$ that have a leading one in them. Denote the $r$ column vectors of $B^t$, the vectors in $S$, as $B_1, B_2, B_3, \ldots, B_r$. To show that $S$ is linearly independent, start with a relation of linear dependence

$$\alpha_1 B_1 + \alpha_2 B_2 + \alpha_3 B_3 + \cdots + \alpha_r B_r = 0$$

Now consider this equation across entries of the vectors in location $d_i$, $1 \leq i \leq r$. Since $B$ is in reduced row-echelon form, the entries of column $d_i$ are all zero, except for a (leading) 1 in row $i$. Considering the column vectors of $B^t$, the linear combination for entry $d_i$ is

$$\alpha_1(0) + \alpha_2(0) + \alpha_3(0) + \cdots + \alpha_i(1) + \cdots + \alpha_r(0) = 0$$

and from this we conclude that $\alpha_i = 0$ for all $1 \leq i \leq r$, establishing the linear independence of $S$. □

**Example IAS**

**Improving a span**

Suppose in the course of analyzing a matrix (its column space, its null space, its...) we encounter the following set of vectors, described by a span

$$X = Sp \left( \begin{bmatrix} 1 & 3 \\ 2 & -1 \\ 1 & 2 \\ 6 & -1 \\ 6 & 6 \end{bmatrix} \right)$$
Let $A$ be the matrix whose rows are the vectors in $X$, so by design $X = \mathcal{R}(A)$,

$$A = \begin{bmatrix} 1 & 2 & 1 & 6 & 6 \\ 3 & -1 & 2 & -1 & 6 \\ 1 & -1 & 0 & -1 & -2 \\ -3 & 2 & -3 & 6 & -10 \end{bmatrix}$$

Row-reduce $A$ to form a row-equivalent matrix in reduced row-echelon form,

$$B = \begin{bmatrix} 1 & 0 & 0 & 2 & -1 \\ 0 & 1 & 0 & 3 & 1 \\ 0 & 0 & 1 & -2 & 5 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Then Theorem BRS \[245\] says we can grab the nonzero columns of $B^t$ and write

$$X = \mathcal{R}(A) = \mathcal{R}(B) = \mathcal{S}p \left( \begin{bmatrix} 1 \\ 0 \\ 0 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -2 \\ 5 \end{bmatrix} \right)$$

These three vectors provide a much-improved description of $X$. There are fewer vectors, and the pattern of zeros and ones in the first three entries makes it easier to determine membership in $X$. And all we had to do was row-reduce the right matrix and toss out a zero row. Next to row operations themselves, this is probably the most powerful computational technique at your disposal as it quickly provides a much improved description of a span, any span. \(\circ\)

Theorem BRS \[245\] and the techniques of Example IAS \[245\] will provide yet another description of the column space of a matrix. First we state a triviality as a theorem, so we can reference it later.

**Theorem CSRST**
**Column Space, Row Space, Transpose**
Suppose $A$ is a matrix. Then $\mathcal{C}(A) = \mathcal{R}(A^t)$ and $\mathcal{R}(A) = \mathcal{C}(A^t)$. \(\square\)

**Proof**

$$\mathcal{C}(A) = \mathcal{C}((A^t)^t) = \mathcal{R}(A^t) \quad \text{Theorem TT \[184\]}$$

$$\mathcal{R}(A^t) = \mathcal{C}(A^t) \quad \text{Definition RSM \[242\]}$$

So to find another expression for the column space of a matrix, build its transpose, row-reduce it, toss out the zero rows, and convert the nonzero rows to column vectors to yield an improved spanning set. We’ll do Archetype I \[599\], then you do Archetype J \[604\].

**Example CSROI**
**Column space from row operations, Archetype I**
To find the column space of the coefficient matrix of Archetype I \[599\], we proceed as follows. The matrix is

$$I = \begin{bmatrix} 1 & 4 & 0 & -1 & 0 & 7 & -9 \\ 2 & 8 & -1 & 0 & 3 & 9 & -13 & 7 \\ 0 & 0 & 2 & -3 & -4 & 12 & -8 \\ -1 & -4 & 2 & 4 & 8 & -31 & 37 \end{bmatrix}$$
The transpose is
\[
\begin{bmatrix}
1 & 2 & 0 & -1 \\
4 & 8 & 0 & -4 \\
0 & -1 & 2 & 2 \\
-1 & 3 & -3 & 4 \\
0 & 9 & -4 & 8 \\
7 & -13 & 12 & -31 \\
-9 & 7 & -8 & 37
\end{bmatrix}
\]
Row-reduced this becomes,
\[
\begin{bmatrix}
1 & 0 & 0 & \frac{-31}{7} \\
0 & 1 & 0 & \frac{12}{7} \\
0 & 0 & 1 & \frac{13}{7} \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Now, using Theorem CSRST 246 and Theorem BRS 245

\[
\mathcal{C}(I) = \mathcal{R}(I^t) = Sp\left(\left\{\begin{bmatrix} 1 \\ 0 \\ -\frac{31}{7} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{12}{7} \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ \frac{13}{7} \end{bmatrix}\right\}\right)
\]

This is a very nice description of the column space. Fewer vectors than the 7 involved in the definition, and the pattern of the zeros and ones in the first 3 slots can be used to advantage. For example, Archetype I 599 is presented as a consistent system of equations with a vector of constants

\[
b = \begin{bmatrix} 3 \\ 9 \\ 1 \\ 4 \end{bmatrix}
\]

Since \(\mathcal{L}\mathcal{S}(I, b)\) is consistent, Theorem CS\(\mathcal{S}\) 236 tells us that \(b \in \mathcal{C}(I)\). But we could see this quickly with the following computation, which really only involves any work in the 4th entry of the vectors as the scalars in the linear combination are \emph{dictated} by the first three entries of \(b\).

\[
b = \begin{bmatrix} 3 \\ 9 \\ 1 \\ 4 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 0 \\ 0 \\ -\frac{31}{7} \end{bmatrix} + 9 \begin{bmatrix} 0 \\ 1 \\ 0 \\ \frac{12}{7} \end{bmatrix} + 1 \begin{bmatrix} 0 \\ 0 \\ 1 \\ \frac{13}{7} \end{bmatrix}
\]

Can you now rapidly construct several vectors, \(b\), so that \(\mathcal{L}\mathcal{S}(I, b)\) is consistent, and several more so that the system is inconsistent?

Example COV 154 and Example CSROI 246 each describes the column space of the coefficient matrix from Archetype I 599 as the span of a set of \(r = 3\) linearly independent vectors. It is no accident that these two different sets both have the same size. If we (you?) were to calculate the column space of this matrix using the null space...
of the matrix $L$ from Theorem FS \[262\] then we would again find a set of 3 linearly independent vectors that span the range. More on this later.

So we have two different methods to obtain a description of the column space of a matrix as the span of a linearly independent set. Theorem BCSOC \[238\] is sometimes useful since the vectors it specifies are equal to actual columns of the matrix. Theorem BRS \[245\] and Theorem CSRST \[246\] combine to create vectors with lots of zeros, and strategically placed 1’s near the top of the vector. In Section FS \[255\] we will learn of a third method, where Theorem FS \[262\] tends to create vectors with lots of zeros, and strategically placed 1’s near the bottom of the vector.

**Subsection READ**

**Reading Questions**

1. Write the column space of the matrix below as the span of a set of three vectors.

$$
\begin{bmatrix}
1 & 3 & 1 & 3 \\
2 & 0 & 1 & 1 \\
-1 & 2 & 1 & 0
\end{bmatrix}
$$

2. Suppose that $A$ is an $n \times n$ nonsingular matrix. What can you say about its column space?

3. Is the vector

$$
\begin{bmatrix}
0 \\
5 \\
2 \\
3
\end{bmatrix}
$$

in the row space of the following matrix? Why or why not?

$$
\begin{bmatrix}
1 & 3 & 1 & 3 \\
2 & 0 & 1 & 1 \\
-1 & 2 & 1 & 0
\end{bmatrix}
$$
C30 Example ROCD [239] expresses the column space of the coefficient matrix from Archetype D [577] (call the matrix $A$ here) as the span of the first two columns of $A$. In Example RMCS we determined that the vector

$$c = \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}$$

was not in the column space of $A$ and that the vector

$$b = \begin{bmatrix} 8 \\ -12 \\ 4 \end{bmatrix}$$

was in the range of $A$. Attempt to write $c$ and $b$ as linear combinations of the two vectors in the span construction for the column space in Example ROCD [239] and record your observations.

Contributed by Robert Beezer Solution [253]

C32 In Example CSAA [240], verify that the vector $b$ is not in the column space of the coefficient matrix.

Contributed by Robert Beezer

C33 Find a linearly independent set $S$ so that the span of $S$, $\text{Sp}(S)$, is row space of the matrix $B$, and $S$ is linearly independent.

$$B = \begin{bmatrix} 2 & 3 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ -1 & 2 & 3 & -4 \end{bmatrix}$$

Contributed by Robert Beezer Solution [253]

C40 The following archetypes are systems of equations. For each system, write the vector of constants as a linear combination of the vectors in the span construction for the column space provided by Theorem BCSOC [238] (these vectors are listed for each of these archetypes).

Archetype A [563]
Archetype B [568]
Archetype C [573]
Archetype D [577]
Archetype E [581]
Archetype F [585]
Archetype G [590]
Archetype H [594]
Archetype I [599]
Archetype J [604]
Contributed by Robert Beezer

C42 The following archetypes are either matrices or systems of equations with coefficient matrices. For each matrix, compute a set of column vectors such that (1) the vectors are columns of the matrix, (2) the set is linearly independent, and (3) the span of the set is the column space of the matrix. See Theorem BCSOC 238.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577 /Archetype E 581
Archetype F 585
Archetype G 590 /Archetype H 594
Archetype I 599
Archetype J 604
Archetype K 609
Archetype L 613

Contributed by Robert Beezer

C50 The following archetypes are either matrices or systems of equations with coefficient matrices. For each matrix, compute a set of column vectors such that (1) the set is linearly independent, and (2) the span of the set is the row space of the matrix. See Theorem BRS 245.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577 /Archetype E 581
Archetype F 585
Archetype G 590 /Archetype H 594
Archetype I 599
Archetype J 604
Archetype K 609
Archetype L 613

Contributed by Robert Beezer

C51 The following archetypes are either matrices or systems of equations with coefficient matrices. For each matrix, compute the column space as the span of a linearly independent set as follows: transpose the matrix, row-reduce, toss out zero rows, convert rows into column vectors. See Example CSROI 246.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577 /Archetype E 581
Archetype F 585
Archetype G 590 /Archetype H 594
The following archetypes are systems of equations. For each different coefficient matrix build two new vectors of constants. The first should lead to a consistent system and the second should lead to an inconsistent system. Descriptions of the column space as spans of linearly independent sets of vectors with “nice patterns” of zeros and ones might be most useful and instructive in connection with this exercise. (See the end of Example CSROI [246].)

For the matrix \( E \) below, find vectors \( b \) and \( c \) so that the system \( \mathcal{L}S(E, b) \) is consistent and \( \mathcal{L}S(E, c) \) is inconsistent.

\[
E = \begin{bmatrix}
-2 & 1 & 1 & 0 \\
3 & -1 & 0 & 2 \\
4 & 1 & 1 & 6
\end{bmatrix}
\]

Usually the column space and null space of a matrix contain vectors of different sizes. For a square matrix, though, the vectors in these two sets are the same size. Usually the two sets will be different. Construct an example of a square matrix where the column space and null space are equal.
In each case, begin with a vector equation where one side contains a linear combination of the two vectors from the span construction that gives the column space of $A$ with unknowns for scalars, and then use Theorem SLSLC to set up a system of equations. For $c$, the corresponding system has no solution, as we would expect.

For $b$ there is a solution, as we would expect. What is interesting is that the solution is unique. This is a consequence of the linear independence of the set of two vectors in the span construction. If we wrote $b$ as a linear combination of all four columns of $A$, then there would be infinitely many ways to do this.

Theorem BRS is the most direct route to a set with these properties. Row-reduce, toss zero rows, keep the others. You could also transpose the matrix, then look for the range by row-reducing the transpose and applying Theorem BCSOC. We'll do the former,

$$
B \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & -1 & 2 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \end{bmatrix}
$$

So the set $S$ is

$$
S = \left\{ \begin{bmatrix} 1 \\ 0 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \\ 1 \end{bmatrix} \right\}
$$

Any vector from $C^3$ will lead to a consistent system, and therefore there is no vector that will lead to an inconsistent system.

How do we convince ourselves of this? First, row-reduce $E$,

$$
E \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}
$$

If we augment $E$ with any vector of constants, and row-reduce the augmented matrix, we will never find a leading 1 in the final column, so by Theorem RCLS the system will always be consistent.

Said another way, the column space of $E$ is all of $C^3$, $C(E) = C^3$. So by Theorem CSCS any vector of constants will create a consistent system (and none will create an inconsistent system).

The $2 \times 2$ matrix $\begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$ has $C(A) = N(A) = S_{p\left(\begin{bmatrix} 1 \\ -1 \end{bmatrix}\right)}$. 
Section FS
Four Subsets

There are four natural subsets associated with a matrix. We have met three already: the null space, the column space and the row space. In this section we will introduce a fourth, the left null space. The objective of this section is to describe one procedure that will allow us to find linearly independent sets that span each of these four sets of column vectors. Along the way, we will make a connection with the inverse of a matrix, so Theorem FS \[262\] will tie together most all of this section (and the entire course so far).

Subsection LNS
Left Null Space

Definition LNS
Left Null Space
Suppose $A$ is an $m \times n$ matrix. Then the **left null space** is defined as $L(A) = N(A^t) \subseteq \mathbb{C}^m$.

The left null space will not feature prominently in the sequel, but we can explain its name and connect it to row operations. Suppose $y \in L(A)$. Then by Definition LNS \[255\], $A^t y = 0$. We can then write

\[0^t = (A^t y)^t = y^t (A^t)^t = y^t A\]

Theorem MMT \[198\]
Theorem TT \[184\]

The product $y^t A$ can be viewed as the components of $y$ acting as the scalars in a linear combination of the rows of $A$. And the result is a “row vector”, $0^t$ that is totally zeros. When we apply a sequence of row operations to a matrix, each row of the resulting matrix is some linear combination of the rows. These observations tell us that the vectors in the left null space are scalars that record a sequence of row operations that result in a row of zeros in the row-reduced version of the matrix. We will see this idea more explicitly in the course of proving Theorem FS \[262\].

Subsection CRS
Computing Column Spaces

We have three ways to build the column space of a matrix. First, we can use just the definition, Definition CSM \[235\], and express the column space as a span of the columns
of the matrix. A second approach gives us the column space as the span of some of the columns of the matrix, but this set is linearly independent (Theorem BCSOC 238). Finally, we can transpose the matrix, row-reduce the transpose, kick out zero rows, and transpose the remaining rows back into column vectors. Theorem CSRST 246 and Theorem BRS 245 tell us that the resulting vectors are linearly independent and their span is the column space of the original matrix.

We will now demonstrate a fourth method by way of a rather complicated example. Study this example carefully, but realize that its main purpose is to motivate a theorem that simplifies much of the apparent complexity. So other than an instructive exercise or two, the procedure we are about to describe will not be a usual approach to computing a column space.

Example CSANS
Column space as null space
Lets find the column space of the matrix $A$ below with a new approach.

$$A = \begin{bmatrix} 10 & 0 & 3 & 8 & 7 \\ -16 & -1 & -4 & -10 & -13 \\ -6 & 1 & -3 & -6 & -6 \\ 0 & 2 & -2 & -3 & -2 \\ 3 & 0 & 1 & 2 & 3 \\ -1 & -1 & 1 & 1 & 0 \end{bmatrix}$$

By Theorem CSCS 236 we know that the column vector $b$ is in the column space of $A$ if and only if the linear system $LS(A, b)$ is consistent. So let’s try to solve this system in full generality, using a vector of variables for the vector of constants. So we begin by forming the augmented matrix $[A | b]$

$$[A | b] = \begin{bmatrix} 10 & 0 & 3 & 8 & 7 & b_1 \\ -16 & -1 & -4 & -10 & -13 & b_2 \\ -6 & 1 & -3 & -6 & -6 & b_3 \\ 0 & 2 & -2 & -3 & -2 & b_4 \\ 3 & 0 & 1 & 2 & 3 & b_5 \\ -1 & -1 & 1 & 1 & 0 & b_6 \end{bmatrix}$$

To identify solutions we will row-reduce this matrix and bring it to reduced row-echelon form. Despite the presence of variables in the last column, there is nothing to stop us from doing this. Except our numerical routines on calculators can’t be used, and even some of the symbolic algebra routines do some unexpected maneuvers with this computation. So do it by hand. Yes, it is a bit of work. But worth it. We’ll still be here when you get back. Notice along the way that the row operations are exactly the same ones you would do if you were just row-reducing the coefficient matrix alone, say in connection with a homogeneous system of equations. The column with the $b_i$ acts as a sort of bookkeeping device. There are many different possibilities for the result, depending on what order you choose to perform the row operations, but shortly we’ll all be on the same page. Here’s one possibility (you can find this same result by doing additional row operations with the fifth and sixth rows to remove any occurrences of $b_5$ and $b_6$ from the first four rows of
Subsection FS.CRS  Computing Column Spaces  257

Our goal is to identify those vectors \( \mathbf{b} \) which make \( \mathcal{L}(A, \mathbf{b}) \) consistent. By Theorem RCLS \[53\] we know that the consistent systems are precisely those without a leading 1 in the last column. Are the expressions in the last column of rows 5 and 6 equal to zero, or are they leading 1’s? The answer is: maybe. It depends on \( \mathbf{b} \). With a nonzero value for either of these expressions, we would scale the row and produce a leading 1. So we get a consistent system, and \( \mathbf{b} \) is in the column space, if and only if these two expressions are both simultaneously zero. In other words, members of the column space of \( A \) are exactly those vectors \( \mathbf{b} \) that satisfy

\[
\begin{align*}
    b_1 + 3b_3 - b_4 + 3b_5 + b_6 &= 0 \\
    b_2 - 2b_3 + b_4 + b_5 - b_6 &= 0
\end{align*}
\]

Hmmm. Looks suspiciously like a homogeneous system of two equations with six variables. If you’ve been playing along (and we hope you have) then you may have a slightly different system, but you should have just two equations. Form the coefficient matrix and row-reduce (notice that the system above has a coefficient matrix that is already in reduced row-echelon form). We should all be together now with the same matrix,

\[
L = \begin{bmatrix}
1 & 0 & 3 & -1 & 3 & 1 \\
0 & 1 & -2 & 1 & 1 & -1
\end{bmatrix}
\]

So, \( \mathcal{C}(A) = \mathcal{N}(L) \) and we can apply Theorem BNS \[141\] to obtain a linearly independent set to use in a span construction,

\[
\mathcal{C}(A) = \mathcal{N}(L) = \mathcal{S}\left(\begin{bmatrix}
-3 & 1 & -3 & -1 \\
2 & -1 & 0 & 1 \\
1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 \\
0 & 0 & 0 & 1
\end{bmatrix}\right)
\]

Whew! As a postscript to this central example, you may wish to convince yourself that the four vectors above really are elements of the column space? Do they create consistent systems with \( A \) as coefficient matrix? Can you recognize the constant vector in your description of these solution sets?

OK, that was so much fun, let’s do it again. But simpler this time. And we’ll all get the same results all the way through. Doing row operations by hand with variables can be a bit error prone, so let’s see if we can improve the process some. Rather than row-reduce a column vector \( \mathbf{b} \) full of variables, let’s write \( \mathbf{b} = I_6 \mathbf{b} \) and we will row-reduce the matrix \( I_6 \) and when we finish row-reducing, then we will compute the matrix-vector product. You should first convince yourself that we can operate like this (see Exercise xx \[??\] on commuting operations). Rather than augmenting \( A \) with \( \mathbf{b} \), we will instead augment it...
with $I_6$ (does this feel familiar?),

$$M = \begin{bmatrix} 10 & 0 & 3 & 8 & 7 & 1 & 0 & 0 & 0 & 0 & 0 \\ -16 & -1 & -4 & -10 & -13 & 0 & 1 & 0 & 0 & 0 & 0 \\ -6 & 1 & -3 & -6 & -6 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 2 & -2 & -3 & -2 & 0 & 0 & 0 & 1 & 0 & 0 \\ 3 & 0 & 1 & 2 & 3 & 0 & 0 & 0 & 0 & 1 & 0 \\ -1 & -1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

We want to row-reduce the left-hand side of this matrix, but we will apply the same row operations to the right-hand side as well. And once we get the left-hand side in reduced row-echelon form, we will continue on to put leading 1’s in the final two rows, as well as clearing out the columns containing those two additional leading 1’s. It is these additional row operations that will ensure that we all get to the same place, since the reduced row-echelon form is unique (Theorem RREFU [112]),

$$N = \begin{bmatrix} 1 & 0 & 0 & 0 & 2 & 0 & 0 & 1 & -1 & 2 & -1 \\ 0 & 1 & 0 & 0 & -3 & 0 & 0 & -2 & 3 & -3 & 3 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 3 & 3 \\ 0 & 0 & 0 & 1 & -2 & 0 & 0 & -2 & 1 & -4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 3 & -1 & 3 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -2 & 1 & 1 & -1 \end{bmatrix}$$

We are after the final six columns of this matrix, which we will multiply by $b$

$$J = \begin{bmatrix} 0 & 0 & 1 & -1 & 2 & -1 \\ 0 & 0 & -2 & 3 & -3 & 3 \\ 0 & 0 & 1 & 1 & 3 & 3 \\ 0 & 0 & -2 & 1 & -4 & 0 \\ 1 & 0 & 3 & -1 & 3 & 1 \\ 0 & 1 & -2 & 1 & 1 & -1 \end{bmatrix}$$

so

$$Jb = \begin{bmatrix} 0 & 0 & 1 & -1 & 2 & -1 \\ 0 & 0 & -2 & 3 & -3 & 3 \\ 0 & 0 & 1 & 1 & 3 & 3 \\ 0 & 0 & -2 & 1 & -4 & 0 \\ 1 & 0 & 3 & -1 & 3 & 1 \\ 0 & 1 & -2 & 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \\ b_6 \end{bmatrix} = \begin{bmatrix} b_3 - b_4 + 2b_5 - b_6 \\ -2b_3 + 3b_4 - 3b_5 + 3b_6 \\ b_3 + b_4 + 3b_5 + 3b_6 \\ -2b_3 + b_4 - 4b_5 \\ b_1 + 3b_3 - b_4 + 3b_5 + b_6 \\ b_2 - 2b_3 + b_4 + b_5 - b_6 \end{bmatrix}$$

So by applying to the identity matrix the same row operations that row-reduce $A$ (which we could do with a calculator once $I_6$ is placed alongside of $A$), we can then arrive at the result of row-reducing a column of symbols where the vector of constants usually resides. Since the row-reduced version of $A$ has two zero rows, for a consistent system we require that

$$b_1 + 3b_3 - b_4 + 3b_5 + b_6 = 0$$
$$b_2 - 2b_3 + b_4 + b_5 - b_6 = 0$$

Now we are exactly back where we were on the first go-round. Notice that we obtain the matrix $L$ as simply the last two rows and last six columns of $N$. ☞
This example motivates the remainder of this section, so it is worth careful study. You
might attempt to mimic the second approach with the coefficient matrices of [Archetype I][599]
and [Archetype J][604]. We will see shortly that the matrix $L$ contains more information
about $A$ than just the column space.

### Subsection EEF
Extended echelon form

The final matrix that we row-reduced in [Example CSANS][256] should look familiar in
most respects to the procedure we used to compute the inverse of a nonsingular matrix,
[Theorem CINSM][213]. We will now generalize that procedure to matrices that are not
necessarily nonsingular, or even square. First a definition.

#### Definition EEF
Extended Echelon Form
Suppose $A$ is an $m \times n$ matrix. Add $n$ new columns to $A$ that together equal an $m \times m$
identity matrix to form an $m \times (n + m)$ matrix $M$. Use row operations to bring $M$ to
reduced row-echelon form and call the result $N$. $N$ is the **extended reduced row-
echelon form** of $A$, and we will standardize on names for five submatrices ($B, C, J, K, L$) of $N$.

Let $B$ denote the $m \times n$ matrix formed from the first $n$ columns of $N$ and let $J$ denote
the $m \times m$ matrix formed from the last $m$ columns of $N$. Suppose that $B$ has $r$ nonzero
rows. Further partition $N$ by letting $C$ denote the $r \times n$ matrix formed from all of the
non-zero rows of $B$. Let $K$ be the $r \times m$ matrix formed from the first $r$ rows of $J$, while
$L$ will be the $(m - r) \times m$ matrix formed from the bottom $m - r$ rows of $J$. Pictorially,

$$M = [A|I_m] \xrightarrow{\text{RREF}} N = [B|J] = \begin{bmatrix} C & K \\ 0 & L \end{bmatrix}$$

#### Example SEEF
Submatrices of extended echelon form
We illustrate [Definition EEF][259] with the matrix $A$,

$$A = \begin{bmatrix} 1 & -1 & -2 & 7 & 1 & 6 \\ -6 & 2 & -4 & -18 & -3 & -26 \\ 4 & -1 & 4 & 10 & 2 & 17 \\ 3 & -1 & 2 & 9 & 1 & 12 \end{bmatrix}$$

Augmenting with the $4 \times 4$ identity matrix, $M =

$$\begin{bmatrix} 1 & -1 & -2 & 7 & 1 & 6 & 1 & 0 & 0 & 0 \\ -6 & 2 & -4 & -18 & -3 & -26 & 0 & 1 & 0 & 0 \\ 4 & -1 & 4 & 10 & 2 & 17 & 0 & 0 & 1 & 0 \\ 3 & -1 & 2 & 9 & 1 & 12 & 0 & 0 & 0 & 1 \end{bmatrix}$$

and row-reducing, we obtain

$$N = \begin{bmatrix} 1 & 0 & 2 & 1 & 0 & 3 & 0 & 1 & 1 & 1 \\ 0 & 1 & 4 & -6 & 0 & -1 & 0 & 2 & 3 & 0 \\ 0 & 0 & 0 & 0 & 1 & 2 & 0 & -1 & 0 & -2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 2 & 2 & 1 \end{bmatrix}$$
So we then obtain

\[
B = \begin{bmatrix}
1 & 0 & 2 & 1 & 0 & 3 \\
0 & 1 & 4 & -6 & 0 & -1 \\
0 & 0 & 0 & 0 & 1 & 2 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

\[
C = \begin{bmatrix}
1 & 0 & 2 & 1 & 0 & 3 \\
0 & 1 & 4 & -6 & 0 & -1 \\
0 & 0 & 0 & 0 & 1 & 2
\end{bmatrix}
\]

\[
J = \begin{bmatrix}
0 & 1 & 1 & 1 \\
0 & 2 & 3 & 0 \\
0 & -1 & 0 & -2 \\
1 & 2 & 2 & 1
\end{bmatrix}
\]

\[
K = \begin{bmatrix}
0 & 1 & 1 & 1 \\
0 & 2 & 3 & 0 \\
0 & -1 & 0 & -2
\end{bmatrix}
\]

\[
L = \begin{bmatrix}
1 & 2 & 2 & 1
\end{bmatrix}
\]

You can observe (or verify) the properties of the following theorem with this example. ⊓⊔

**Theorem PEEF**

**Properties of Extended Echelon Form**

Suppose that \( A \) is an \( m \times n \) matrix and that \( N \) is its extended echelon form. Then

1. \( J \) is nonsingular.
2. \( B = JA \).
3. If \( x \in \mathbb{C}^n \) and \( y \in \mathbb{C}^m \), then \( Ax = y \) if and only if \( Bx = Jy \).
4. \( C \) is in reduced row-echelon form, has no zero rows and has \( r \) pivot columns.
5. \( L \) is in reduced row-echelon form, has no zero rows and has \( m - r \) pivot columns. ⊐

**Proof** \( J \) is the result of applying a sequence of row operations to \( I_m \), as such \( J \) and \( I_m \) are row-equivalent. \( LS(I_m, 0) \) has only the zero solution, since \( I_m \) is nonsingular (Theorem NSRRI [77]). Thus, \( LS(J, 0) \) also has only the zero solution (Theorem REMES [32], Definition ES [16]) and \( J \) is therefore nonsingular (Definition NSM [68]).

To prove the second part of this conclusion, first convince yourself that row operations and the matrix-vector are commutative operations. By this we mean the following. Suppose that \( F \) is an \( m \times n \) matrix that is row-equivalent to the matrix \( G \). Apply to the column vector \( Fw \) the same sequence of row operations that converts \( F \) to \( G \). Then the result is \( Gw \). So we can do row operations on the matrix, then do a matrix-vector product, or do a matrix-vector product and then do row operations on a column vector, and the result will be the same either way. Since matrix multiplication is defined by a collection of matrix-vector products (), if we apply to the matrix product \( FH \) the same sequence of row operations that converts \( F \) to \( G \) then the result will equal \( GH \). Now apply these observations to \( A \).
Write $AI_n = I_mA$ and apply the row operations that convert $M$ to $N$. $A$ is converted to $B$, while $I_m$ is converted to $J$, so we have $BI_n = JA$. Simplifying the left side gives the desired conclusion.

For the third conclusion, we now establish the two equivalences

$$Ax = y \iff JAx = Jy \iff Bx = Jy$$

The forward direction of the first equivalence is accomplished by multiplying both sides of the matrix equality by $J$, while the backward direction is accomplished by multiplying by the inverse of $J$ (which we know exists by Theorem NSI [225] since $J$ is nonsingular). The second equivalence is obtained simply by the substitutions given by $JA = B$.

The first $r$ rows of $N$ are in reduced row-echelon form, since any contiguous collection of rows taken from a matrix in reduced row-echelon form will form a matrix that is again in reduced row-echelon form. Since the matrix $C$ is formed by removing the last $n$ entries of each of these rows, the remainder is still in reduced row-echelon form. By its construction, $C$ has no zero rows. $C$ has $r$ rows and each contains a leading 1, so there are $r$ pivot columns in $C$.

The final $n - r$ rows of $N$ are in reduced row-echelon form, since any contiguous collection of rows taken from a matrix in reduced row-echelon form will form a matrix that is again in reduced row-echelon form. Since the matrix $L$ is formed by removing the first $n$ entries of each of these rows, and these entries are all zero (they form the zero rows of $B$), the remainder is still in reduced row-echelon form. $L$ is the final $n - r$ rows of the nonsingular matrix $J$, so none of these rows can be totally zero, or $J$ would not row-reduce to the identity matrix. $L$ has $m - r$ rows and each contains a leading 1, so there are $m - r$ pivot columns in $L$.

Notice that in the case where $A$ is a nonsingular matrix we know that the reduced row-echelon form of $A$ is the identity matrix (Theorem NSRRI [77]), so $B = I_n$. Then the second conclusion above says $JA = B = I_n$, so $J$ is the inverse of $A$. Thus this theorem generalizes Theorem CINSM [213], though the result is a “left-inverse” of $A$ rather than a “right-inverse.”

The third conclusion of Theorem PEEF [260] is the most telling. It says that $x$ is a solution to the linear system $LS(A, y)$ if and only if $x$ is a solution to the linear system $LS(B, Jy)$. Or said differently, if we row-reduce the augmented matrix $[A \vert x]$ we will get the augmented matrix $[B \vert Jy]$. The matrix $J$ tracks the cumulative effect of the row operations that converts $A$ to reduced row-echelon form, here effectively applying them to the vector of constants in a system of equations having $A$ as a coefficient matrix. When $A$ row-reduces to a matrix with zero rows, then $Jy$ should also have zero entries in the same rows if the system is to be consistent.

**Subsection FS**

**Four Subsets**

With all the preliminaries in place we can state our main result for this section. In essence this result will allow us to say that we can find linearly independent sets to use in span constructions for all four subsets (null space, column space, row space, left null space) by analyzing only the extended echelon form of the matrix, and specifically, just
the two submatrices $C$ and $L$, which will be ripe for analysis since they are already in reduced row-echelon form (Theorem PEEF [260]).

**Theorem FS**

**Four Subsets**

Suppose $A$ is an $m \times n$ matrix with extended echelon form $N$. Suppose the reduced row-echelon form of $A$ has $r$ nonzero rows. Then $C$ is the submatrix of $N$ formed from the first $r$ rows and the first $n$ columns and $L$ is the submatrix of $N$ formed from the last $m$ columns and the last $m - r$ rows. Then

1. The null space of $A$ is the null space of $C$, $\mathcal{N}(A) = \mathcal{N}(C)$.
2. The row space of $A$ is the row space of $C$, $\mathcal{R}(A) = \mathcal{R}(C)$.
3. The column space of $A$ is the null space of $L$, $\mathcal{C}(A) = \mathcal{N}(L)$.
4. The left null space of $A$ is the row space of $L$, $\mathcal{L}(A) = \mathcal{R}(L)$. □

**Proof** TO DO

The first two conclusions of this theorem are nearly trivial. But they set up a pattern of results for $C$ that is reflected in the latter two conclusions about $L$. In total, they tell us that we can compute all four subsets just by finding null spaces and row spaces of matrices already in reduced row-echelon form ($C$ and $L$). A linearly independent set that spans the null space of a matrix in reduced row-echelon form can be found easily with Theorem BNS [141]. It is an even easier matter to find a linearly independent set that spans the row space of a matrix in reduced row-echelon form with Theorem BRS [245], especially when there are no zero rows present.

The properties of the matrix $L$ described by this theorem can be explained informally as follows. A column vector $\mathbf{y} \in \mathbb{C}^m$ is in the column space of $A$ if the linear system $\mathcal{L}S(A, \mathbf{y})$ is consistent (Theorem CSCS [236]). By Theorem RCLS [53], the reduced row-echelon form of the augmented matrix $[A | \mathbf{y}]$ of a consistent system will have zeros in the bottom $m - r$ locations of the last column. By Theorem PEEF [260] this final column is the vector $J\mathbf{y}$ and so should then have zeros in the final $m - r$ locations. But since $L$ comprises the final $m - r$ rows of $J$, this condition is expressed by saying $\mathbf{y} \in \mathcal{N}(L)$.

Additionally, the rows of $J$ are the scalars in linear combinations of the rows of $A$ that create the rows of $B$. That is, the rows of $J$ record the net effect of the sequence of row operations that takes $A$ to its reduced row-echelon form, $B$. This can be seen in the equation $JA = B$ (Theorem PEEF [260]). As such, the rows of $L$ are scalars for linear combinations of the rows of $A$ that yield zero rows. But such linear combinations are precisely the elements of the left null space. So any element of the row space of $L$ is also an element of the left null space of $A$. We will now illustrate Theorem FS [262] with a few examples.

**Example FS1**

**Four subsets, #1**

In Example SEEF [259] we found the five relevant submatrices of the matrix

$$A = \begin{bmatrix}
1 & -1 & -2 & 7 & 1 & 6 \\
-6 & 2 & -4 & -18 & -3 & -26 \\
4 & -1 & 4 & 10 & 2 & 17 \\
3 & -1 & 2 & 9 & 1 & 12
\end{bmatrix}$$
To apply Theorem FS \[262\] we only need \(C\) and \(L\),
\[
C = \begin{bmatrix}
1 & 0 & 2 & 1 & 0 & 3 \\
0 & 1 & 4 & -6 & 0 & -1 \\
0 & 0 & 0 & 0 & 1 & 2
\end{bmatrix}
\]
\[
L = \begin{bmatrix}
1 & 2 & 2 & 1
\end{bmatrix}
\]

Then we use Theorem FS \[262\] to obtain
\[
\mathcal{N}(A) = \mathcal{N}(C) = \text{Sp} \begin{bmatrix}
-3 & 1 & 0 & -2 \\
-1 & 0 & 6 & 0 \\
0 & -2 & 0 & 0 \\
1 & 0 & 0 & 0
\end{bmatrix}
\]
\[
\mathcal{R}(A) = \mathcal{R}(C) = \text{Sp} \begin{bmatrix}
1 & 0 & 2 & 1 & 0 & 3 \\
0 & 1 & 4 & -6 & 0 & -1 \\
0 & 0 & 0 & 0 & 1 & 2 \\
\end{bmatrix}
\]
\[
\mathcal{C}(A) = \mathcal{N}(L) = \text{Sp} \begin{bmatrix}
-2 & 1 & 0 & -2 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix}
\]
\[
\mathcal{L}(A) = \mathcal{R}(L) = \text{Sp} \begin{bmatrix}
1 & 2 & 2 & 1
\end{bmatrix}
\]

Boom!

**Example FS2**

**Four subsets, #2**

Now let's return to the matrix \(A\) that we used to motivate this section in Example CSANS \[256\],
\[
A = \begin{bmatrix}
10 & 0 & 3 & 8 & 7 \\
-16 & -1 & -4 & -10 & -13 \\
-6 & 1 & -3 & -6 & -6 \\
0 & 2 & -2 & -3 & -2 \\
3 & 0 & 1 & 2 & 3 \\
-1 & -1 & 1 & 1 & 0
\end{bmatrix}
\]

We form the matrix \(M\) by adjoining the \(6 \times 6\) identity matrix \(I_6\),
\[
M = \begin{bmatrix}
10 & 0 & 3 & 8 & 7 & 1 & 0 & 0 & 0 & 0 & 0 \\
-16 & -1 & -4 & -10 & -13 & 0 & 1 & 0 & 0 & 0 & 0 \\
-6 & 1 & -3 & -6 & -6 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 2 & -2 & -3 & -2 & 0 & 0 & 0 & 1 & 0 & 0 \\
3 & 0 & 1 & 2 & 3 & 0 & 0 & 0 & 0 & 1 & 0 \\
-1 & -1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
\]
and row-reduce to obtain $N$

$$N = \begin{bmatrix}
1 & 0 & 0 & 0 & 2 & 0 & 0 & 1 & -1 & 2 & -1 \\
0 & 1 & 0 & 0 & -3 & 0 & 0 & -2 & 3 & -3 & 3 \\
0 & 0 & 1 & 0 & 0 & 1 & 1 & 3 & 3 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & -2 & 1 & -4 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & -2 & 1 & 1 & -1
\end{bmatrix}$$

To find the four subsets for $A$, we only need identify the $4 \times 5$ matrix $C$ and the $2 \times 6$ matrix $L$,

$$C = \begin{bmatrix}
1 & 0 & 0 & 0 & 2 \\
0 & 1 & 0 & 0 & -3 \\
0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix} \quad L = \begin{bmatrix}
1 & 0 & 3 & -1 & 3 & 1 \\
0 & 1 & -2 & 1 & 1 & -1
\end{bmatrix}$$

Then we apply **Theorem FS** 262,

$$\mathcal{N}(A) = \mathcal{N}(C) = \text{Sp} \left\{ \begin{bmatrix} -2 \\ 3 \\ -1 \\ 2 \\ 1 \end{bmatrix} \right\} \quad \text{Theorem BNS} \ 141$$

$$\mathcal{R}(A) = \mathcal{R}(C) = \text{Sp} \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\
0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -3 \\ 1 \\ -2 \end{bmatrix} \right\} \quad \text{Theorem BRS} \ 245$$

$$\mathcal{C}(A) = \mathcal{N}(L) = \text{Sp} \left\{ \begin{bmatrix} -3 \\ 2 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\
1 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\
0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\
0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \right\} \quad \text{Theorem BNS} \ 141$$

$$\mathcal{L}(A) = \mathcal{R}(L) = \text{Sp} \left\{ \begin{bmatrix} 1 \\ 0 \\ 3 \\ -1 \\ 3 \\ 1 \end{bmatrix} \right\} \quad \text{Theorem BRS} \ 245$$

The next example is just a bit different since the matrix has more rows than columns, and a trivial null space.

**Example FSAG**

**Four subsets, Archetype G**

Archetype G 590 and Archetype H 594 are both systems of $m = 5$ equations in $n = 2$
variables. They have identical coefficient matrices, which we will denote here as the matrix $G$,

$$G = \begin{bmatrix} 2 & 3 \\ -1 & 4 \\ 3 & 10 \\ 3 & -1 \\ 6 & 9 \end{bmatrix}.$$

Adjoin the $5 \times 5$ identity matrix, $I_5$, to form

$$M = \begin{bmatrix} 2 & 3 & 1 & 0 & 0 & 0 & 0 \\ -1 & 4 & 0 & 1 & 0 & 0 & 0 \\ 3 & 10 & 0 & 0 & 1 & 0 & 0 \\ 3 & -1 & 0 & 0 & 0 & 1 & 0 \\ 6 & 9 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

This row-reduces to

$$N = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \frac{3}{11} & \frac{1}{33} \\ 0 & 1 & 0 & 0 & 0 & -\frac{2}{11} & \frac{1}{11} \\ 0 & 0 & 1 & 0 & 0 & 0 & -\frac{1}{3} \\ 0 & 0 & 0 & 1 & 0 & 1 & -\frac{1}{3} \\ 0 & 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix}.$$

The first $n = 2$ columns contain $r = 2$ leading 1’s, so we obtain $C$ as the $2 \times 2$ identity matrix and extract $L$ from the final $m - r = 3$ rows in the final $m = 5$ columns.

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad L = \begin{bmatrix} 1 & 0 & 0 & 0 & -\frac{1}{3} \\ 0 & 1 & 0 & 1 & -\frac{1}{3} \\ 0 & 0 & 1 & 1 & -1 \end{bmatrix}.$$
Then we apply Theorem FS 262,

\[ N(G) = N(C) = S_p() = \{0\} \]

\[ R(G) = R(C) = S_p(\left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}) = \mathbb{C}^2 \]

\[ C(G) = N(L) = S_p(\left\{ \begin{bmatrix} 0 \\ -1 \\ -1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 1 \\ 0 \end{bmatrix} \right\}) \]

\[ L(G) = R(L) = S_p(\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ -\frac{1}{3} \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -\frac{1}{3} \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}) \]

As mentioned earlier, Archetype G 590 is consistent, while Archetype H 594 is inconsistent. See if you can write the two different vectors of constants from these two archetypes as linear combinations of the two vectors in \( C(G) \). How about the two columns of \( G \), can you write each individually as a linear combination of the two vectors in \( C(G) \)? They must be in the column space of \( G \) also. Are your answers unique? Do you notice anything about the scalars that appear in the linear combinations you are forming?

*** hw: on commuting operations ****
*** hw: take a basis vector for \( N(L) \), solve linear system with \( A \) and basis vector as constants, then constant vector is corresponding column of \( K \). ****
*** hw: Archetype G questions below ***

**Subsection READ**

**Reading Questions**

1. Find a nontrivial element of the left null space of \( A \).

\[ A = \begin{bmatrix} 2 & 1 & -3 & 4 \\ -1 & -1 & 2 & -1 \\ 0 & -1 & 1 & 2 \end{bmatrix} \]
2. Find the matrices $C$ and $L$ in the extended echelon form of $A$.

\[
A = \begin{bmatrix}
-9 & 5 & -3 \\
2 & -1 & 1 \\
-5 & 3 & -1 
\end{bmatrix}
\]

3. Why is Theorem FS 262 a great way to conclude Chapter M 179?
Subsection EXC Exercises

C41 The following archetypes are systems of equations. For each system, write the vector of constants as a linear combination of the vectors in the span construction for the column space provided by Theorem FS \[262\] and Theorem BNS \[141\] (these vectors are listed for each of these archetypes).

- Archetype A 563
- Archetype B 568
- Archetype C 573
- Archetype D 577
- Archetype E 581
- Archetype F 585
- Archetype G 590
- Archetype H 594
- Archetype I 599
- Archetype J 604

Contributed by Robert Beezer

C43 The following archetypes are either matrices or systems of equations with coefficient matrices. For each matrix, compute the extended echelon form \(N\) and identify the matrices \(C\) and \(L\). Using Theorem FS \[262\], Theorem BNS \[141\] and Theorem BRS \[245\] express the null space, the row space, the column space and left null space of each coefficient matrix as a span of a linearly independent set.

- Archetype A 563
- Archetype B 568
- Archetype C 573
- Archetype D 577
- Archetype E 581
- Archetype F 585
- Archetype G 590
- Archetype H 594
- Archetype I 599
- Archetype J 604
- Archetype K 609
- Archetype L 613

Contributed by Robert Beezer

C60 For the matrix \(B\) below, find sets of vectors whose span equals the column space of \(B\) \((\text{C}(B))\) and which individually meet the following extra requirements.

(a) The set illustrates the definition of the column space.
(b) The set is linearly independent and the members of the set are columns of \(B\).
(c) The set is linearly independent with a “nice pattern of zeros and ones” at the top of each vector.
(d) The set is linearly independent with a “nice pattern of zeros and ones” at the bottom.
of each vector.

\[ B = \begin{bmatrix}
2 & 3 & 1 & 1 \\
1 & 1 & 0 & 1 \\
-1 & 2 & 3 & -4
\end{bmatrix} \]

Contributed by Robert Beezer Solution [271]

**C61** Let \( A \) be the matrix below, and find the indicated sets with the requested properties.

\[ A = \begin{bmatrix}
2 & -1 & 5 & -3 \\
-5 & 3 & -12 & 7 \\
1 & 1 & 4 & -3
\end{bmatrix} \]

(a) A linearly independent set \( S \) so that \( \mathcal{C}(A) = \mathcal{S}p(S) \) and \( S \) is composed of columns of \( A \).

(b) A linearly independent set \( S \) so that \( \mathcal{C}(A) = \mathcal{S}p(S) \) and the vectors in \( S \) have a nice pattern of zeros and ones at the top of the vectors.

(c) A linearly independent set \( S \) so that \( \mathcal{C}(A) = \mathcal{S}p(S) \) and the vectors in \( S \) have a nice pattern of zeros and ones at the bottom of the vectors.

(d) A linearly independent set \( S \) so that \( \mathcal{R}(A) = \mathcal{S}p(S) \).

Contributed by Robert Beezer Solution [272]
Subsection SOL
Solutions

(a) The definition of the column space is the span of the set of columns (Definition CSM 235). So the desired set is just the four columns of $B$,

$$S = \left\{ \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ -4 \end{bmatrix} \right\}$$

(b) Theorem BCSOC 238 suggests row-reducing the matrix and using the columns of $B$ that correspond to the pivot columns.

$$B \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & -1 & 2 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

So the pivot columns are numbered by elements of $D = \{1, 2\}$, so the requested set is

$$S = \left\{ \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix} \right\}$$

(c) We can find this set by row-reducing the transpose of $B$, deleting the zero rows, and using the nonzero rows as column vectors in the set. This is an application of Theorem CSRST 246 followed by Theorem BRS 245.

$$B^t \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -7 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

So the requested set is

$$S = \left\{ \begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -7 \end{bmatrix} \right\}$$

(d) With the column space expressed as a null space, the vectors obtained via Theorem BNS 141 will be of the desired shape. So we first proceed with Theorem FS 262 and create the extended echelon form,

$$[B | I_3] = \begin{bmatrix} 2 & 3 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 \\ -1 & 2 & 3 & -4 & 0 & 1 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & -1 & 2 & 0 & \frac{2}{3} \\ 0 & 1 & 1 & -1 & 0 & \frac{1}{3} \\ 0 & 0 & 0 & 0 & 1 & \frac{-7}{3} \end{bmatrix}$$

So, employing Theorem FS 262, we have $C(B) = N(L)$, where

$$L = \begin{bmatrix} 1 & \frac{-7}{3} \\ \frac{-1}{3} \end{bmatrix}$$
We can find the desired set of vectors from Theorem BNS [141] as

\[
S = \left\{ \begin{bmatrix} \frac{7}{3} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{4}{3} \\ 0 \\ 1 \end{bmatrix} \right\}
\]

C61 Contributed by Robert Beezer Statement 270
(a) First find a matrix \( B \) that is row-equivalent to \( A \) and in reduced row-echelon form

\[
B = \begin{bmatrix} 1 & 0 & 3 & -2 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \end{bmatrix}
\]

By Theorem BCSOC [238] we can choose the columns of \( A \) that correspond to dependent variables \( D = \{1, 2\} \) as the elements of \( S \) and obtain the desired properties. So

\[
S = \left\{ \begin{bmatrix} 2 \\ -5 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 3 \end{bmatrix} \right\}
\]

(b) We can write the column space of \( A \) as the row space of the transpose (Theorem CSRST [246]). So we row-reduce the transpose of \( A \) to obtain the row-equivalent matrix \( C \) in reduced row-echelon form

\[
C = \begin{bmatrix} 1 & 0 & 8 \\ 0 & 1 & 3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

The nonzero rows (written as columns) will be a linearly independent set that spans the row space of \( A^t \), by Theorem BRS [245], and the zeros and ones will be at the top of the vectors,

\[
S = \left\{ \begin{bmatrix} 1 \\ 0 \\ 8 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} \right\}
\]

(c) In preparation for Theorem FS [262], augment \( A \) with the \( 3 \times 3 \) identity matrix \( I_3 \) and row-reduce to obtain the extended echelon form,

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 & \frac{1}{8} \\
0 & 1 & 1 & -1 & 0 & \frac{3}{8} \\
0 & 0 & 0 & 0 & 1 & \frac{1}{8}
\end{bmatrix}
\]

Then since the first four columns of row 3 are all zeros, we extract

\[
L = \begin{bmatrix} 1 & \frac{3}{8} & -\frac{1}{8} \end{bmatrix}
\]

Theorem FS [262] says that \( C(A) = \mathcal{N}(L) \). We can then use Theorem BNS [141] to construct the desired set \( S \), based on the free variables with indices in \( F = \{2, 3\} \) for the homogeneous system \( LS(L, 0) \), so

\[
S = \left\{ \begin{bmatrix} -\frac{3}{8} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{1}{8} \\ 0 \\ 1 \end{bmatrix} \right\}
\]
Notice that the zeros and ones are at the bottom of the vectors.
(d) This is a straightforward application of Theorem BRS [245]. Use the row-reduced matrix $B$ from part (a), grab the nonzero rows, and write them as column vectors,

$$S = \left\{ \begin{bmatrix} 1 \\ 0 \\ 3 \\ -2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ -1 \end{bmatrix} \right\}$$
We now have a computational toolkit in place and so we can now begin our study of linear algebra in a more theoretical style.

Linear algebra is the study of two fundamental objects, vector spaces and linear transformations (see Chapter LT [429]). Here we present an axiomatic definition of vector spaces, which will lead to an extra increment of abstraction. The power of mathematics is often derived from generalizing many different situations into one abstract formulation, and that is exactly what we will be doing now.

Subsection VS
Vector Spaces

Here is one of our two most important definitions.

Definition VS
Vector Space
Suppose that $V$ is a set upon which we have defined two operations: (1) vector addition, which combines two elements of $V$ and is denoted by “$+$”, and (2) scalar multiplication, which combines a complex number with an element of $V$ and is denoted by juxtaposition. Then $V$, along with the two operations, is a vector space if the following ten requirements (better known as “axioms”) are met.

1. AC Additive Closure
   If $u, v \in V$, then $u + v \in V$.

2. SC Scalar Closure
   If $\alpha \in \mathbb{C}$ and $u \in V$, then $\alpha u \in V$.

3. C Commutativity
   If $u, v \in V$, then $u + v = v + u$. 
4. **AA Additive Associativity**
   If \( u, v, w \in V \), then \( u + (v + w) = (u + v) + w \).

5. **Z Zero Vector**
   There is a vector, \( 0 \), called the **zero vector**, such that \( u + 0 = u \) for all \( u \in V \).

6. **AI Additive Inverses**
   If \( u \in V \), then there exists a vector \(-u \in V\) so that \( u + (-u) = 0 \).

7. **SMA Scalar Multiplication Associativity**
   If \( \alpha, \beta \in \mathbb{C} \) and \( u \in V \), then \( \alpha(\beta u) = (\alpha\beta)u \).

8. **DVA Distributivity across Vector Addition**
   If \( \alpha \in \mathbb{C} \) and \( u, v \in V \), then \( \alpha(u + v) = \alpha u + \alpha v \).

9. **DSA Distributivity across Scalar Addition**
   If \( \alpha, \beta \in \mathbb{C} \) and \( u \in V \), then \( (\alpha + \beta)u = \alpha u + \beta u \).

10. **O One**
    If \( u \in V \), then \( 1u = u \).

The objects in \( V \) are called **vectors**, no matter what else they might really be, simply by virtue of being elements of a vector space.

Now, there are several important observations to make. Many of these will be easier to understand on a second or third reading, and especially after carefully studying the examples in Subsection VS.EVS [277].

An **axiom** is often a “self-evident” truth. Something so fundamental that we all agree it is true and accept it without proof. Typically, it would be the logical underpinning that we would begin to build theorems upon. Here, the use is slightly different. The ten requirements in Definition VS [275] are the most basic properties of the objects relevant to a study of linear algebra, and all of our theorems will be built upon them, as we will begin to see in Subsection VS.VSP [282]. So we will refer to “the vector space axioms.”

After studying the remainder of this chapter, you might return here and remind yourself how all our forthcoming theorems and definitions rest on this foundation.

As we will see shortly, the objects in \( V \) can be anything, even though we will call them vectors. We have been working with vectors frequently, but we should stress here that these have so far just been **column** vectors — scalars arranged in a columnar list of fixed length. In a similar vein, you have used the symbol “+” for many years to represent the addition of numbers (scalars). We have extended its use to the addition of column vectors and to the addition of matrices, and now we are going to recycle it even further and let it denote vector addition in any possible vector space. So when describing a new vector space, we will have to define exactly what “+” is. Similar comments apply to scalar multiplication. Conversely, we can define our operations any way we like, so long as the ten axioms are fulfilled (see Example CVS [280]).

A vector space is composed of three objects, a set and two operations. However, we usually use the same symbol for both the set and the vector space itself. Do not let this convenience fool you into thinking the operations are secondary!

This discussion has either convinced you that we are really embarking on a new level of abstraction, or they have seemed cryptic, mysterious or nonsensical. In any case, let’s look at some concrete examples.
Subsection EVS  
Examples of Vector Spaces

Our aim in this subsection is to give you a storehouse of examples to work with, to become comfortable with the ten vector space axioms and to convince you that the multitude of examples justifies (at least initially) making such a broad definition as Definition VS [275]. Some our claims will be justified by reference to previous theorems, we will prove some facts from scratch, and we will do one non-trivial example completely. In other places, our usual thoroughness will be neglected, so grab paper and pencil and play along.

Example VSCV  
The vector space $\mathbb{C}^m$  
Set: $\mathbb{C}^m$, all column vectors of size $m$, Definition VSCV [87].  
Vector Addition: The “usual” addition, given in Definition CVA [89].  
Scalar Multiplication: The “usual” scalar multiplication, given in Definition CVSM [90].

Does this set with these operations fulfill the ten axioms? Yes. And by design all we need to do is quote Theorem VSPCV [92]. That was easy. ⊖

Example VSM  
The vector space of matrices, $M_{mn}$  
Set: $M_{mn}$, the set of all matrices of size $m \times n$ and entries from $\mathbb{C}$, Example VSM [277].  
Vector Addition: The “usual” addition, given in Definition MA [180].  
Scalar Multiplication: The “usual” scalar multiplication, given in Definition MSM [180].

Does this set with these operations fulfill the ten axioms? Yes. And all we need to do is quote Theorem VSPM [181]. Another easy one (by design). ⊖

So, the set of all matrices of a fixed size forms a vector space. That entitles us to call a matrix a vector, since a matrix is an element of a vector space. This could lead to some confusion, but it is not too great a danger. But it is worth comment.

The previous two examples may be less than satisfying. We made all the relevant definitions long ago. And the required verifications were all handled by quoting old theorems. However, it is important to consider these two examples first. We have been studying vectors and matrices carefully (Chapter V [87], Chapter M [179]), and both objects, along with their operations, have certain properties in common, as you may have noticed in comparing Theorem VSPCV [92] with Theorem VSPM [181]. Indeed, it is these two theorems that motivate us to formulate the abstract definition of a vector space, Definition VS [275]. Now, should we prove some general theorems about vector spaces (as we will shortly in Section VS.VSP [282]), we can instantly apply the conclusions to both $\mathbb{C}^m$ and $M_{mn}$. Notice how we have taken six definitions and two theorems and reduced them down to two examples. With greater generalization and abstraction our old ideas get downgraded in stature.

Let us look at some more examples, now considering some new vector spaces.

Example VSP  
The vector space of polynomials, $P_n$  
Set: $P_n$, the set of all polynomials of degree $n$ or less in the variable $x$ with coefficients...
from \( \mathbb{C} \).

Vector Addition:

\[
(a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n) + (b_0 + b_1 x + b_2 x^2 + \cdots + b_n x^n) =
(a_0 + b_0) + (a_1 + b_1)x + (a_2 + b_2)x^2 + \cdots + (a_n + b_n)x^n
\]

Scalar Multiplication:

\[
\alpha(a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n) = (\alpha a_0) + (\alpha a_1)x + (\alpha a_2)x^2 + \cdots + (\alpha a_n)x^n
\]

This set, with these operations, will fulfill the ten axioms, though we will not work all the details here. However, we will make a few comments and prove one of the axioms. First, the zero vector (Property Z [276]) is what you might expect, and you can check that it has the required property.

\[
0 = 0 + 0x + 0x^2 + \cdots + 0x^n
\]

The additive inverse (Property AI [276]) is also no surprise, though consider how we have chosen to write it.

\[
-(a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n) = (-a_0) + (-a_1)x + (-a_2)x^2 + \cdots + (-a_n)x^n
\]

Now let’s prove the associativity of vector addition (Property AA [276]). This is a bit tedious, though necessary. Throughout, the plus sign (“+”) does triple-duty. You might ask yourself what each plus sign represents as you work through this proof.

\[
u + (v + w) = (a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n) + ((b_0 + b_1 x + b_2 x^2 + \cdots + b_n x^n) + (c_0 + c_1 x + c_2 x^2 + \cdots + c_n x^n)
\]

\[
= (a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n) + ((b_0 + c_0) + (b_1 + c_1)x + (b_2 + c_2)x^2 + \cdots + (b_n + c_n)x^n)
\]

\[
= (a_0 + (b_0 + c_0)) + (a_1 + (b_1 + c_1))x + (a_2 + (b_2 + c_2))x^2 + \cdots + (a_n + (b_n + c_n))x^n
\]

\[
= ((a_0 + b_0) + c_0) + ((a_1 + b_1) + c_1)x + ((a_2 + b_2) + c_2)x^2 + \cdots + ((a_n + b_n) + c_n)x^n
\]

\[
= ((a_0 + b_0) + (a_1 + b_1)x + (a_2 + b_2)x^2 + \cdots + (a_n + b_n)x^n) + (c_0 + c_1 x + c_2 x^2 + \cdots + c_n x^n)
\]

\[
= ((a_0 + b_0) + (a_1 + b_1)x + (a_2 + b_2)x^2 + \cdots + (a_n + b_n)x^n) + (c_0 + c_1 x + c_2 x^2 + \cdots + c_n x^n)
\]

\[
= (u + v) + w
\]

Notice how it is the application of the associativity of the (old) addition of complex numbers in the middle of this chain of equalities that makes the whole proof happen. The remainder is successive applications of our (new) definition of vector (polynomial) addition. Proving the remainder of the ten axioms is similar in style, and tedious. You might try proving the commutativity of vector addition (Property C [275]), or one of the distributivity axioms (Property DVA [276], Property DSA [276]), or both.

Example VSIS

The vector space of infinite sequences

Set: \( \mathbb{C}^\infty = \{(c_0, c_1, c_2, c_3, \ldots) | c_i \in \mathbb{C}\} \).

Vector Addition: \((c_0, c_1, c_2, \ldots) + (d_0, d_1, d_2, \ldots) = (c_0 + d_0, c_1 + d_1, c_2 + d_2, \ldots)\).

Scalar Multiplication: \(\alpha(c_0, c_1, c_2, c_3, \ldots) = (\alpha c_0, \alpha c_1, \alpha c_2, \alpha c_3, \ldots)\).

This should remind you of the vector space \( \mathbb{C}^n \), though now our lists of scalars are written horizontally with commas as delimiters and they are allowed to be infinite in
Subsection VS.EVS  Examples of Vector Spaces  279

length. What does the zero vector look like (Property Z [276])? Additive inverses (Property AI [276])? Can you prove the associativity of vector addition (Property AA [276])?

Example VSF

The vector space of functions

Set:  \( F = \{ f \mid f : \mathbb{C} \rightarrow \mathbb{C} \} \).

Vector Addition:  \( f + g \) is the function defined by \( (f + g)(x) = f(x) + g(x) \).

Scalar Multiplication:  \( \alpha f \) is the function defined by \( (\alpha f)(x) = \alpha f(x) \).

So this is the set of all functions of one variable that take a complex number to a complex number. You might have studied functions of one variable that take a real number to a real number, and that might be a more natural set to study. But since we are allowing our scalars to be complex numbers, we need to expand the domain and range of our functions also. Study carefully how the definitions of the operation are made, and think about the different uses of “+” and juxtaposition. As an example of what is required when verifying that this is a vector space, consider that the zero vector (Property Z [276]) is the function \( z \) whose definition is \( z(x) = 0 \) for every input \( x \).

While vector spaces of functions are very important in mathematics and physics, we will not devote them much more attention.

Here’s a unique example.

Example VSS

The singleton vector space

Set:  \( Z = \{ z \} \).

Vector Addition:  \( z + z = z \).

Scalar Multiplication:  \( \alpha z = z \).

This should look pretty wild. First, just what is \( z \)? Column vector, matrix, polynomial, sequence, function? Mineral, plant, or animal? We aren’t saying! \( z \) just is. And we have definitions of vector addition and scalar multiplication that are sufficient for an occurrence of either that may come along.

Our only concern is if this set, along with the definitions of two operations, fulfills the ten axioms of Definition VS [275]. Let’s check associativity of vector addition (Property AA [276]). For all \( u, v, w \in Z \),

\[
\begin{align*}
  u + (v + w) &= z + (z + z) \\
  &= z + z \\
  &= z \\
  &= z + z \\
  &= (z + z) + z \\
  &= (u + v) + w
\end{align*}
\]

What is the zero vector in this vector space (Property Z [276])? With only one element in the set, we do not have much choice. Is \( z = 0 \)? It appears that \( z \) behaves like the zero vector should, so it gets the title. Maybe now the definition of this vector space does not seem so bizarre. It is a set whose only element is the element that behaves like the zero vector, so that lone element is the zero vector.
Perhaps some of the above definitions and verifications seem obvious or like splitting hairs, but the next example should convince you that they are necessary. We will study this one carefully. Ready? Check your preconceptions at the door.

**Example CVS**

The crazy vector space

Set: \( C = \{(x_1, x_2) \mid x_1, x_2 \in \mathbb{C} \} \).

Vector Addition: \((x_1, x_2) + (y_1, y_2) = (x_1 + y_1 + 1, x_2 + y_2 + 1)\).

Scalar Multiplication: \(\alpha(x_1, x_2) = (\alpha x_1 + \alpha - 1, \alpha x_2 + \alpha - 1)\).

Now, the first thing I hear you say is “You can’t do that!” And my response is, “Oh yes, I can!” I am free to define my set and my operations any way I please. They may not look natural, or even useful, but we will now verify that they provide us with another example of a vector space. And that is enough. If you are adventurous, you might try first checking some of the axioms yourself. What is the zero vector? Additive inverses? Can you prove associativity? Here we go.

**Property AC** [275]: The result of each operation is a pair of complex numbers, so these two closure axioms are fulfilled.

**Property C** [275]:

\[
\begin{align*}
\mathbf{u} + \mathbf{v} &= (x_1, x_2) + (y_1, y_2) = (x_1 + y_1 + 1, x_2 + y_2 + 1) \\
&= (y_1 + x_1 + 1, x_2 + y_2 + 1) = (y_1, y_2) + (x_1, x_2) \\
&= \mathbf{v} + \mathbf{u}
\end{align*}
\]

**Property AA** [276]:

\[
\begin{align*}
\mathbf{u} + (\mathbf{v} + \mathbf{w}) &= (x_1, x_2) + ((y_1, y_2) + (z_1, z_2)) \\
&= (x_1, x_2) + (y_1 + z_1 + 1, y_2 + z_2 + 1) \\
&= (x_1 + (y_1 + z_1 + 1) + 1, x_2 + (y_2 + z_2 + 1) + 1) \\
&= (x_1 + y_1 + z_1 + 2, x_2 + y_2 + z_2 + 2) \\
&= ((x_1 + y_1 + 1) + z_1 + 1, (x_2 + y_2 + 1) + z_2 + 1) \\
&= (x_1 + y_1 + 1, x_2 + y_2 + 1) + (z_1, z_2) \\
&= ((x_1, x_2) + (y_1, y_2)) + (z_1, z_2) \\
&= (\mathbf{u} + \mathbf{v}) + \mathbf{w}
\end{align*}
\]

**Property Z** [276]: The zero vector is \( \mathbf{0} = (-1, -1) \). Now I hear you say, “No, no, that can’t be, it must be \((0, 0)\)”! Indulge me for a moment and let us check my proposal.

\[
\mathbf{u} + \mathbf{0} = (x_1, x_2) + (-1, -1) = (x_1 + (-1) + 1, x_2 + (-1) + 1) = (x_1, x_2) = \mathbf{u}
\]

Feeling better? Or worse?

**Property AI** [276]: For each vector, \( \mathbf{u} \), we must locate an additive inverse, \( -\mathbf{u} \). Here it is, \(-x_1, x_2\) = \((-x_1 - 2, -x_2 - 2)\). As odd as it may look, I hope you are withholding judgment. Check:

\[
\mathbf{u} + (-\mathbf{u}) = (x_1, x_2) + (-x_1 - 2, -x_2 - 2) = (x_1 + (-x_1 - 2) + 1, -x_2 + (x_2 - 2) + 1) = (-1, -1) = \mathbf{0}
\]
Property SMA [276]:

\[
\alpha(\beta u) = \alpha(\beta(x_1, x_2)) \\
= \alpha(\beta x_1 + \beta - 1, \beta x_2 + \beta - 1) \\
= (\alpha(\beta x_1 + \beta - 1) + 1, \alpha(\beta x_2 + \beta - 1) + 1) \\
= ((\alpha \beta x_1 + \alpha \beta - \alpha) + 1, (\alpha \beta x_2 + \alpha \beta - \alpha) + 1) \\
= (\alpha \beta x_1 + \alpha \beta - 1, \alpha \beta x_2 + \alpha \beta - 1) \\
= (\alpha \beta)(x_1, x_2) \\
= (\alpha \beta)u
\]

Property DVA [276]: If you have hung on so far, here’s where it gets even wilder. In the next two axioms we mix and mash the two operations.

\[
\alpha(u + v) = \alpha ((x_1, x_2) + (y_1, y_2)) \\
= \alpha (x_1 + y_1 + 1, x_2 + y_2 + 1) \\
= (\alpha x_1 + \alpha y_1 + \alpha + 1, \alpha x_2 + \alpha y_2 + \alpha + 1) \\
= ((\alpha x_1 + \alpha y_1 + \alpha + 1) + 1, (\alpha x_2 + \alpha y_2 + \alpha + 1) + 1) \\
= (\alpha x_1 + \alpha y_1 + \alpha + 1, \alpha x_2 + \alpha y_2 + \alpha + 1) \\
= \alpha (x_1, x_2) + \alpha (y_1, y_2) \\
= \alpha u + \alpha v
\]

Property DSA [276]:

\[
(\alpha + \beta) u = (\alpha + \beta) (x_1, x_2) \\
= ((\alpha + \beta) x_1 + (\alpha + \beta) - 1, (\alpha + \beta) x_2 + (\alpha + \beta) - 1) \\
= (\alpha x_1 + \beta x_1 + \alpha + \beta - 1, \alpha x_2 + \beta x_2 + \alpha + \beta - 1) \\
= (\alpha x_1 + \alpha - 1 + \beta x_1 + \beta - 1 + 1, \alpha x_2 + \alpha - 1 + \beta x_2 + \beta - 1 + 1) \\
= ((\alpha x_1 + \alpha - 1) + (\beta x_1 + \beta - 1) + 1, (\alpha x_2 + \alpha - 1) + (\beta x_2 + \beta - 1) + 1) \\
= (\alpha x_1 + \alpha - 1, \alpha x_2 + \alpha - 1) + (\beta x_1 + \beta - 1, \beta x_2 + \beta - 1) \\
= \alpha (x_1, x_2) + \beta (x_1, x_2) \\
= \alpha u + \beta u
\]

Property O [276]: After all that, this one is easy, but no less pleasing.

\[
1u = 1(x_1, x_2) = (x_1 + 1 - 1, x_2 + 1 - 1) = (x_1, x_2) = u
\]

That’s it, \( C \) is a vector space, as crazy as that may seem.

Notice that in the case of the zero vector and additive inverses, we only had to propose possibilities and then verify that they were the correct choices. You might try to discover how you would arrive at these choices, though you should understand why the process of discovering them is not a necessary component of the proof itself.
Subsection VSP
Vector Space Properties

Subsection VS.EVS has provided us with an abundance of examples of vector spaces, most of them containing useful and interesting mathematical objects along with natural operations. In this subsection we will prove some general properties of vector spaces. Some of these results will again seem obvious, but it is important to understand why it is necessary to state and prove them. A typical hypothesis will be “Let $V$ be a vector space.” From this we may assume the ten axioms, and nothing more. Its like starting over, as we learn about what can happen in this new algebra we are learning. But the power of this careful approach is that we can apply these theorems to any vector space we encounter, those in the previous examples, or new ones we have not contemplated. Or perhaps new ones that nobody has ever contemplated. We will illustrate some of these results with examples from the crazy vector space (Example CVS), but mostly we are stating theorems and doing proofs. These proofs do not get too involved, but are not trivial either, so these are good theorems to try proving yourself before you study the proof given here. (See Technique P.)

First we show that there is just one zero vector. Notice that the axioms only require there to be one, and say nothing about there being more. That is because we can use the axioms to learn that there can never be more than one. To require that this extra condition be stated in the axioms would make them more complicated than they need to be.

Theorem ZVU
Zero Vector is Unique
Suppose that $V$ is a vector space. The zero vector, $0$, is unique. □

Proof To prove uniqueness, a standard technique is to suppose the existence of two objects (Technique U). So let $0_1$ and $0_2$ be two zero vectors in $V$. Then

$$0_1 = 0_1 + 0_2 = 0_2$$

Notice that we have implicitly used the commutativity of vector addition so that we can apply the defining property of a zero vector on either side of the addition. This proves the uniqueness since the two zero vectors are really the same. □

Theorem AIU
Additive Inverses are Unique
Suppose that $V$ is a vector space. For each $u \in V$, the additive inverse, $-u$, is unique. □

Proof To prove uniqueness, a standard technique is to suppose the existence of two objects (Technique U). So let $-u_1$ and $-u_2$ be two additive inverses for $u$. Then

$$-u_1 = -u_1 + 0 = -u_1 + (u + -u_2) = (-u_1 + u) + -u_2 = 0 + -u_2 = -u_2$$
So the two additive inverses are really the same.

As obvious as the next theorem appears, it is not guaranteed that the zero scalar, scalar multiplication and the zero vector all interact this way. Until we have proved it, anyway.

**Theorem ZSSM**

**Zero Scalar in Scalar Multiplication**

Suppose that $V$ is a vector space and $u \in V$. Then $0u = 0$. □

**Proof** Notice that $0$ is a scalar, $u$ is a vector, so Property SC \[275\] says $0u$ is again a vector. As such, $0u$ has an additive inverse, $-(0u)$ by Property AI \[276\].

\[
0u = 0 + 0u \\
= (-0u) + 0u \\
= -0u + (0 + 0u) \\
= -(0u) + (0 + 0) \\
= -(0u) + 0u \\
= 0
\]

Here’s another theorem that *looks* like it should be obvious, but is still in need of a proof.

**Theorem ZVSM**

**Zero Vector in Scalar Multiplication**

Suppose that $V$ is a vector space and $\alpha \in \mathbb{C}$. Then $\alpha 0 = 0$. □

**Proof** Notice that $\alpha$ is a scalar, $0$ is a vector, so Property SC \[275\] means $\alpha 0$ is again a vector. As such, $\alpha 0$ has an additive inverse, $-(\alpha 0)$ by Property AI \[276\].

\[
\alpha 0 = 0 + \alpha 0 \\
= (-\alpha 0) + \alpha 0 \\
= -(\alpha 0) + (\alpha 0 + \alpha 0) \\
= -(\alpha 0) + \alpha (0 + 0) \\
= -(\alpha 0) + \alpha 0 \\
= 0
\]

Here’s another one that sure looks obvious. But understand that we have chosen to use certain notation because it makes the theorem’s conclusion look so nice. The theorem is not true because the notation looks so good, it still needs a proof. If we had really wanted to make this point, we might have defined the additive inverse of $u$ as $u^\sharp$. Then we would have written the defining property, Property AI \[276\], as $u + u^\sharp = 0$. This theorem would become $u^\sharp = (-1)u$. Not really quite as pretty, is it?

**Theorem AISM**

**Additive Inverses from Scalar Multiplication**

Suppose that $V$ is a vector space and $u \in V$. Then $-u = (-1)u$. □
Proof

\[-u = -u + 0 \quad \text{Property Z} \quad 276\]
\[= -u + 0u \quad \text{Theorem ZSSM} \quad 283\]
\[= -u + (1 + (-1))u \quad \text{Property DSA} \quad 276\]
\[= -u + (1u + (-1)u) \quad \text{Property O} \quad 276\]
\[= -u + (u + (-1)u) \quad \text{Property AA} \quad 276\]
\[= (-u + u) + (-1)u \quad \text{Property AI} \quad 276\]
\[= 0 + (-1)u \quad \text{Property Z} \quad 276\]
\[= (-1)u \quad \text{Property Z} \quad 276\]

Because of this theorem, we can now write linear combinations like \(6u_1 + (-4)u_2\) as \(6u_1 - 4u_2\), even though we have not formally defined an operation called vector subtraction.

Example PCVS
Properties for the Crazy Vector Space

Several of the above theorems have interesting demonstrations when applied to the crazy vector space, \(C\) (Example CVS 280). We are not proving anything new here, or learning anything we did not know already about \(C\). It is just plain fun to see how these general theorems apply in a specific instance. For most of our examples, the applications are obvious or trivial, but not with \(C\).

Suppose \(u \in C\).
Then by Theorem ZSSM 283,
\[0u = 0(x_1, x_2) = (0x_1 + 0 - 1, 0x_2 + 0 - 1) = (-1, -1) = 0\]

By Theorem ZVSM 283,
\[\alpha 0 = \alpha(-1, -1) = (\alpha(-1) + \alpha(-1), \alpha(-1) + \alpha(-1)) = (-\alpha + \alpha - 1, -\alpha + \alpha - 1) = (-1, -1)\]

By Theorem AISM 283,
\[(-1)u = (-1)(x_1, x_2) = ((-1)x_1 + (-1) - 1, (-1)x_2 + (-1) - 1) = (-x_1 - 2, -x_2 - 2) = -u\]

Our next theorem is a bit different from several of the others in the list. Rather than making a declaration (“the zero vector is unique”) it is an implication (“if…, then…”) and so can be used in proofs to move from one statement to another.

Theorem SMEZV
Scalar Multiplication Equals the Zero Vector

Suppose that \(V\) is a vector space and \(\alpha \in \mathbb{C}\). Then if \(\alpha u = 0\), then either \(\alpha = 0\) or \(u = 0\) (or both).

Proof We prove this theorem by breaking up the analysis into two cases. The first seems too trivial, and it is, but the logic of the argument is still legitimate.

Case 1. Suppose \(\alpha = 0\). In this case our conclusion is true (the first part of the either/or is true) and we are done. That was easy.
Case 2. Suppose \( \alpha \neq 0 \).

\[
\begin{align*}
\mathbf{u} &= 1\mathbf{u} & & \text{Property O 276} \\
&= \left( \frac{1}{\alpha} \right) \mathbf{u} & & \alpha \neq 0 \\
&= \frac{1}{\alpha} (\alpha \mathbf{u}) & & \text{Property SMA 276} \\
&= \frac{1}{\alpha} (0) & & \text{Hypothesis} \\
&= 0 & & \text{Theorem ZVSM 283}
\end{align*}
\]

So in this case, the conclusion is true (the second part of the either/or is true) and we are done since the conclusion was true in each of the cases. □

The next three theorems give us cancellation properties. The two concerned with scalar multiplication are intimately connected with [Theorem SMEZV 284]. All three are implications. So we will prove each once, here and now, and then we can apply them at will in the future, saving several steps in a proof whenever we do.

**Theorem VAC**

**Vector Addition Cancellation**

Suppose that \( V \) is a vector space, and \( \mathbf{u}, \mathbf{v}, \mathbf{w} \in V \). If \( \mathbf{w} + \mathbf{u} = \mathbf{w} + \mathbf{v} \), then \( \mathbf{u} = \mathbf{v} \). □

**Proof**

\[
\begin{align*}
\mathbf{u} &= 0 + \mathbf{u} & & \text{Property Z 276} \\
&= (-\mathbf{w} + \mathbf{w}) + \mathbf{u} & & \text{Property AI 276} \\
&= -\mathbf{w} + (\mathbf{w} + \mathbf{u}) & & \text{Property AA 276} \\
&= -\mathbf{w} + (\mathbf{w} + \mathbf{v}) & & \text{Hypothesis} \\
&= (-\mathbf{w} + \mathbf{w}) + \mathbf{v} & & \text{Property AA 276} \\
&= 0 + \mathbf{v} & & \text{Property AI 276} \\
&= \mathbf{v} & & \text{Property Z 276}
\end{align*}
\]

**Theorem CSSM**

**Canceling Scalars in Scalar Multiplication**

Suppose \( V \) is a vector space, \( \mathbf{u}, \mathbf{v} \in V \) and \( \alpha \) is a nonzero scalar from \( \mathbb{C} \). If \( \alpha \mathbf{u} = \alpha \mathbf{v} \), then \( \mathbf{u} = \mathbf{v} \). □

**Proof**

\[
\begin{align*}
\mathbf{u} &= 1\mathbf{u} & & \text{Property O 276} \\
&= \left( \frac{1}{\alpha} \right) \mathbf{u} & & \alpha \neq 0 \\
&= \frac{1}{\alpha} (\alpha \mathbf{u}) & & \text{Property SMA 276} \\
&= \frac{1}{\alpha} (\alpha \mathbf{v}) & & \text{Hypothesis} \\
&= \left( \frac{1}{\alpha} \right) \mathbf{v} & & \text{Property SMA 276} \\
&= 1\mathbf{v} & & \text{Property O 276} \\
&= \mathbf{v} & & \text{Property O 276}
\end{align*}
\]
Theorem CVSM
Canceling Vectors in Scalar Multiplication
Suppose $V$ is a vector space, $u \neq 0$ is a vector in $V$ and $\alpha, \beta \in \mathbb{C}$. If $\alpha u = \beta u$, then $\alpha = \beta$. □

Proof
\[
0 = \alpha u + - (\alpha u) \quad \text{Property AI 276}
\]
\[
= \beta u + - (\alpha u) \quad \text{Hypothesis}
\]
\[
= \beta u + (-1)(\alpha u) \quad \text{Theorem AISM 283}
\]
\[
= \beta u + ((-1)\alpha)u \quad \text{Property SMA 276}
\]
\[
= \beta u + (-\alpha)u \quad \text{Property DSA 276}
\]
\[
= (\beta - \alpha)u
\]
By hypothesis, $u \neq 0$, so Theorem SMEZV 284 implies

\[
0 = \beta - \alpha
\]
\[
\alpha = \beta
\]

So with these three theorems in hand, we can return to our practice of “slashing” out parts of an equation, so long as we are careful about not canceling a scalar that might possibly be zero, or canceling a vector in a scalar multiplication that might be the zero vector.

Subsection RD
Recycling Definitions

When we say that $V$ is a vector space, we know we have a set of objects, but we also know we have been provided with two operations. One combines two vectors and produces a vector, the other takes a scalar and a vector, producing a vector as the result. So if $u_1, u_2, u_3 \in V$ then an expression like

\[
5u_1 + 7u_2 - 13u_3
\]

would be unambiguous in any of the vector spaces we have discussed in this section. And the resulting object would be another vector in the vector space. If you were tempted to call the above expression a linear combination, you would be right. Four of the definitions that were central to our discussions in Chapter V 87 were stated in the context of vectors being column vectors, but were purposely kept broad enough that they could be applied in the context of any vector space. They only rely on the presence of scalars, vectors, vector addition and scalar multiplication to make sense. We will restate them shortly, unchanged, except that their titles and acronyms no longer refer to column vectors, and the hypothesis of being in a vector space has been added. Take the time now to look forward and review each one, and begin to form some connections to what we have done earlier and what we will be doing in subsequent sections and chapters.

(See Definition LCCV 99 and Definition LC 297, Definition SSCV 119 and Definition SS 298, Definition RLDCV 133 and Definition RLD 309, Definition LICV 133 and Definition LI 309.)
1. Comment on how the vector space $\mathbb{C}^m$ went from a theorem (Theorem VSPCV 92) to an example (Example VSCV 277).

2. In the crazy vector space, $C$, (Example CVS 280) compute the linear combination $2(3, 4) + (-6)(1, 2)$.

3. Suppose that $\alpha$ is a scalar and $\mathbf{0}$ is the zero vector. Why should we prove anything as obvious as $\alpha \mathbf{0} = \mathbf{0}$ as we did in Theorem ZVSM 283?
Subsection EXC
Exercises

**T10** Prove each of the ten axioms of Definition VS [275] for each of the following examples of a vector space:
- Example VSP 277
- Example VSIS 278
- Example VSF 279
- Example VSS 279

Contributed by Robert Beezer

**M10** Define a possibly new vector space by beginning with the set and vector addition from $\mathbb{C}^2$ (Example VSCV [277]) but change the definition of scalar multiplication to

$$\alpha x = 0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \alpha \in \mathbb{C}, \ x \in \mathbb{C}^2$$

Prove that the first nine properties required for a vector space hold, but Property O [276] does not hold.

This example shows us that we cannot expect to be able to derive Property O [276] as a consequence of assuming the first nine axioms. In other words, we cannot slim down our list of axioms by jettisoning the last one, and still have the same collection of objects qualify as vector spaces.

Contributed by Robert Beezer
A subspace is a vector space that is contained within another vector space. So every subspace is a vector space in its own right, but it is also defined relative to some other (larger) vector space. We will discover shortly that we are already familiar with a wide variety of subspaces from previous sections. Here’s the definition.

**Definition S Subspace**

Suppose that $V$ and $W$ are two vector spaces that have identical definitions of vector addition and scalar multiplication, and that $W$ is a subset of $V$, $W \subseteq V$. Then $W$ is a subspace of $V$.

Let’s look at an example of a vector space inside another vector space.

**Example SC3 A subspace of $\mathbb{C}^3$**

We know that $\mathbb{C}^3$ is a vector space (Example VSCV [277]). Consider the subset,

$$W = \begin{Bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \mid 2x_1 - 5x_2 + 7x_3 = 0 \end{Bmatrix}$$

It is clear that $W \subseteq V$, since the objects in $W$ are column vectors of size 3. But is $W$ a vector space? Does it satisfy the ten axioms of Definition VS [275] when we use the same operations? That is the main question. Suppose $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ and $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$ are vectors from $W$. Then we know that these vectors cannot be totally arbitrary, they must have gained membership in $W$ by virtue of meeting the membership test. For example, we know that $\mathbf{x}$ must satisfy $2x_1 - 5x_2 + 7x_3 = 0$ while $\mathbf{y}$ must satisfy $2y_1 - 5y_2 + 7y_3 = 0$. Our first axiom (Property AC [275]) asks the question, is $\mathbf{x} + \mathbf{y} \in W$? When our set of vectors was $\mathbb{C}^3$, this was an easy question to answer. Now it is not so obvious. Notice first that

$$\mathbf{x} + \mathbf{y} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ x_3 + y_3 \end{bmatrix}$$

and we can test this vector for membership in $W$ as follows,

$$2(x_1 + y_1) - 5(x_2 + y_2) + 7(x_3 + y_3) = 2x_1 + 2y_1 - 5x_2 - 5y_2 + 7x_3 + 7y_3$$

$$= (2x_1 - 5x_2 + 7x_3) + (2y_1 - 5y_2 + 7y_3)$$

$$= 0 + 0$$

$$= 0$$

and by this computation we see that $\mathbf{x} + \mathbf{y} \in W$. One axiom down, nine to go.
If $\alpha$ is a scalar and $\mathbf{x} \in W$, is it always true that $\alpha \mathbf{x} \in W$? This is what we need to establish [Property SC 275]. Again, the answer is not as obvious as it was when our set of vectors was all of $\mathbb{C}^3$. Let’s see.

$$\alpha \mathbf{x} = \alpha \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} \alpha x_1 \\ \alpha x_2 \\ \alpha x_3 \end{bmatrix}$$

and we can test this vector for membership in $W$ with

$$2(\alpha x_1) - 5(\alpha x_2) + 7(\alpha x_3) = \alpha(2x_1 - 5x_2 + 7x_3) = \alpha 0 = 0$$

and we see that indeed $\alpha \mathbf{x} \in W$. Always.

If $W$ has a zero vector, it will be unique [Theorem ZVU 282]). The zero vector for $\mathbb{C}^3$ should also perform the required duties when added to elements of $W$. So the likely candidate for a zero vector in $W$ is the same zero vector that we know $\mathbb{C}^3$ has. You can check that $\mathbf{0} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$ is a zero vector in $W$ too [Property Z 276].

With a zero vector, we can now ask about additive inverses [Property AI 276]. As you might suspect, the natural candidate for an additive inverse in $W$ is the same as the additive inverse from $\mathbb{C}^3$. However, we must insure that these additive inverses actually are elements of $W$. Given $\mathbf{x} \in W$, is $-\mathbf{x} \in W$?

$$-\mathbf{x} = \begin{bmatrix} -x_1 \\ -x_2 \\ -x_3 \end{bmatrix}$$

and we can test this vector for membership in $W$ with

$$(-x_1) - 5(-x_2) + 7(-x_3) = -(2x_1 - 5x_2 + 7x_3) = 0$$

and we now believe that $-\mathbf{x} \in W$.

Is the vector addition in $W$ commutative [Property C 275]? Is $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$? Of course! Nothing about restricting the scope of our set of vectors will prevent the operation from still being commutative. Indeed, the remaining five axioms are unaffected by the transition to a smaller set of vectors, and so remain true. That was convenient.

So $W$ satisfies all ten axioms, is therefore a vector space, and thus earns the title of being a subspace of $\mathbb{C}^3$.

\[\square\]

Subsection TS

Testing Subspaces

In Example SC3 291 we proceeded through all ten of the vector space axioms before believing that a subset was a subspace. But six of the axioms were easy to prove, and we
can lean on some of the properties of the vector space (the superset) to make the other four easier. Here is a theorem that will make it easier to test if a subset is a vector space. A shortcut if there ever was one.

**Theorem TSS**

**Testing Subsets for Subspaces**

Suppose that $V$ is a vector space and $W$ is a subset of $V$, $W \subseteq V$. Endow $W$ with the same operations as $V$. Then $W$ is a subspace if and only if three conditions are met

1. $W$ is non-empty, $W \neq \emptyset$.
2. Whenever $x \in W$ and $y \in W$, then $x + y \in W$.
3. Whenever $\alpha \in \mathbb{C}$ and $x \in W$, then $\alpha x \in W$.

□

**Proof** $(\Rightarrow)$ We have the hypothesis that $W$ is a subspace, so by Definition VS [275] we know that $W$ contains a zero vector. This is enough to show that $W \neq \emptyset$. Also, since $W$ is a vector space it satisfies the additive and scalar multiplication closure axioms, and so exactly meets the second and third conditions. If that was easy, the other direction might require a bit more work.

$(\Leftarrow)$ We have three properties for our hypothesis, and from this we should conclude that $W$ has the ten defining properties of a vector space. The second and third conditions of our hypothesis are exactly Property AC [275] and Property SC [275]. Our hypothesis that $V$ is a vector space implies that Property C [275], Property AA [276], Property SMA [276], Property DVA [276], Property DSA [276] and Property O [276] all hold. They continue to be true for vectors from $W$ since passing to a subset leaves their statements unchanged. Eight down, two to go.

Since $W$ is non-empty, we can choose some vector $z \in W$. Then by the third part of our hypothesis (scalar closure), we know $(-1)z \in W$. By Theorem AISM [283] $(-1)z = -z$. Now by Property AI [276] for $V$ and then by the second part of our hypothesis (additive closure) we see that

$$0 = z + (-z) \in W$$

So $W$ contain the zero vector from $V$. Since this vector performs the required duties of a zero vector in $V$, it will continue in that role as an element of $W$. So $W$ has a zero vector. Property Z [276] established, we have just one axiom left.

Suppose $x \in W$. Then by the third part of our hypothesis (scalar closure), we know that $(-1)x \in W$. By Theorem AISM [283] $(-1)x = -x$, so together these statements show us that $-x \in W$. $-x$ is the additive inverse of $x$ in $V$, but will continue in this role when viewed as element of the subset $W$. So every element of $W$ has an additive inverse that is an element of $W$ and Property AI [276] is completed.

Three conditions, plus being a subset, gets us all ten axioms. Fabulous! ■

This theorem can be paraphrased by saying that a subspace is “a non-empty subset (of a vector space) that is closed under vector addition and scalar multiplication.”

You might want to go back and rework Example SC3 [291] in light of this result, perhaps seeing where we can now economize or where the work done in the example mirrored the proof and where it did not. We will press on and apply this theorem in a slightly more abstract setting.
Example SP4
A subspace of $P_4$

$P_4$ is the vector space of polynomials with degree at most 4 (Example VSP 277). Define a subset $W$ as

$$W = \{ p(x) \mid p \in P_4, \ p(2) = 0 \}$$

so $W$ is the collection of those polynomials (with degree 4 or less) whose graphs cross the $x$-axis at $x = 2$. Whenever we encounter a new set it is a good idea to gain a better understanding of the set by finding a few elements in the set, and a few outside it. For example $x^2 - x - 2 \in W$, while $x^4 + x^3 - 7 \not\in W$.

Is $W$ nonempty? Yes, $x - 2 \in W$.

Additive closure? Suppose $p \in W$ and $q \in W$. Is $p + q \in W$? $p$ and $q$ are not totally arbitrary, we know that $p(2) = 0$ and $q(2) = 0$. Then we can check $p + q$ for membership in $W$,

$$\begin{align*}
(p + q)(2) &= p(2) + q(2) \\
&= 0 + 0 \\
&= 0
\end{align*}$$

so we see that $p + q$ qualifies for membership in $W$.

Scalar multiplication closure? Suppose that $\alpha \in \mathbb{C}$ and $p \in W$. Then we know that $p(2) = 0$. Testing $\alpha p$ for membership,

$$\begin{align*}
(\alpha p)(2) &= \alpha p(2) \\
&= \alpha 0 \\
&= 0
\end{align*}$$

so $\alpha p \in W$.

We have shown that $W$ meets the three conditions of Theorem TSS 293 and so qualifies as a subspace of $P_4$. Notice that by Definition S 291 we now know that $W$ is also a vector space. So all the axioms of a vector space (Definition VS 275) and the theorems of Section VS 275 apply in full.

Much of the power of Theorem TSS 293 is that we can easily establish new vector spaces if we can locate them as subsets of other vector spaces, such as the ones presented in Subsection VS.VSP 282.

It can be as instructive to consider some subsets that are not subspaces. Since Theorem TSS 293 is an equivalence (see Technique E 52) we can be assured that a subset is not a subspace if it violates one of the three conditions, and in any example of interest this will not be the “non-empty” condition. However, since a subspace has to be a vector space in its own right, we can also search for a violation of any one of the ten defining axioms in Definition VS 275 or any inherent property of a vector space, such as those given by the basic theorems of Subsection VS.VSP 282. Notice also that a violation need only be for a specific vector or pair of vectors.

Example NSC2Z
A non-subspace in $\mathbb{C}^2$, zero vector

Consider the subset $W$ below as a candidate for being a subspace of $\mathbb{C}^2$

$$W = \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mid 3x_1 - 5x_2 = 12 \right\}$$
The zero vector of $\mathbb{C}^2$, $0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ will need to be the zero vector in $W$ also. However, $0 \notin W$ since $3(0) - 5(0) = 0 \neq 12$. So $W$ has no zero vector and fails Property Z of Definition VS. This subspace also fails to be closed under addition and scalar multiplication. Can you find examples of this?

Example NSC2A
A non-subspace in $\mathbb{C}^2$, additive closure
Consider the subset $X$ below as a candidate for being a subspace of $\mathbb{C}^2$

$$X = \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mid x_1x_2 = 0 \right\}$$

You can check that $0 \in X$, so the approach of the last example will not get us anywhere. However, notice that $x = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \in X$ and $y = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \in X$. Yet

$$x + y = \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \notin X$$

So $X$ fails the additive closure requirement of either Property AC or Theorem TSS, and is therefore not a subspace.

Example NSC2S
A non-subspace in $\mathbb{C}^2$, scalar multiplication closure
Consider the subset $Y$ below as a candidate for being a subspace of $\mathbb{C}^2$

$$Y = \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mid x_1 \in \mathbb{Z}, \ x_2 \in \mathbb{Z} \right\}$$

$\mathbb{Z}$ is the set of integers, so we are only allowing “whole numbers” as the constituents of our vectors. Now, $0 \in Y$, and additive closure also holds (can you prove these claims?). So we will have to try something different. Note that $\alpha = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \in \mathbb{C}$ and $\begin{bmatrix} 2 \\ 3 \end{bmatrix} \in Y$, but

$$\alpha x = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \\ 3/2 \end{bmatrix} \notin Y$$

So $Y$ fails the scalar multiplication closure requirement of either Property SC or Theorem TSS, and is therefore not a subspace.

There are two examples of subspaces that are trivial. Suppose that $V$ is any vector space. Then $V$ is a subset of itself and is a vector space. By Definition S, $V$ qualifies as a subspace of itself. The set containing just the zero vector $Z = \{0\}$ is also a subspace as can be seen by applying Theorem TSS or by simple modifications of the techniques hinted at in Example VSS. Since these subspaces are so obvious (and therefore not too interesting) we will refer to them as being trivial.

Definition TS
Trivial Subspaces
Given the vector space $V$, the subspaces $V$ and $\{0\}$ are each called a trivial subspace.

We can also use Theorem TSS to prove more general statements about subspaces, as illustrated in the next theorem.
Theorem NSMS
Null Space of a Matrix is a Subspace
Suppose that $A$ is an $m \times n$ matrix. Then the null space of $A$, $\mathcal{N}(A)$, is a subspace of $\mathbb{C}^n$.

**Proof** We will examine the three requirements of Theorem TSS [293]. Recall that $\mathcal{N}(A) = \{ x \in \mathbb{C}^n | Ax = 0 \}$.

First, $0 \in \mathcal{N}(A)$, which can be inferred as a consequence of Theorem HSC [64]. So $\mathcal{N}(A) \neq \emptyset$.

Second, check additive closure by supposing that $x \in \mathcal{N}(A)$ and $y \in \mathcal{N}(A)$. So we know a little something about $x$ and $y$: $Ax = 0$ and $Ay = 0$, and that is all we know. Question: Is $x + y \in \mathcal{N}(A)$? Let's check.

$A(x + y) = Ax + Ay$  \hspace{1cm} \text{Theorem MMDAA [195]}

$= 0 + 0$  \hspace{1cm} $x \in \mathcal{N}(A), y \in \mathcal{N}(A)$

$= 0$  \hspace{1cm} \text{Theorem VSPCV [92]}

So, yes, $x + y$ qualifies for membership in $\mathcal{N}(A)$.

Third, check scalar multiplication closure by supposing that $\alpha \in \mathbb{C}$ and $x \in \mathcal{N}(A)$. So we know a little something about $x$: $Ax = 0$, and that is all we know. Question: Is $\alpha x \in \mathcal{N}(A)$? Let's check.

$A(\alpha x) = \alpha (Ax)$  \hspace{1cm} \text{Theorem MMSMM [196]}

$= \alpha 0$  \hspace{1cm} $x \in \mathcal{N}(A)$

$= 0$  \hspace{1cm} \text{Theorem ZVSM [283]}

So, yes, $\alpha x$ qualifies for membership in $\mathcal{N}(A)$.

Having met the three conditions in Theorem TSS [293] we can now say that the null space of a matrix is a subspace (and hence a vector space in its own right!).

Here is an example where we can exercise Theorem NSMS [296].

**Example RSNS**
**Recasting a subspace as a null space**
Consider the subset of $\mathbb{C}^5$ defined as

$$W = \left\{ \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} | \begin{array}{l} 3x_1 + x_2 - 5x_3 + 7x_4 + x_5 = 0, \\ 4x_1 + 6x_2 + 3x_3 - 6x_4 - 5x_5 = 0, \\ -2x_1 + 4x_2 + 7x_4 + x_5 = 0 \end{array} \right\}$$

It is possible to show that $W$ is a subspace of $\mathbb{C}^5$ by checking the three conditions of Theorem TSS [293] directly, but it will get tedious rather quickly. Instead, give $W$ a fresh look and notice that it is a set of solutions to a homogeneous system of equations.

Define the matrix

$$A = \begin{bmatrix} 3 & 1 & -5 & 7 & 1 \\ 4 & 6 & 3 & -6 & -5 \\ -2 & 4 & 0 & 7 & 1 \end{bmatrix}$$

and then recognize that $W = \mathcal{N}(A)$. By Theorem NSMS [296] we can immediately see that $W$ is a subspace. Boom!  

\[\square\]
The span of a set of column vectors got a heavy workout in Chapter V and Chapter M. The definition of the span depended only on being able to formulate linear combinations. In any of our more general vector spaces we always have a definition of vector addition and of scalar multiplication. So we can build linear combinations and manufacture spans. This subsection contains two definitions that are just mild variants of definitions we have seen earlier for column vectors. If you haven’t already, compare them with Definition LCCV and Definition SSCV.

Definition LC
Linear Combination
Suppose that $V$ is a vector space. Given $n$ vectors $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \ldots, \mathbf{u}_n$ and $n$ scalars $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n$, their linear combination is the vector

$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_n \mathbf{u}_n.$$  

Example LCM
A linear combination of matrices
In the vector space $M_{23}$ of $2 \times 3$ matrices, we have the vectors

$$\mathbf{x} = \begin{bmatrix} 1 & 3 & -2 \\ 2 & 0 & 7 \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} 3 & -1 & 2 \\ 5 & 5 & 1 \end{bmatrix}, \quad \mathbf{z} = \begin{bmatrix} 4 & 2 & -4 \\ 1 & 1 & 1 \end{bmatrix}$$

and we can form linear combinations such as

$$2\mathbf{x} + 4\mathbf{y} + (-1)\mathbf{z} = 2 \begin{bmatrix} 1 & 3 & -2 \\ 2 & 0 & 7 \end{bmatrix} + 4 \begin{bmatrix} 3 & -1 & 2 \\ 5 & 5 & 1 \end{bmatrix} + (-1) \begin{bmatrix} 4 & 2 & -4 \\ 1 & 1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 6 & -4 \\ 4 & 14 \end{bmatrix} + \begin{bmatrix} 12 & -4 & 8 \\ 20 & 20 & 4 \end{bmatrix} + \begin{bmatrix} -4 & -2 & 4 \\ -1 & -1 & -1 \end{bmatrix}$$

$$= \begin{bmatrix} 10 & 0 & 8 \\ 23 & 19 & 17 \end{bmatrix}.$$

or,

$$4\mathbf{x} - 2\mathbf{y} + 3\mathbf{z} = 4 \begin{bmatrix} 1 & 3 & -2 \\ 2 & 0 & 7 \end{bmatrix} - 2 \begin{bmatrix} 3 & -1 & 2 \\ 5 & 5 & 1 \end{bmatrix} + 3 \begin{bmatrix} 4 & 2 & -4 \\ 1 & 1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 4 & 12 & -8 \\ 8 & 0 & 28 \end{bmatrix} + \begin{bmatrix} -6 & 2 & -4 \\ -10 & -10 & -2 \end{bmatrix} + \begin{bmatrix} 12 & 6 & -12 \\ 3 & 3 & 3 \end{bmatrix}$$

$$= \begin{bmatrix} 10 & 20 & -24 \\ 1 & -7 & 29 \end{bmatrix}.$$

When we realize that we can form linear combinations in any vector space, then it is natural to revisit our definition of the span of a set, since it is the set of all possible linear combinations of a set of vectors.
Definition SS
Span of a Set
Suppose that \( V \) is a vector space. Given a set of vectors \( S = \{u_1, u_2, u_3, \ldots, u_t\} \), their span, \( \text{span} \), \( S \), is the set of all possible linear combinations of \( u_1, u_2, u_3, \ldots, u_t \). Symbolically,

\[
\text{span}(S) = \{ \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t \}
\]

Theorem SSS
Span of a Set is a Subspace
Suppose \( V \) is a vector space. Given a set of vectors \( S = \{u_1, u_2, u_3, \ldots, u_t\} \subseteq V \), their span, \( \text{span}(S) \), is a subspace.

Proof We will verify the three conditions of Theorem TSS \[293\]. First,

\[
0 = 0 + 0 + 0 + \ldots + 0
= 0u_1 + 0u_2 + 0u_3 + \cdots + 0u_t
\]

So we have written \( 0 \) as a linear combination of the vectors in \( S \) and by Definition SS \[298\], \( 0 \in \text{span}(S) \) and therefore \( S \neq \emptyset \).

Second, suppose \( x \in \text{span}(S) \) and \( y \in \text{span}(S) \). Can we conclude that \( x + y \in \text{span}(S) \)? What do we know about \( x \) and \( y \) by virtue of their membership in \( \text{span}(S) \)? There must be scalars from \( \mathbb{C} \), \( \alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_t \) and \( \beta_1, \beta_2, \beta_3, \ldots, \beta_t \) so that

\[
x = \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t
y = \beta_1 u_1 + \beta_2 u_2 + \beta_3 u_3 + \cdots + \beta_t u_t
\]

Then

\[
x + y = \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t
+ \beta_1 u_1 + \beta_2 u_2 + \beta_3 u_3 + \cdots + \beta_t u_t
= (\alpha_1 + \beta_1)u_1 + (\alpha_2 + \beta_2)u_2
+ (\alpha_3 + \beta_3)u_3 + \cdots + (\alpha_t + \beta_t)u_t
\]

Since each \( \alpha_i + \beta_i \) is again a scalar from \( \mathbb{C} \) we have expressed the vector sum \( x + y \) as a linear combination of the vectors from \( S \), and therefore by Definition SS \[298\] we can say that \( x + y \in \text{span}(S) \).

Third, suppose \( \alpha \in \mathbb{C} \) and \( x \in \text{span}(S) \). Can we conclude that \( \alpha x \in \text{span}(S) \)? What do we know about \( x \) by virtue of its membership in \( \text{span}(S) \)? There must be scalars from \( \mathbb{C} \), \( \alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_t \) so that

\[
x = \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t
\]
Then
\[ \alpha x = \alpha (\alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_t u_t)\]
\[ = \alpha(\alpha_1 u_1) + \alpha(\alpha_2 u_2) + \alpha(\alpha_3 u_3) + \cdots + \alpha(\alpha_t u_t) \quad \text{Property DVA} \]
\[ = (\alpha \alpha_1) u_1 + (\alpha \alpha_2) u_2 + (\alpha \alpha_3) u_3 + \cdots + (\alpha \alpha_t) u_t \quad \text{Property SMA} \]

Since each \( \alpha \alpha_i \) is again a scalar from \( \mathbb{C} \) we have expressed the scalar multiple \( \alpha x \) as a linear combination of the vectors from \( S \), and therefore by [Definition SS 298] we can say that \( \alpha x \in Sp(S) \).

With the three conditions of [Theorem TSS 293] met, we can say that \( Sp(S) \) is a subspace (and so is also vector space, [Definition VS 275]).

**Example SSP**

**Span of a set of polynomials**

In [Example SP4 294] we proved that
\[ W = \{ p(x) \mid p \in P_4, \ p(2) = 0 \} \]
is a subspace of \( P_4 \), the vector space of polynomials of degree at most 4. Since \( W \) is a vector space itself, let’s construct a span within \( W \). First let
\[ S = \{ x^4 - 4 x^3 + 5 x^2 - x - 2, \ 2 x^4 - 3 x^3 - 6 x^2 + 6 x + 4 \} \]
and verify that \( S \) is a subset of \( W \) by checking that each of these two polynomials has \( x = 2 \) as a root. Now, if we define \( U = Sp(S) \), then [Theorem SSS 298] tells us that \( U \) is a subspace of \( W \). So quite quickly we have built a chain of subspaces, \( U \) inside \( W \), and \( W \) inside \( P_4 \).

Rather than dwell on how quickly we can build subspaces, let’s try to gain a better understanding of just how the span construction creates subspaces, in the context of this example. We can quickly build representative elements of \( U \),
\[ 3(x^4 - 4 x^3 + 5 x^2 - x - 2) + 5(2 x^4 - 3 x^3 - 6 x^2 + 6 x + 4) = 13 x^4 - 27 x^3 - 15 x^2 + 27 x + 14 \]
and
\[ (-2)(x^4 - 4 x^3 + 5 x^2 - x - 2) + 8(2 x^4 - 3 x^3 - 6 x^2 + 6 x + 4) = 14 x^4 - 16 x^3 - 58 x^2 + 50 x + 36 \]
and each of these polynomials must be in \( W \) since it is closed under addition and scalar multiplication. But you might check for yourself that both of these polynomials have \( x = 2 \) as a root.

I can tell you that \( y = 3 x^4 - 7 x^3 - x^2 + 7 x - 2 \) is not in \( U \), but would you believe me? A first check shows that \( y \) does have \( x = 2 \) as a root, but that only shows that \( y \in W \). What does \( y \) have to do to gain membership in \( U = Sp(S) \)? It must be a linear combination of the vectors in \( S \), \( x^4 - 16 \) and \( x^2 - x - 2 \). So let’s suppose that \( y \) is such a linear combination,
\[ y = 3 x^4 - 7 x^3 - x^2 + 7 x - 2 \]
\[ = \alpha_1 (x^4 - 4 x^3 + 5 x^2 - x - 2) + \alpha_2 (2 x^4 - 3 x^3 - 6 x^2 + 6 x + 4) \]
\[ = (\alpha_1 + 2 \alpha_2) x^4 + (-4 \alpha_1 - 3 \alpha_2) x^3 + (5 \alpha_1 - 6 \alpha_2) x^2 + (-\alpha_1 + 6 \alpha_2) x - (-2 \alpha_1 + 4 \alpha_2) \]
Notice that operations above are done in accordance with the definition of the vector space of polynomials (Example VSP [277]). Now, if we equate coefficients (which is implicitly the definition of equality for polynomials) then we obtain the system of five linear equations in two variables

\[
\begin{align*}
\alpha_1 + 2\alpha_2 &= 3 \\
-4\alpha_1 - 3\alpha_2 &= -7 \\
5\alpha_1 - 6\alpha_2 &= -1 \\
-\alpha_1 + 6\alpha_2 &= 7 \\
-2\alpha_1 + 4\alpha_2 &= -2
\end{align*}
\]

Build an augmented matrix from the system and row-reduce,

\[
\begin{bmatrix}
1 & 2 & 3 \\
-4 & -3 & -7 \\
5 & -6 & -1 \\
-1 & 6 & 7 \\
-2 & 4 & -2
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

With a leading 1 in the final column of the row-reduced augmented matrix, Theorem RCLS [53] tells us the system of equations is inconsistent. Therefore, there are no scalars, \(\alpha_1\) and \(\alpha_2\), to establish \(y\) as a linear combination of the elements in \(U\). So \(y \notin U\).

Let’s again examine membership in a span.

**Example SM32**

**A subspace of \(M_{32}\)**

The set of all \(3 \times 2\) matrices forms a vector space when we use the operations of matrix addition (Definition MA [180]) and scalar matrix multiplication (Definition MSM [180]), as was show in Example VSM [277]. Consider the subset

\[
S = \left\{ \begin{bmatrix} 3 & 1 \\ 4 & 2 \\ 5 & -5 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 2 & -1 \\ 14 & -1 \end{bmatrix}, \begin{bmatrix} 3 & -1 \\ -1 & 2 \\ -19 & -11 \end{bmatrix}, \begin{bmatrix} 4 & 2 \\ 1 & -2 \\ 14 & -2 \end{bmatrix}, \begin{bmatrix} 3 & 1 \\ -4 & 0 \\ -17 & 7 \end{bmatrix} \right\}
\]

and define a new subset of vectors \(W\) in \(M_{32}\) using the span (Definition SS [298]), \(W = Sp(S)\). So by Theorem SSS [298] we know that \(W\) is a subspace of \(M_{32}\). While \(W\) is an infinite set, and this is a precise description, it would still be worthwhile to investigate whether or not \(W\) contains certain elements.

First, is

\[
y = \begin{bmatrix} 9 & 3 \\ 7 & 3 \\ 10 & -11 \end{bmatrix}
\]

in \(W\)? To answer this, we want to determine if \(y\) can be written as a linear combination
of the five matrices in $S$. Can we find scalars, $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ so that

$$
\begin{bmatrix}
9 & 3 \\
7 & 3 \\
10 & -11
\end{bmatrix}
= \alpha_1 \begin{bmatrix}
3 & 1 \\
4 & 2 \\
5 & -5
\end{bmatrix}
+ \alpha_2 \begin{bmatrix}
1 & 1 \\
2 & -1 \\
14 & -1
\end{bmatrix}
+ \alpha_3 \begin{bmatrix}
3 & -1 \\
-1 & 2 \\
-19 & -11
\end{bmatrix}
+ \alpha_4 \begin{bmatrix}
4 & 2 \\
1 & -2 \\
14 & -2
\end{bmatrix}
+ \alpha_5 \begin{bmatrix}
3 & 1 \\
-4 & 0 \\
-17 & 7
\end{bmatrix}
$$

Using our definition of matrix equality (Definition ME 179) we can translate this statement into six equations in the five unknowns,

$$
\begin{align*}
3\alpha_1 + \alpha_2 + 3\alpha_3 + 4\alpha_4 + 3\alpha_5 &= 9 \\
\alpha_1 + \alpha_2 - \alpha_3 + 2\alpha_4 + \alpha_5 &= 3 \\
4\alpha_1 + 2\alpha_2 - \alpha_3 + \alpha_4 - 4\alpha_5 &= 7 \\
2\alpha_1 - \alpha_2 + 2\alpha_3 - 2\alpha_4 &= 3 \\
5\alpha_1 + 14\alpha_2 - 19\alpha_3 + 14\alpha_4 - 17\alpha_5 &= 10 \\
-5\alpha_1 - \alpha_2 - 11\alpha_3 - 2\alpha_4 + 7\alpha_5 &= -11
\end{align*}
$$

This is a linear system of equations, which we can represent with an augmented matrix and row-reduce in search of solutions. The matrix that is row-equivalent to the augmented matrix is

$$
\begin{bmatrix}
1 & 0 & 0 & 0 & 5 \\
0 & 1 & 0 & 0 & -19 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

So we recognize that the system is consistent since there is no leading 1 in the final column (Theorem RCLS 53), and compute $n-\text{r} = 5-4 = 1$ free variables (Theorem FVCS 55).

While there are infinitely many solutions, we are only in pursuit of a single solution, so let’s choose the free variable $\alpha_5 = 0$ for simplicity’s sake. Then we easily see that $\alpha_1 = 2$, $\alpha_2 = -1$, $\alpha_3 = 0$, $\alpha_4 = 1$. So the scalars $\alpha_1 = 2$, $\alpha_2 = -1$, $\alpha_3 = 0$, $\alpha_4 = 1$, $\alpha_5 = 0$ will provide a linear combination of the elements of $S$ that equals $y$, as we can verify by checking,

$$
\begin{bmatrix}
9 & 3 \\
7 & 3 \\
10 & -11
\end{bmatrix}
= 2 \begin{bmatrix}
3 & 1 \\
4 & 2 \\
5 & -5
\end{bmatrix} + (-1) \begin{bmatrix}
1 & 1 \\
2 & -1 \\
14 & -1
\end{bmatrix} + (1) \begin{bmatrix}
4 & 2 \\
1 & -2 \\
14 & -2
\end{bmatrix}
$$

So with one particular linear combination in hand, we are convinced that $y$ deserves to be a member of $W = S_p(S)$. Second, is

$$
x = \begin{bmatrix}
2 & 1 \\
3 & 1 \\
4 & -2
\end{bmatrix}
$$
in $W$? To answer this, we want to determine if $x$ can be written as a linear combination of the five matrices in $S$. Can we find scalars, $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ so that

$$\begin{bmatrix} 2 & 1 \\ 3 & 1 \\ 4 & -2 \end{bmatrix} = \alpha_1 \begin{bmatrix} 3 & 1 \\ 4 & 2 \\ 5 & -5 \end{bmatrix} + \alpha_2 \begin{bmatrix} 1 & 1 \\ 2 & -1 \\ 14 & -1 \end{bmatrix} + \alpha_3 \begin{bmatrix} 3 & -1 \\ -1 & 2 \\ -19 & -11 \end{bmatrix} + \alpha_4 \begin{bmatrix} 4 & 2 \\ 1 & -2 \\ 14 & -2 \end{bmatrix} + \alpha_5 \begin{bmatrix} 3 & 1 \\ -4 & 0 \\ -17 & 7 \end{bmatrix}$$

Using our definition of matrix equality (Definition ME [179]) we can translate this statement into six equations in the five unknowns,

$$3\alpha_1 + \alpha_2 + 3\alpha_3 + 4\alpha_4 + 3\alpha_5 = 2$$
$$\alpha_1 + \alpha_2 - \alpha_3 + 2\alpha_4 + \alpha_5 = 1$$
$$4\alpha_1 + 2\alpha_2 - \alpha_3 + \alpha_4 - 4\alpha_5 = 3$$
$$2\alpha_1 - \alpha_2 + 2\alpha_3 - 2\alpha_4 = 1$$
$$5\alpha_1 + 14\alpha_2 - 19\alpha_3 + 14\alpha_4 - 17\alpha_5 = 4$$
$$-5\alpha_1 - \alpha_2 - 11\alpha_3 - 2\alpha_4 + 7\alpha_5 = -2$$

This is a linear system of equations, which we can represent with an augmented matrix and row-reduce in search of solutions. The matrix that is row-equivalent to the augmented matrix is

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \frac{5}{8} & 0 \\ 0 & 1 & 0 & 0 & -\frac{38}{9} & 0 \\ 0 & 0 & 1 & 0 & -\frac{28}{9} & 0 \\ 0 & 0 & 0 & 1 & -\frac{17}{9} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

With a leading 1 in the last column Theorem RCLS [53] tells us that the system is inconsistent. Therefore, there are no values for the scalars that will place $x$ in $W$, and so we conclude that $x \not\in W$.

Notice how Example SSP [299] and Example SM32 [300] contained questions about membership in a span, but these questions quickly became questions about solutions to a system of linear equations. This will be a common theme going forward.

Subsection SC
Subspace Constructions

Several of the subsets of vectors spaces that we worked with in Chapter M [179] are also subspaces — they are closed under vector addition and scalar multiplication in $\mathbb{C}^m$.

Theorem RMS
Range of a Matrix is a Subspace
Suppose that $A$ is an $m \times n$ matrix. Then $\mathcal{C}(A)$ is a subspace of $\mathbb{C}^m$. \qed
Proof Definition CSM 235 shows us that $C(A)$ is a subset of $\mathbb{C}^m$, and that it is defined as the span of a set of vectors from $\mathbb{C}^m$ (the columns of the matrix). Since $C(A)$ is a span, Theorem SSS 298 says it is a subspace.

That was easy! Notice that we could have used this same approach to prove that the null space is a subspace, since Theorem SSNS 122 provided a description of the null space of a matrix as the span of a set of vectors. However, I much prefer the current proof of Theorem NSMS 296. Speaking of easy, here is a very easy theorem that exposes another of our constructions as creating subspaces.

**Theorem RSMS**

**Row Space of a Matrix is a Subspace**

Suppose that $A$ is an $m \times n$ matrix. Then $R(A)$ is a subspace of $\mathbb{C}^n$. □

Proof Definition RSM 242 says $R(A) = C(A^t)$, so the row space of a matrix is a column space, and every column space is a subspace by Theorem RMS 302. That’s enough. ■

So the span of a set of vectors, and the null space, column space, and row space of a matrix are all subspaces, and hence are all vector spaces, meaning they have all the properties detailed in Section VS 275. We have worked with these objects as just sets in Chapter V 87 and Chapter M 179, but now we understand that they have much more structure. In particular, being closed under vector addition and scalar multiplication means a subspace is also closed under linear combinations.

**Subsection READ**

**Reading Questions**

1. Summarize the three conditions that allow us to quickly test if a set is a subspace.

2. Consider the set of vectors

$$\left\{ \begin{bmatrix} a \\ b \\ c \end{bmatrix} \mid 3a - 2b + c = 5 \right\}$$

Is this set a subspace of $\mathbb{C}^3$?

3. Name four general constructions of sets of vectors that we can now automatically deem as subspaces.
Subsection EXC Exercises

C20 Working within the vector space $P_3$ of polynomials of degree 3 or less, determine if $p(x) = x^3 + 6x + 4$ is in the subspace $W$ below.

$$W = \mathcal{S}p\left( \{ x^3 + x^2 + x, x^3 + 2x - 6, x^2 - 5 \} \right)$$

Contributed by Robert Beezer Solution 307

C25 Show that the set $W = \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \ \middle| \ 3x_1 - 5x_2 = 12 \right\}$ from Example NSC2Z 294 fails Property AC 275 and Property SC 275. Contributed by Robert Beezer

C26 Show that the set $Y = \left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \ \middle| \ x_1 \in \mathbb{Z}, x_2 \in \mathbb{Z} \right\}$ from Example NSC2S 295 has Property AC 275. Contributed by Robert Beezer

M20 In $C^3$, the vector space of column vectors of size 3, prove that the set $Z$ is a subspace.

$$Z = \left\{ \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \ \middle| \ 4x_1 - x_2 + 5x_3 = 0 \right\}$$

Contributed by Robert Beezer Solution 307
The question is if \( p \) can be written as a linear combination of the vectors in \( W \). To check this, we set \( p \) equal to a linear combination and massage with the definitions of vector addition and scalar multiplication that we get with \( P_3 \) (Example VSP [277])

\[
p(x) = a_1(x^3 + x^2 + x) + a_2(x^3 + 2x - 6) + a_3(x^2 - 5)
\]

\[
x^3 + 6x + 4 = (a_1 + a_2)x^3 + (a_1 + a_3)x^2 + (a_1 + 2a_2)x + (-6a_2 - 5a_3)
\]

Equating coefficients of equal powers of \( x \), we get the system of equations,

\[
\begin{align*}
  a_1 + a_2 &= 1 \\
  a_1 + a_3 &= 0 \\
  a_1 + 2a_2 &= 6 \\
  -6a_2 - 5a_3 &= 4
\end{align*}
\]

The augmented matrix of this system of equations row-reduces to

\[
\begin{bmatrix}
  1 & 0 & 0 & 0 \\
  0 & 1 & 0 & 0 \\
  0 & 0 & 1 & 0 \\
  0 & 0 & 0 & 1
\end{bmatrix}
\]

There is a leading 1 in the last column, so Theorem RCLS [53] implies that the system is inconsistent. So there is no way for \( p \) to gain membership in \( W \), so \( p \notin W \).

The membership criteria for \( Z \) is a single linear equation, which comprises a homogeneous system of equations. As such, we can recognize \( Z \) as the solutions to this system, and therefore \( Z \) is a null space. Specifically, \( Z = \mathcal{N}([4 -1 5]) \). Every null space is a subspace by Theorem NSMS [296].

A less direct solution appeals to Theorem TSS [293].

First, we want to be certain \( Z \) is non-empty. The zero vector of \( \mathbb{C}^3 \), \( \mathbf{0} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \), is a good candidate, since if it fails to be in \( Z \), we will know that \( Z \) is not a vector space. Check that

\[
4(0) - (0) + 5(0) = 0
\]

so that \( \mathbf{0} \in Z \).

Suppose \( \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \) and \( \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \) are vectors from \( Z \). Then we know that these vectors cannot be totally arbitrary, they must have gained membership in \( Z \) by virtue of meeting the membership test. For example, we know that \( \mathbf{x} \) must satisfy \( 4x_1 - x_2 + 5x_3 = 0 \)
while $y$ must satisfy $4y_1 - y_2 + 5y_3 = 0$. Our second criteria asks the question, is $x + y \in Z$? Notice first that

$$x + y = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} x_1 + y_1 \\ x_2 + y_2 \\ x_3 + y_3 \end{bmatrix}$$

and we can test this vector for membership in $Z$ as follows,

$$4(x_1 + y_1) - 1(x_2 + y_2) + 4(x_3 + y_3)$$

$$= 4x_1 + 4y_1 - x_2 - y_2 + 5x_3 + 5y_3$$

$$= (4x_1 - x_2 + 5x_3) + (4y_1 - y_2 + 5y_3)$$

$$= 0 + 0$$

$$= 0$$

and by this computation we see that $x + y \in Z$.

If $\alpha$ is a scalar and $x \in Z$, is it always true that $\alpha x \in Z$? To check our third criteria, we examine

$$\alpha x = \alpha \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} \alpha x_1 \\ \alpha x_2 \\ \alpha x_3 \end{bmatrix}$$

and we can test this vector for membership in $Z$ with

$$4(\alpha x_1) - (\alpha x_2) + 5(\alpha x_3)$$

$$= \alpha(4x_1 - x_2 + 5x_3)$$

$$= \alpha 0$$

$$= 0$$

and we see that indeed $\alpha x \in Z$. With the three conditions of Theorem TSS fulfilled, we can conclude that $Z$ is a subspace of $\mathbb{C}^3$. 
A basis of a vector space is one of the most useful concepts in linear algebra. It often provides a finite description of an infinite vector space. But before we can define a basis we need to return to the idea of linear independence.

Subsection LI
Linear independence

Our previous definition of linear independence (Definition LI [309]) employed a relation of linear dependence that had a linear combination on one side of the equality. As a linear combination in a vector space (Definition LC [297]) depends only on vector addition and scalar multiplication we can extend our definition of linear independence from the setting of $\mathbb{C}^m$ to the setting of a general vector space $V$. Compare these definitions with Definition RLDCV [133] and Definition LICV [133].

**Definition RLD**
Relation of Linear Dependence
Suppose that $V$ is a vector space. Given a set of vectors $S = \{ u_1, u_2, u_3, \ldots, u_n \}$, an equation of the form
\[
\alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \cdots + \alpha_n u_n = 0
\]
is a relation of linear dependence on $S$. If this equation is formed in a trivial fashion, i.e. $\alpha_i = 0$, $1 \leq i \leq n$, then we say it is a trivial relation of linear dependence on $S$.

**Definition LI**
Linear Independence
Suppose that $V$ is a vector space. The set of vectors $S = \{ u_1, u_2, u_3, \ldots, u_n \}$ is linearly dependent if there is a relation of linear dependence on $S$ that is not trivial. In the case where the only relation of linear dependence on $S$ is the trivial one, then $S$ is a linearly independent set of vectors.

Notice the emphasis on the word “only.” This might remind you of the definition of a nonsingular matrix, where if the matrix is employed as the coefficient matrix of a homogeneous system then the only solution is the trivial one.

**Example LIP4**
Linear independence in $P_4$
In the vector space of polynomials with degree 4 or less, $P_4$ (Example VSP [277]) consider the set
\[
S = \{ 2x^4 + 3x^3 + 2x^2 - x + 10, -x^4 - 2x^3 + x^2 + 5x - 8, 2x^4 + x^3 + 10x^2 + 17x - 2 \}.
\]
Is this set of vectors linearly independent or dependent? Consider that
\[
3 \left( 2x^4 + 3x^3 + 2x^2 - x + 10 \right) + 4 \left( -x^4 - 2x^3 + x^2 + 5x - 8 \right) \\
+ (-1) \left( 2x^4 + x^3 + 10x^2 + 17x - 2 \right) = 0x^4 + 0x^3 + 0x^2 + 0x + 0 = 0
\]
This is a nontrivial relation of linear dependence (Definition RLD [309]) on the set \( S \) and so convinces us that \( S \) is linearly dependent (Definition LI [309]).

Now, I hear you say, “Where did those scalars come from?” Do not worry about that right now, just be sure you understand why the above explanation is sufficient to prove that \( S \) is linearly dependent. The remainder of the example will demonstrate how we might find these scalars if they had not been provided so readily. Let’s look at another set of vectors (polynomials) from \( P_4 \). Let
\[
T = \{ 3x^4 - 2x^3 + 4x^2 + 6x - 1, -3x^4 + 1x^3 + 0x^2 + 4x + 2, \\
4x^4 + 5x^3 - 2x^2 + 3x + 1, 2x^4 - 7x^3 + 4x^2 + 2x + 1 \}
\]
Suppose we have a relation of linear dependence on this set,
\[
0 = \alpha_1 \left( 3x^4 - 2x^3 + 4x^2 + 6x - 1 \right) + \alpha_2 \left( -3x^4 + 1x^3 + 0x^2 + 4x + 2 \right) \\
+ \alpha_3 \left( 4x^4 + 5x^3 - 2x^2 + 3x + 1 \right) + \alpha_4 \left( 2x^4 - 7x^3 + 4x^2 + 2x + 1 \right)
\]
Using our definitions of vector addition and scalar multiplication in \( P_4 \) (Example VSP [277]), we arrive at,
\[
0x^4 + 0x^3 + 0x^2 + 0x + 0 = (3\alpha_1 - 3\alpha_2 + 4\alpha_3 + 2\alpha_4) x^4 + (-2\alpha_1 + \alpha_2 + 5\alpha_3 - 7\alpha_4) x^3 \\
+ (4\alpha_1 - 2\alpha_3 + 4\alpha_4) x^2 + (6\alpha_1 + 4\alpha_2 + 3\alpha_3 + 2\alpha_4) x \\
+ (-\alpha_1 + 2\alpha_2 + \alpha_3 + \alpha_4).
\]
Equating coefficients, we arrive at the homogeneous system of equations,
\[
3\alpha_1 - 3\alpha_2 + 4\alpha_3 + 2\alpha_4 = 0 \\
-2\alpha_1 + \alpha_2 + 5\alpha_3 - 7\alpha_4 = 0 \\
4\alpha_1 - 2\alpha_3 + 4\alpha_4 = 0 \\
6\alpha_1 + 4\alpha_2 + 3\alpha_3 + 2\alpha_4 = 0 \\
-\alpha_1 + 2\alpha_2 + \alpha_3 + \alpha_4 = 0
\]
We form the coefficient matrix of this homogeneous system of equations and row-reduce to find
\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]
We expected the system to be consistent (Theorem HSC [64]) and so can compute \( n - r = 4 - 4 = 0 \) and Theorem CSRN [54] tells us that the solution is unique. Since this is a homogeneous system, this unique solution is the trivial solution (Definition TSHSE [64]), \( \alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 0, \alpha_4 = 0 \). So by Definition LI [309] the set \( T \) is linearly independent.
A few observations. If we had discovered infinitely many solutions, then we could have used one of the non-trivial ones to provide a linear combination in the manner we used to show that $S$ was linearly dependent. It is important to realize that this is not interesting that we can create a relation of linear dependence with zero scalars — we can always do that — but that for $T$, this is the only way to create a relation of linear dependence. It was no accident that we arrived at a homogeneous system of equations in this example, it is related to our use of the zero vector in defining a relation of linear dependence. It is easy to present a convincing statement that a set is linearly dependent (just exhibit a nontrivial relation of linear dependence) but a convincing statement of linear independence requires demonstrating that there is no relation of linear dependence other than the trivial one. Notice how we relied on theorems from Chapter SLE 3 to provide this demonstration. Whew! There’s a lot going on in this example. Spend some time with it, we’ll be waiting patiently right here when you get back. ⊗

**Example LIM32**

**Linear Independence in $M_{32}$**

Consider the two sets of vectors $R$ and $S$ from the vector space of all $3 \times 2$ matrices, $M_{32}$ (Example VSM 277)

$$
R = \left\{ \begin{bmatrix} 3 & -1 \\ 1 & 4 \\ 6 & -6 \end{bmatrix}, \begin{bmatrix} -2 & 3 \\ 1 & -3 \\ -2 & -6 \end{bmatrix}, \begin{bmatrix} 6 & -6 \\ -1 & 0 \\ 7 & -9 \end{bmatrix}, \begin{bmatrix} 7 & 9 \\ -4 & -5 \\ 2 & 5 \end{bmatrix} \right\}
$$

$$
S = \left\{ \begin{bmatrix} 2 & 0 \\ 1 & -1 \\ 1 & 3 \end{bmatrix}, \begin{bmatrix} -4 & 0 \\ -2 & 2 \\ -2 & -6 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ -2 & 1 \\ 2 & 4 \end{bmatrix}, \begin{bmatrix} -5 & 3 \\ -10 & 7 \\ 2 & 0 \end{bmatrix} \right\}
$$

One set is linearly independent, the other is not. Which is which? Let’s examine $R$ first.

Build a generic relation of linear dependence (Definition RLD 309),

$$
\alpha_1 \begin{bmatrix} 3 & -1 \\ 1 & 4 \\ 6 & -6 \end{bmatrix} + \alpha_2 \begin{bmatrix} -2 & 3 \\ 1 & -3 \\ -2 & -6 \end{bmatrix} + \alpha_3 \begin{bmatrix} 6 & -6 \\ -1 & 0 \\ 7 & -9 \end{bmatrix} + \alpha_4 \begin{bmatrix} 7 & 9 \\ -4 & -5 \\ 2 & 5 \end{bmatrix} = \mathbf{0}
$$

Massaging the left-hand side with our definitions of vector addition and scalar multiplication in $M_{32}$ (Example VSM 277) we obtain,

$$
\begin{bmatrix} 3\alpha_1 - 2\alpha_2 + 6\alpha_3 + 7\alpha_4 & -1\alpha_1 + 3\alpha_2 - 6\alpha_3 + 9\alpha_4 \\ \alpha_1 + \alpha_2 - \alpha_3 - 4\alpha_4 & 4\alpha_1 - 3\alpha_2 + -5\alpha_4 \\ 6\alpha_1 - 2\alpha_2 + 7\alpha_3 + 2\alpha_4 & -6\alpha_1 - 6\alpha_2 - 9\alpha_3 + 5\alpha_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}
$$

Using our definition of matrix equality (Definition ME 179) and equating corresponding entries we get the homogeneous system of six equations in four variables,

$$
\begin{align*}
3\alpha_1 - 2\alpha_2 + 6\alpha_3 + 7\alpha_4 &= 0 \\
-1\alpha_1 + 3\alpha_2 - 6\alpha_3 + 9\alpha_4 &= 0 \\
\alpha_1 + \alpha_2 - \alpha_3 - 4\alpha_4 &= 0 \\
4\alpha_1 - 3\alpha_2 + -5\alpha_4 &= 0 \\
6\alpha_1 - 2\alpha_2 + 7\alpha_3 + 2\alpha_4 &= 0 \\
-6\alpha_1 - 6\alpha_2 - 9\alpha_3 + 5\alpha_4 &= 0
\end{align*}
$$
Form the coefficient matrix of this homogeneous system and row-reduce to obtain
\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analyzing this matrix we are led to conclude that \(\alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 0, \alpha_4 = 0\). This means there is only a trivial relation of linear dependence on the vectors of \(R\) and so we call \(R\) a linearly independent set (Definition LI [309]).

So it must be that \(S\) is linearly dependent. Let’s see if we can find a non-trivial relation of linear dependence on \(S\). We will begin as with \(R\), by constructing a relation of linear dependence (Definition RLD [309]) with unknown scalars,
\[
\alpha_1 \begin{bmatrix} 2 & 0 \\ 1 & 1 \\ 1 & 3 \end{bmatrix} + \alpha_2 \begin{bmatrix} -4 & 0 \\ -2 & 2 \\ -2 & -6 \end{bmatrix} + \alpha_3 \begin{bmatrix} 1 & 1 \\ -2 & 1 \\ 2 & 4 \end{bmatrix} + \alpha_4 \begin{bmatrix} -5 & 3 \\ -10 & 7 \\ 2 & 0 \end{bmatrix} = \mathbf{0}
\]

Massaging the left-hand side with our definitions of vector addition and scalar multiplication in \(M_{32}\) (Example VSM [277]) we obtain,
\[
\begin{bmatrix}
2\alpha_1 - 4\alpha_2 + \alpha_3 - 5\alpha_4 \\
\alpha_1 - 2\alpha_2 - 2\alpha_3 - 10\alpha_4 \\
\alpha_1 - 2\alpha_2 + 2\alpha_3 + 2\alpha_4
\end{bmatrix}
= \begin{bmatrix} \alpha_2 + \alpha_3 + 3\alpha_4 \\ -\alpha_1 + 2\alpha_2 + \alpha_3 + 7\alpha_4 \\ 3\alpha_1 - 6\alpha_2 + 4\alpha_3 \end{bmatrix}
\]

Using our definition of matrix equality (Definition ME [179]) and equating corresponding entries we get the homogeneous system of six equations in four variables,
\[
\begin{align*}
2\alpha_1 - 4\alpha_2 + \alpha_3 - 5\alpha_4 & = 0 \\
\alpha_2 + \alpha_3 + 3\alpha_4 & = 0 \\
\alpha_1 - 2\alpha_2 - 2\alpha_3 - 10\alpha_4 & = 0 \\
-\alpha_1 + 2\alpha_2 + \alpha_3 + 7\alpha_4 & = 0 \\
\alpha_1 - 2\alpha_2 + 2\alpha_3 + 2\alpha_4 & = 0 \\
3\alpha_1 - 6\alpha_2 + 4\alpha_3 & = 0
\end{align*}
\]

Form the coefficient matrix of this homogeneous system and row-reduce to obtain
\[
\begin{bmatrix}
1 & -2 & 0 & -4 \\
0 & 0 & 1 & 3 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analyzing this we see that the system is consistent (we expected that since the system is homogeneous, Theorem HSC [64]) and has \(n - r = 4 - 2 = 2\) free variables, namely \(\alpha_2\) and \(\alpha_4\). This means there are infinitely many solutions, and in particular, we can find a non-trivial solution, so long as we do not pick all of our free variables to be zero. The mere presence of a nontrivial solution for these scalars is enough to conclude that \(S\) a
linearly dependent set (Definition LI [309]). But let’s go ahead and explicitly construct a non-trivial relation of linear dependence.

Choose \( \alpha_2 = 1 \) and \( \alpha_4 = -1 \). There is nothing special about this choice, there are infinitely many possibilities, some “easier” than this one, just avoid picking both variables to be zero. Then we find the corresponding dependent variables to be \( \alpha_1 = -2 \) and \( \alpha_3 = 3 \). So the relation of linear dependence,

\[
\begin{pmatrix}
-2 & 0 \\
1 & -1 \\
1 & 3
\end{pmatrix} + (1) \begin{pmatrix}
-4 & 0 \\
-2 & 2 \\
-2 & -6
\end{pmatrix} + (3) \begin{pmatrix}
1 & 1 \\
-2 & 1 \\
2 & 4
\end{pmatrix} + (-1) \begin{pmatrix}
-5 & 3 \\
-10 & 7 \\
2 & 0
\end{pmatrix} = \begin{pmatrix}
0 & 0 \\
0 & 0 \\
0 & 0
\end{pmatrix}
\]

is an iron-clad demonstration that \( S \) is linearly dependent. Can you construct another such demonstration? 

Subsection SS
Spanning Sets

In a vector space \( V \), suppose we are given a set of vectors \( S \subseteq V \). Then we can immediately construct a subspace, \( S_p(S) \), using Definition SS [298] and then be assured by Theorem SSS [298] that the construction does provide a subspace. We now turn the situation upside-down. Suppose we are first given a subspace \( W \subseteq V \). Can we find a set \( S \) so that \( S_p(S) = W \)? Typically \( W \) is infinite and we are searching for a finite set of vectors \( S \) that we can combine in linear combinations and “build” all of \( W \).

I like to think of \( S \) as the raw materials that are sufficient for the construction of \( W \). If you have nails, lumber, wire, copper pipe, drywall, plywood, carpet, shingles, paint (and a few other things), then you can combine them in many different ways to create a house (or infinitely many different houses for that matter). A fast-food restaurant may have beef, chicken, beans, cheese, tortillas, taco shells and hot sauce and from this small list of ingredients build a wide variety of items for sale. Or maybe a better analogy comes from Ben Cordes — the additive primary colors (red, green and blue) can be combined to create many different colors by varying the intensity of each. The intensity is like a scalar multiple, and the combination of the three intensities is like vector addition. The three individual colors, red, green and blue, are the elements of the spanning set.

Because we will use terms like “spanned by” and “spanning set,” there is the potential for confusion with “the span.” Come back and reread the first paragraph of this subsection whenever you are uncertain about the difference. Here’s the working definition.

Definition TSS
To Span a Subspace
Suppose \( V \) is a vector space and \( W \) is a subspace. A subset \( S \) of \( W \) is a spanning set for \( W \) if \( S_p(S) = W \). In this case, we also say \( S \) spans \( W \). 

The definition of a spanning set requires that two sets (subspaces actually) be equal. If \( S \) is a subset of \( W \), then \( S_p(S) \subseteq W \), always. Thus it is usually only necessary to prove that \( W \subseteq S_p(S) \). Now would be a good time to review Technique SE [17].

Example SSP4
Spanning set in \( P_4 \)
In Example SP4, we showed that

\[ W = \{ p(x) \mid p \in P_4, \ p(2) = 0 \} \]

is a subspace of \( P_4 \), the vector space of polynomials with degree at most 4 (Example VSP). In this example, we will show that the set

\[ S = \{ x - 2, x^2 - 4x + 4, x^3 - 6x^2 + 12x - 8, x^4 - 8x^3 + 24x^2 - 32x + 16 \} \]

is a spanning set for \( W \). To do this, we require that \( W = Sp(S) \). This is an equality of sets. We can check that every polynomial in \( S \) has \( x = 2 \) as a root and therefore \( S \subseteq W \).

Since \( W \) is closed under addition and scalar multiplication, \( Sp(S) \subseteq W \) also.

So it remains to show that \( W \subseteq Sp(S) \) (Technique SE). To do this, begin by choosing an arbitrary polynomial in \( W \), say \( r(x) = ax^4 + bx^3 + cx^2 + dx + e \in W \). This polynomial is not as arbitrary as it would appear, since we also know it must have \( x = 2 \) as a root. This translates to

\[ 0 = a(2)^4 + b(2)^3 + c(2)^2(2) + d(2) + e = 16a + 8b + 4c + 2d + e \]

as a condition on \( r \).

We wish to show that \( r \) is a polynomial in \( Sp(S) \), that is, we want to show that \( r \) can be written as a linear combination of the vectors (polynomials) in \( S \). So let’s try.

\[
\begin{align*}
r(x) &= ax^4 + bx^3 + cx^2 + dx + e \\
&= \alpha_1 (x - 2) + \alpha_2 (x^2 - 4x + 4) + \alpha_3 (x^3 - 6x^2 + 12x - 8) \\
&\quad + \alpha_4 (x^4 - 8x^3 + 24x^2 - 32x + 16) \\
&= \alpha_4 x^4 + (\alpha_3 - 8\alpha_4) x^3 + (\alpha_2 - 6\alpha_3 + 24\alpha_2) x^2 \\
&\quad + (\alpha_1 - 4\alpha_2 + 12\alpha_3 - 32\alpha_4) x + (-2\alpha_1 + 4\alpha_2 - 8\alpha_3 + 16\alpha_4)
\end{align*}
\]

Equating coefficients (vector equality in \( P_4 \)) gives the system of five equations in four variables,

\[
\begin{align*}
\alpha_4 &= a \\
\alpha_3 - 8\alpha_4 &= b \\
\alpha_2 - 6\alpha_3 + 24\alpha_2 &= c \\
\alpha_1 - 4\alpha_2 + 12\alpha_3 - 32\alpha_4 &= d \\
-2\alpha_1 + 4\alpha_2 - 8\alpha_3 + 16\alpha_4 &= e
\end{align*}
\]

Any solution to this system of equations will provide the linear combination we need to determine if \( r \in Sp(S) \), but we need to be convinced there is a solution for any values of \( a, b, c, d, e \) that qualify \( r \) to be a member of \( W \). So the question is: is this system of equations consistent? We will form the augmented matrix, and row-reduce. (We probably need to do this by hand, since the matrix is symbolic — reversing the order of the first four rows is the best way to start). We obtain a matrix in reduced row-echelon...
Subsection B.SS  Spanning Sets 315

form

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 32a - 12b + 4c + d \\
0 & 1 & 0 & 0 & -24a + 6b + c \\
0 & 0 & 1 & 0 & 8a + b \\
0 & 0 & 0 & 1 & 16a + 8b + 4c + 2d + e \\
0 & 0 & 0 & 0 & a
\end{bmatrix}
= \begin{bmatrix}
1 & 0 & 0 & 0 & 32a - 12b + 4c + d \\
0 & 1 & 0 & 0 & -24a + 6b + c \\
0 & 0 & 1 & 0 & 8a + b \\
0 & 0 & 0 & 1 & a \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

where the last entry of the last column has been simplified to zero according to the one condition we were able to impose on an arbitrary polynomial from \( W \). So with no leading 1’s in the last column, Theorem RCLS \[53\] tells us this system is consistent. Therefore, \( \text{any} \) polynomial from \( W \) can be written as a linear combination of the polynomials in \( S \), so \( W \subseteq sp(S) \). Therefore, \( W = sp(S) \) and \( S \) is a spanning set for \( W \) by Definition TSS \[313\].

Notice that an alternative to row-reducing the augmented matrix by hand would be to appeal to Theorem FS \[262\] by expressing the column space of the coefficient matrix as a null space, and then verifying that the condition on \( r \) guarantees that \( r \) is in the column space, thus implying that the system is always consistent. Give it a try, we’ll wait. This has been a complicated example, but worth studying carefully. ⊙

Given a subspace and a set of vectors, as in Example SSP4 \[313\] it can take some work to determine that the set actually is a spanning set. An even harder problem is to be confronted with a subspace and required to construct a spanning set with no guidance. We will now work an example of this flavor, but some of the steps will be unmotivated. Fortunately, we will have some better tools for this type of problem later on.

Example SSM22  
Spanning set in \( M_{22} \)

In the space of all \( 2 \times 2 \) matrices, \( M_{22} \) consider the subspace

\[
Z = \left\{ \begin{bmatrix} a & b \\ c & d \end{bmatrix} \mid a + 2b - 7d = 0, \ 3a - b + 7c - 7d = 0 \right\}
\]

We need to construct a limited number of matrices in \( Z \) and hope that they form a spanning set. Notice that the first restriction on elements of \( Z \) can be solved for \( d \) in terms of \( a \) and \( b \),

\[
7d = a + 2b \\
d = \frac{1}{7} (a + 2b)
\]

Then we rearrange the second restriction as an expression for \( c \) in terms of \( a \) and \( b \),

\[
7c = -3a + b + 7d \\
= -3a + b + (a + 2b) \\
= -2a + 3b \\
c = \frac{1}{7} (-2a + 3b)
\]
These two equations will allow us to rewrite a generic element of $Z$ as follows,

$$
\begin{bmatrix}
a & b \\
c & d
\end{bmatrix}
= \frac{1}{7} \begin{bmatrix}
-2a + 3b & \frac{1}{7} (a + 2b) \\
7a & 7b
\end{bmatrix}
= \frac{1}{7} \begin{bmatrix}
7a & 0 \\
-2a & a + 2b
\end{bmatrix}
= \frac{1}{7} \left( \begin{bmatrix}
7 & 0 \\
-2 & 1
\end{bmatrix} + \begin{bmatrix}
0 & 7b \\
3 & 2
\end{bmatrix} \right)
= \alpha_1 \begin{bmatrix}
7 & 0 \\
-2 & 1
\end{bmatrix} + \frac{1}{7} \begin{bmatrix}
0 & 7 \\
3 & 2
\end{bmatrix}
\]}

These computations have been entirely unmotivated, but the result would appear to say that we can write any matrix for $Z$ as a linear combination using the scalars $\frac{a}{7}$ and $\frac{b}{7}$.

The “vectors” (matrices, really) in this linear combination are

$$
\begin{bmatrix}
7 & 0 \\
-2 & 1
\end{bmatrix} \quad \begin{bmatrix}
0 & 7 \\
3 & 2
\end{bmatrix}
$$

This all suggests a spanning set for $Z$,

$$Q = \left\{ \begin{bmatrix}
7 & 0 \\
-2 & 1
\end{bmatrix}, \begin{bmatrix}
0 & 7 \\
3 & 2
\end{bmatrix} \right\}
$$

Formally, the question is: If we take an arbitrary element of $Z$, can we write it as a linear combination of the two matrices in $Q$? Let’s try.

$$
\begin{bmatrix}
a & b \\
c & d
\end{bmatrix}
= \alpha_1 \begin{bmatrix}
7 & 0 \\
-2 & 1
\end{bmatrix} + \alpha_2 \begin{bmatrix}
0 & 7 \\
3 & 2
\end{bmatrix}
= \begin{bmatrix}
7\alpha_1 & 7\alpha_2 \\
-2\alpha_1 + 3\alpha_2 & \alpha_1 + 2\alpha_2
\end{bmatrix}
\]

Using our definition of matrix equality (Definition ME 179) we equate corresponding entries and get a system of four equations in two variables,

\begin{align*}
7\alpha_1 &= a \\
7\alpha_2 &= b \\
-2\alpha_1 + 3\alpha_2 &= c \\
\alpha_1 + 2\alpha_2 &= d
\end{align*}

Form the augmented matrix and row-reduce (by hand),

$$
\begin{bmatrix}
1 & 0 & \frac{a}{7} \\
0 & 1 & \frac{b}{7} \\
0 & 0 & \frac{1}{7} (2a - 3b + 7c) \\
0 & 0 & \frac{1}{7} (a + 2b - 7d)
\end{bmatrix}
$$
In order to believe that $Q$ is a spanning set for $Z$, we need to be certain that this system has a solution for any matrix $\begin{bmatrix} a & b \\ c & d \end{bmatrix} \in Z$, i.e. the system should always be consistent. However, the generic matrix from $Z$ is not as generic as it appears, since its membership in $Z$ tells us that $a + 2b - 7d = 0$ and $3a - b + 7c - 7d = 0$. To arrive at a consistent system, Theorem RCLS \[53\] says we need to have no leading 1’s in the final column of the row-reduced matrix. We see that the expression in the fourth row is

$$\frac{1}{7} (a + 2b - 7d) = \frac{1}{7} (0) = 0$$

With a bit more finesse, the expression in the third row is

$$\frac{1}{7} (2a - 3b + 7c) = \frac{1}{7} (2a - 3b + 7c + 0)$$
$$= \frac{1}{7} (2a - 3b + 7c + (a + 2b - 7d))$$
$$= \frac{1}{7} (3a - b + 7c - 7d)$$
$$= \frac{1}{7} (0)$$
$$= 0$$

So the system is consistent, and the scalars $\alpha_1$ and $\alpha_2$ can always be found to express any matrix in $Z$ as a linear combination of the matrices in $Q$. Therefore, $Z \subseteq S p(Q)$ and $Q$ is a spanning set for $Z$. ⊙

**Subsection B**

**Bases**

We now have all the tools in place to define a basis of a vector space.

**Definition B**

**Basis**

Suppose $V$ is a vector space. Then a subset $S \subseteq V$ is a basis of $V$ if it is linearly independent and spans $V$. △

So, a basis is a linearly independent spanning set for a vector space. The requirement that the set spans insures that $S$ has enough raw material to build $V$, while the linear independence requirement insures that we do not have any more raw material than we need. As we shall see soon in Section D \[331\], a basis is a minimal spanning set.

You may have noticed that we used the term basis for some of the titles of previous theorems (e.g. Theorem BNS \[141\], Theorem BCSOC \[238\], Theorem BRS \[245\]) and if you review each of these theorems you will see that their conclusions provide linearly independent spanning sets for sets that we now recognize as subspaces of $\mathbb{C}^m$. Examples associated with these theorems include Example NSLII \[141\], Example ROCD \[239\] and Example IAS \[245\]. As we will see, these three theorems will continue to be powerful tools, even in the setting of more general vector spaces.
Furthermore, the archetypes contain an abundance of bases. For each coefficient matrix of a system of equations, and for each archetype defined simply as a matrix, there is a basis for the null space, three bases for the column space, and a basis for the row space. For this reason, our subsequent examples will concentrate on bases for vector spaces other than $\mathbb{C}^m$. Notice that Definition B [317] does not preclude a vector space from having many bases, and this is the case, as hinted above by the statement that the archetypes contain three bases for the column space of a matrix. More generally, we can grab any basis for a vector space, multiply any one basis vector by a non-zero scalar and create a slightly different set that is still a basis. For "important" vector spaces, it will be convenient to have a collection of "nice" bases. When a vector space has a single particularly nice basis, it is sometimes called the standard basis though there is nothing precise enough about this term to allow us to define it formally — it is a question of style. Here are some nice bases for important vector spaces.

**Theorem SUVB**

**Standard Unit Vectors are a Basis**
The set of standard unit vectors for $\mathbb{C}^m$, $B = \{e_1, e_2, e_3, \ldots, e_m\} = \{e_i \mid 1 \leq i \leq m\}$ is a basis for the vector space $\mathbb{C}^m$.

**Proof** We must show that the set $B$ is both linearly independent and a spanning set for $\mathbb{C}^m$. First, the vectors in $B$ are, by Definition SUV [210], the columns of the identity matrix, which we know is nonsingular (since it row-reduces to the identity matrix!). And the columns of a nonsingular matrix are linearly independent by Theorem NSLIC [139].

Suppose we grab an arbitrary vector from $\mathbb{C}^m$, say

$$
v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}.
$$

Can we write $v$ as a linear combination of the vectors in $B$? Yes, and quite simply.

$$
v = v_1 e_1 + v_2 e_2 + v_3 e_3 + \cdots + v_m e_m
$$

this shows that $\mathbb{C}^m \subseteq Sp(B)$, which is sufficient to show that $B$ is a spanning set for $\mathbb{C}^m$. □

**Example BP**

**Bases for $P_n$**
The vector space of polynomials with degree at most $n$, $P_n$, has the basis

$$
B = \{1, x, x^2, x^3, \ldots, x^n\}.
$$
Another nice basis for \( P_n \) is
\[
C = \{1, 1 + x, 1 + x + x^2, 1 + x + x^2 + x^3, \ldots, 1 + x + x^2 + x^3 + \cdots + x^n \}.
\]

Checking that each of \( B \) and \( C \) is a linearly independent spanning set are good exercises. ⊓⊔

**Example BM**

**A basis for the vector space of matrices**

In the vector space \( M_{mn} \) of matrices [Example VSM 277] define the matrices \( B_{k\ell}, \) \( 1 \leq k \leq m, \) \( 1 \leq \ell \leq n \) by
\[
[B_{k\ell}]_{ij} = \begin{cases} 
1 & \text{if } k = i, \ell = j \\
0 & \text{otherwise}
\end{cases}
\]

So these matrices have entries that are all zeros, with the exception of a lone entry that is one. The set of all \( mn \) of them,
\[
B = \{ B_{k\ell} \mid 1 \leq k \leq m, \, 1 \leq \ell \leq n \}
\]
forms a basis for \( M_{mn}. \) ⊓⊔

The bases described above will often be convenient ones to work with. However a basis doesn’t have to obviously look like a basis.

**Example BSP4**

**A basis for a subspace of \( P_4 \)**

In [Example SSP4 313] we showed that
\[
S = \{ x - 2, \, x^2 - 4x + 4, \, x^3 - 6x^2 + 12x - 8, \, x^4 - 8x^3 + 24x^2 - 32x + 16 \}
\]
is a spanning set for \( W = \{ p(x) \mid p \in P_4, \, p(2) = 0 \}. \) We will now show that \( S \) is also linearly independent in \( W. \) Begin with a relation of linear dependence,
\[
0 + 0x + 0x^2 + 0x^3 + 0x^4 = \alpha_1 (x - 2) + \alpha_2 (x^2 - 4x + 4) + \alpha_3 (x^3 - 6x^2 + 12x - 8) + \alpha_4 (x^4 - 8x^3 + 24x^2 - 32x + 16)
\]
\[
= \alpha_4 x^4 + (\alpha_3 - 8\alpha_4) x^3 + (\alpha_2 - 6\alpha_3 + 24\alpha_4) x^2 + (\alpha_1 - 4\alpha_2 + 12\alpha_3 - 32\alpha_4) x + (-2\alpha_1 + 4\alpha_2 - 8\alpha_3 + 16\alpha_4)
\]

Equating coefficients (vector equality in \( P_4 \)) gives the homogeneous system of five equations in four variables,
\[
\begin{align*}
\alpha_4 &= 0 \\
\alpha_3 - 8\alpha_4 &= 0 \\
\alpha_2 - 6\alpha_3 + 24\alpha_4 &= 0 \\
\alpha_1 - 4\alpha_2 + 12\alpha_3 - 32\alpha_4 &= 0 \\
-2\alpha_1 + 4\alpha_2 - 8\alpha_3 + 16\alpha_4 &= 0
\end{align*}
\]
We form the coefficient matrix, and row-reduce to obtain a matrix in reduced row-echelon form

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

With only the trivial solution to this homogeneous system, we conclude that only scalars that will form a relation of linear dependence are the trivial ones, and therefore the set \( S \) is linearly independent (Definition LI [309]). Finally, \( S \) has earned the right to be called a basis for \( W \) (Definition B [317]).

Example BSM22
A basis for a subspace of \( M_{22} \)
In Example SSM22 [315] we discovered that

\[
Q = \left\{ \begin{bmatrix} 7 & 0 \\ -2 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 7 \\ 3 & 2 \end{bmatrix} \right\}
\]

is a spanning set for the subspace

\[
Z = \left\{ \begin{bmatrix} a & b \\ c & d \end{bmatrix} \mid a + 2b - 7d = 0, \ 3a - b + 7c - 7d = 0 \right\}
\]

of the vector space of all \( 2 \times 2 \) matrices, \( M_{22} \). If we can also determine that \( Q \) is linearly independent in \( Z \) (or in \( M_{22} \)), then it will qualify as a basis for \( Z \). Let’s begin with a relation of linear dependence.

\[
\begin{bmatrix}
0 & 0 \\
0 & 0
\end{bmatrix} = \alpha_1 \begin{bmatrix} 7 & 0 \\ -2 & 1 \end{bmatrix} + \alpha_2 \begin{bmatrix} 0 & 7 \\ 3 & 2 \end{bmatrix}
\]

\[
= \begin{bmatrix}
7\alpha_1 & 7\alpha_2 \\
-2\alpha_1 + 3\alpha_2 & \alpha_1 + 2\alpha_2
\end{bmatrix}
\]

Using our definition of matrix equality (Definition ME [179]) we equate corresponding entries and get a homogeneous system of four equations in two variables,

\[
7\alpha_1 = 0 \\
7\alpha_2 = 0 \\
-2\alpha_1 + 3\alpha_2 = 0 \\
\alpha_1 + 2\alpha_2 = 0
\]

We could row-reduce the coefficient matrix of this homogeneous system, but it is not necessary. The first two equations tell us that \( \alpha_1 = 0, \alpha_2 = 0 \) is the only solution to this homogeneous system. This qualifies the set \( Q \) as being linearly independent, since the only relation of linear dependence is trivial (Definition LI [309]). Therefore \( Q \) is a basis for \( Z \) (Definition B [317]).

Version 0.52
We have seen several examples of bases in different vector spaces. In this subsection, and the next (Subsection B.BNSM [323]), we will consider building bases for $\mathbb{C}^m$ and its subspaces.

Suppose we have a subspace of $\mathbb{C}^m$ that is expressed as the span of a set of vectors, $S$, and $S$ is not necessarily linearly independent, or perhaps not very attractive. Theorem REMRS [243] says that row-equivalent matrices have identical row spaces, while Theorem BRS [245] says the nonzero rows of a matrix in reduced row-echelon form are a basis for the row space. These theorems together give us a great computational tool for quickly finding a basis for a subspace that is expressed originally as a span.

Example RSB
Row space basis
When we first defined the span of a set of vectors, in Example SCAD [124] we looked at the set

$$W = \text{sp}\left(\begin{bmatrix} 2 & -3 & 1 \\ 1 & 4 & 1 \\ 7 & -5 & 4 \\ -7 & -6 & -5 \end{bmatrix}\right)$$

with an eye towards realizing $W$ as the span of a smaller set. By building relations of linear dependence (though we did not know them by that name then) we were able to remove two vectors and write $W$ as the span of the other two vectors. These two remaining vectors formed a linearly independent set, even though we did not know that at the time.

Now we know that $W$ is a subspace and must have a basis. Consider the matrix, $C$, whose rows are the vectors in the spanning set for $W$,

$$C = \begin{bmatrix} 2 & -3 & 1 \\ 1 & 4 & 1 \\ 7 & -5 & 4 \\ -7 & -6 & -5 \end{bmatrix}$$

Then, by Definition RSM [242], the row space of $C$ will be $W$, $\mathcal{R}(C) = W$. Theorem BRS [245] tells us that if we row-reduce $C$, the nonzero rows of the row-equivalent matrix in reduced row-echelon form will be a basis for $\mathcal{R}(C)$, and hence a basis for $W$. Let’s do it — $C$ row-reduces to

$$\begin{bmatrix} 1 & 0 & \frac{7}{11} \\ 0 & 1 & \frac{1}{11} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

If we convert the two nonzero rows to column vectors then we have a basis,

$$B = \left\{ \begin{bmatrix} 1 \\ 0 \\ \frac{7}{11} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{1}{11} \end{bmatrix} \right\}$$
and

\[ W = S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ \frac{7}{17} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \right) \]

Example IAS [245] provides another example of this flavor, though now we can notice that \( X \) is a subspace, and that the resulting set of three vectors is a basis. This is such a powerful technique that we should do one more example.

Example RS
Reducing a span
In Example RSC5 [152] we began with a set of \( n = 4 \) vectors from \( \mathbb{C}^5 \),

\[ R = \{v_1, v_2, v_3, v_4\} = \left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 3 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ -7 \\ 6 \\ -11 \\ -2 \end{bmatrix}, \begin{bmatrix} 4 \\ 1 \\ 2 \\ 1 \\ 6 \end{bmatrix} \right\} \]

and defined \( V = S_p(R) \). Our goal in that problem was to find a relation of linear dependence on the vectors in \( R \), solve the resulting equation for one of the vectors, and re-express \( V \) as the span of a set of three vectors.

Here is another way to accomplish something similar. The row space of the matrix

\[
A = \begin{bmatrix}
1 & 2 & -1 & 3 & 2 \\
2 & 1 & 3 & 1 & 2 \\
0 & -7 & 6 & -11 & -2 \\
4 & 1 & 2 & 1 & 6
\end{bmatrix}
\]

is equal to \( S_p(R) \). By Theorem BRS [245] we can row-reduce this matrix, ignore any zero rows, and use the non-zero rows as column vectors that are a basis for the row space of \( A \). Row-reducing \( A \) creates the matrix

\[
\begin{bmatrix}
1 & 0 & 0 & -\frac{1}{25} & \frac{30}{17} \\
0 & 1 & 0 & \frac{17}{2} & -\frac{7}{8} \\
0 & 0 & 1 & -\frac{2}{17} & -\frac{17}{17} \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

So

\[
\left\{ \begin{bmatrix} 1 \\ 0 \\ -\frac{1}{30} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}
\]

is a basis for \( V \). Our theorem tells us this is a basis, there is no need to verify that the subspace spanned by three vectors (rather than four) is the identical subspace, and there is no need to verify that we have reached the limit in reducing the set, since the set of three vectors is guaranteed to be linearly independent.

Version 0.52
A quick source of diverse bases for $\mathbb{C}^m$ is the set of columns of a nonsingular matrix.

**Theorem CNSMB**

**Columns of NonSingular Matrix are a Basis**

Suppose that $A$ is a square matrix. Then the columns of $A$ are a basis of $\mathbb{C}^m$ if and only if $A$ is nonsingular. □

**Proof** ($\Rightarrow$) Suppose that the columns of $A$ are a basis for $\mathbb{C}^m$. Then [Definition B 317] says the set of columns is linearly independent. [Theorem NSLIC 139] then says that $A$ is nonsingular.

($\Leftarrow$) Suppose that $A$ is nonsingular. Then by [Theorem NSLIC 139] this set of columns is linearly independent. [Theorem CSNSM 241] says that for a nonsingular matrix, $\mathcal{C}(A) = \mathbb{C}^m$. This is equivalent to saying that the columns of $A$ are a spanning set for the vector space $\mathbb{C}^m$. As a linearly independent spanning set, the columns of $A$ qualify as a basis for $\mathbb{C}^m$ (Definition B 317).

**Example CABAK**

**Columns as Basis, Archetype K**

[Archetype K 609] is the $5 \times 5$ matrix

\[
K = \begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20
\end{bmatrix}
\]

which is row-equivalent to the $5 \times 5$ identity matrix $I_5$. So by [Theorem NSRRI 77], $K$ is nonsingular. Then [Theorem CNSMB 323] says the set

\[
\left\{ \begin{bmatrix} 10 \\ 12 \\ -30 \\ 27 \\ 18 \end{bmatrix}, \begin{bmatrix} 18 \\ -2 \\ -21 \\ 30 \\ 24 \end{bmatrix}, \begin{bmatrix} 24 \\ -6 \\ -23 \\ 36 \\ 30 \end{bmatrix}, \begin{bmatrix} 24 \\ 0 \\ -30 \\ 37 \\ 30 \end{bmatrix}, \begin{bmatrix} -12 \\ -18 \\ 39 \\ -30 \\ -20 \end{bmatrix} \right\}
\]

is a (novel) basis of $\mathbb{C}^5$. ⊙

Perhaps we should view the fact that the standard unit vectors are a basis (Theorem SUVE 318) as just a simple corollary of Theorem CNSMB 323?

With a new equivalence for a nonsingular matrix, we can update our list of equivalences (Theorem NSME4 241).

**Theorem NSME5**

**NonSingular Matrix Equivalences, Round 5**

Suppose that $A$ is a square matrix of size $n$. The following are equivalent.

1. $A$ is nonsingular.
2. A row-reduces to the identity matrix.
3. The null space of $A$ contains only the zero vector, $\mathcal{N}(A) = \{0\}$.
4. The linear system $LS(A, b)$ has a unique solution for every possible choice of $b$.
5. The columns of $A$ are a linearly independent set.
6. $A$ is invertible.
7. The column space of $A$ is $\mathbb{C}^n$, $\mathcal{C}(A) = \mathbb{C}^n$.
8. The columns of $A$ are a basis for $\mathbb{C}^n$. $\square$

Subsection VR
Vector Representation

In Chapter R we will take up the matter of representations fully. Now we will prove a critical theorem that tells us how to represent a vector. This theorem could wait, but working with it now will provide some extra insight into the nature of a basis as a minimal spanning set. First an example, then the theorem.

Example AVR
A vector representation

The set
$$\begin{bmatrix} -7 \\ 5 \\ 1 \end{bmatrix}, \begin{bmatrix} -6 \\ 5 \\ 0 \end{bmatrix}, \begin{bmatrix} -12 \\ 7 \\ 4 \end{bmatrix}$$
is a basis for $\mathbb{C}^3$. (This can be verified by applying Theorem CNSMB.) This set comes from the columns of the coefficient matrix of Archetype B. Because $x = \begin{bmatrix} -3 \\ 5 \\ 2 \end{bmatrix}$ is a solution to this system, we can use Theorem SLSLC $\begin{bmatrix} -33 \\ 24 \\ 5 \end{bmatrix} = (-3) \begin{bmatrix} -7 \\ 5 \\ 1 \end{bmatrix} + (5) \begin{bmatrix} -6 \\ 5 \\ 0 \end{bmatrix} + (2) \begin{bmatrix} -12 \\ 7 \\ 4 \end{bmatrix}$.

Further, we know this is the only way we can express $\begin{bmatrix} -33 \\ 24 \\ 5 \end{bmatrix}$ as a linear combination of these basis vectors, since the nonsingularity of the coefficient matrix tells that this solution is unique. This is all an illustration of the following theorem. $\circ$

Theorem VRRB
Vector Representation Relative to a Basis

Suppose that $V$ is a vector space with basis $B = \{v_1, v_2, v_3, \ldots, v_m\}$ and that $w$ is a vector in $V$. Then there exist unique scalars $a_1, a_2, a_3, \ldots, a_m$ such that
$$w = a_1v_1 + a_2v_2 + a_3v_3 + \cdots + a_mv_m.$$
The real question is: Is there more than one way to write \( w \) as a linear combination of \( \{v_1, v_2, v_3, \ldots, v_m\} \)? Are the scalars \( a_1, a_2, a_3, \ldots, a_m \) unique? (Technique U 78)

Assume there are two ways to express \( w \) as a linear combination of \( \{v_1, v_2, v_3, \ldots, v_m\} \).

In other words there exist scalars \( a_1, a_2, a_3, \ldots, a_m \) and \( b_1, b_2, b_3, \ldots, b_m \) so that

\[
\begin{align*}
w &= a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_m v_m \\
w &= b_1 v_1 + b_2 v_2 + b_3 v_3 + \cdots + b_m v_m.
\end{align*}
\]

Then notice that (using the vector space axioms of associativity and distributivity)

\[
0 = w + (-w) = w + (-1)w = (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_m v_m) + \\
-1 (b_1 v_1 + b_2 v_2 + b_3 v_3 + \cdots + b_m v_m) = (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_m v_m) + \\
-1 (b_1 v_1 - b_2 v_2 - b_3 v_3 - \cdots - b_m v_m) = (a_1 - b_1)v_1 + (a_2 - b_2)v_2 + (a_3 - b_3)v_3 + \\
\cdots + (a_m - b_m)v_m.
\]

But this is a relation of linear dependence on a linearly independent set of vectors (Definition RLD 309)! Now we are using the other half of the assumption that \( \{v_1, v_2, v_3, \ldots, v_m\} \) is a basis (Definition B 317). So by Definition LI 309 it must happen that the scalars are all zero. That is,

\[
\begin{align*}
(a_1 - b_1) &= 0 & (a_2 - b_2) &= 0 & (a_3 - b_3) &= 0 & \cdots & (a_m - b_m) &= 0 \\
a_1 &= b_1 & a_2 &= b_2 & a_3 &= b_3 & \cdots & a_m &= b_m.
\end{align*}
\]

And so we find that the scalars are unique. $\blacksquare$

This is a very typical use of the hypothesis that a set is linear independent — obtain a relation of linear dependence and then conclude that the scalars must all be zero.

The result of this theorem tells us that we can write any vector in a vector space as a linear combination of the basis vectors, but only just. There is only enough raw material in the spanning set to write each vector one way as a linear combination. This theorem will be the basis (pun intended) for our future definition of coordinate vectors in Definition VR 505.

Subsection READ
Reading Questions

1. Is the set of matrices below linearly independent or linearly dependent in the vector space \( M_{22} \)? Why or why not?

\[
\begin{bmatrix}
1 & 3 \\
-2 & 4
\end{bmatrix},
\begin{bmatrix}
-2 & 3 \\
3 & -5
\end{bmatrix},
\begin{bmatrix}
0 & 9 \\
-1 & 3
\end{bmatrix}
\]
2. The matrix below is nonsingular. What can you now say about its columns?

\[
A = \begin{bmatrix}
-3 & 0 & 1 \\
1 & 2 & 1 \\
5 & 1 & 6
\end{bmatrix}
\]

3. Write the vector \( \mathbf{w} = \begin{bmatrix} 6 \\ 6 \\ 15 \end{bmatrix} \) as a linear combination of the columns of the matrix \( A \) above. How many ways are there to answer this question?


Subsection EXC
Exercises

C20  In the vector space of $2 \times 2$ matrices, $M_{22}$, determine if the set $S$ below is linearly independent.

$$S = \left\{\begin{bmatrix} 2 & -1 \\ 1 & 3 \end{bmatrix}, \begin{bmatrix} 0 & 4 \\ -1 & 2 \end{bmatrix}, \begin{bmatrix} 4 & 2 \\ 1 & 3 \end{bmatrix}\right\}$$

Contributed by Robert Beezer  Solution 329

C30  In Example LIM32, find another nontrivial relation of linear dependence on the linearly dependent set of $3 \times 2$ matrices, $S$.

Contributed by Robert Beezer

M10  Halfway through Example SSP4, we need to show that the system of equations

$$LS \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & -8 \\ 0 & 1 & -6 & 24 \\ 1 & -4 & 12 & -32 \\ -2 & 4 & -8 & 16 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \end{bmatrix}$$

is consistent for every choice of the vector of constants for which $16a + 8b + 4c + 2d + e = 0$

Express the column space of the coefficient matrix of this system as a null space, using Theorem FS. From this use Theorem CSCS to establish that the system is always consistent. Notice that this approach removes from Example SSP4 the need to row-reduce a symbolic matrix.

Contributed by Robert Beezer  Solution 329

M20  In Example BM, provide the verifications (linear independence and spanning) to show that $B$ is a basis of $M_{mn}$.

Contributed by Robert Beezer
Subsection SOL
Solutions

C20 Contributed by Robert Beezer Statement 327
Begin with a relation of linear dependence on the vectors in $S$ and massage it according to the definitions of vector addition and scalar multiplication in $M_{22}$,

$$0 = a_1 \begin{bmatrix} 2 & -1 \\ 1 & 3 \end{bmatrix} + a_2 \begin{bmatrix} 0 & 4 \\ -1 & 2 \end{bmatrix} + a_3 \begin{bmatrix} 4 & 2 \\ 1 & 3 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 2a_1 + 4a_3 & -a_1 + 4a_2 + 2a_3 \\ a_1 - a_2 + a_3 & 3a_1 + 2a_2 + 3a_3 \end{bmatrix}$$

By our definition of matrix equality (Definition ME 179) we arrive at a homogeneous system of linear equations,

$$2a_1 + 4a_3 = 0$$
$$-a_1 + 4a_2 + 2a_3 = 0$$
$$a_1 - a_2 + a_3 = 0$$
$$3a_1 + 2a_2 + 3a_3 = 0$$

The coefficient matrix of this system row-reduces to the matrix,

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

and from this we conclude that the only solution is $a_1 = a_2 = a_3 = 0$. Since the relation of linear dependence (Definition RLD 309) is trivial, the set $S$ is linearly independent (Definition LI 309).

M10 Contributed by Robert Beezer Statement 327
Theorem FS 262 provides the matrix

$$L = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{4} & \frac{1}{8} & \frac{1}{16} \end{bmatrix}$$

and so if $A$ denotes the coefficient matrix of the system, then $\mathcal{C}(A) = \mathcal{N}(L)$. The single homogeneous equation in $LS(L, 0)$ is equivalent to the condition on the vector of constants (use $a, b, c, d, e$ as variables and then multiply by 16).
Almost every vector space we have encountered has been infinite in size (an exception is Example VSS \[279\]). But some are bigger and richer than others. Dimension, once suitably defined, will be a measure of the size of a vector space, and a useful tool for studying its properties. You probably already have a rough notion of what a mathematical definition of dimension might be — try to forget these imprecise ideas and go with the new ones given here.

**Subsection D Dimension**

**Definition D Dimension**

Suppose that $V$ is a vector space and $\{v_1, v_2, v_3, \ldots, v_t\}$ is a basis of $V$. Then the **dimension** of $V$ is defined by $\dim (V) = t$. If $V$ has no finite bases, we say $V$ has infinite dimension. △

This is a very simple definition, which belies its power. Grab a basis, any basis, and count up the number of vectors it contains. That’s the dimension. However, this simplicity causes a problem. Given a vector space, you and I could each construct different bases — remember that a vector space might have many bases. And what if your basis and my basis had different sizes? Applying Definition D \[331\] we would arrive at different numbers! With our current knowledge about vector spaces, we would have to say that dimension is not “well-defined.” Fortunately, there is a theorem that will correct this problem.

In a strictly logical progression, the next two theorems would precede the definition of dimension. Here is a fundamental result that many subsequent theorems will trace their lineage back to.

**Theorem SSLD Spanning Sets and Linear Dependence**

Suppose that $S = \{v_1, v_2, v_3, \ldots, v_t\}$ is a finite set of vectors which spans the vector space $V$. Then any set of $t + 1$ or more vectors from $V$ is linearly dependent. □

**Proof** We want to prove that any set of $t+1$ or more vectors from $V$ is linearly dependent. So we will begin with a totally arbitrary set of vectors from $V$, $R = \{u_1, u_2, u_3, \ldots, u_m\}$, where $m > t$. We will now construct a nontrivial relation of linear dependence on $R$.

Each vector $u_1, u_2, u_3, \ldots, u_m$ can be written as a linear combination of $v_1, v_2, v_3, \ldots, v_t$ since $S$ is a spanning set of $V$. This means there exist scalars $a_{ij}$, $1 \leq i \leq t$, $1 \leq j \leq m$, \[380\]
so that

\[ u_1 = a_{11}v_1 + a_{21}v_2 + a_{31}v_3 + \cdots + a_{t1}v_t \]
\[ u_2 = a_{12}v_1 + a_{22}v_2 + a_{32}v_3 + \cdots + a_{t2}v_t \]
\[ u_3 = a_{13}v_1 + a_{23}v_2 + a_{33}v_3 + \cdots + a_{t3}v_t \]
\[ \vdots \]
\[ u_m = a_{1m}v_1 + a_{2m}v_2 + a_{3m}v_3 + \cdots + a_{tm}v_t \]

Now we form, unmotivated, the homogeneous system of \( t \) equations in the \( m \) variables, \( x_1, x_2, x_3, \ldots, x_m \), where the coefficients are the just-discovered scalars \( a_{ij} \),

\[
\begin{align*}
    a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \cdots + a_{1m}x_m &= 0 \\
a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \cdots + a_{2m}x_m &= 0 \\
a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + \cdots + a_{3m}x_m &= 0 \\
\vdots & \\
a_{t1}x_1 + a_{t2}x_2 + a_{t3}x_3 + \cdots + a_{tm}x_m &= 0
\end{align*}
\]

This is a homogeneous system with more variables than equations (our hypothesis is expressed as \( m > t \)), so by [Theorem HMVEI][65] there are infinitely many solutions. Choose a nontrivial solution and denote it by \( x_1 = c_1, x_2 = c_2, x_3 = c_3, \ldots, x_m = c_m \). As a solution to the homogeneous system, we then have

\[
\begin{align*}
    a_{11}c_1 + a_{12}c_2 + a_{13}c_3 + \cdots + a_{1m}c_m &= 0 \\
a_{21}c_1 + a_{22}c_2 + a_{23}c_3 + \cdots + a_{2m}c_m &= 0 \\
a_{31}c_1 + a_{32}c_2 + a_{33}c_3 + \cdots + a_{3m}c_m &= 0 \\
\vdots & \\
a_{t1}c_1 + a_{t2}c_2 + a_{t3}c_3 + \cdots + a_{tm}c_m &= 0
\end{align*}
\]

As a collection of nontrivial scalars, \( c_1, c_2, c_3, \ldots, c_m \) will provide the nontrivial relation
of linear dependence we desire,

\[ c_1 \mathbf{u}_1 + c_2 \mathbf{u}_2 + c_3 \mathbf{u}_3 + \cdots + c_m \mathbf{u}_m \\
= c_1 (a_{11} \mathbf{v}_1 + a_{21} \mathbf{v}_2 + a_{31} \mathbf{v}_3 + \cdots + a_{t1} \mathbf{v}_t) \\
+ c_2 (a_{12} \mathbf{v}_1 + a_{22} \mathbf{v}_2 + a_{32} \mathbf{v}_3 + \cdots + a_{t2} \mathbf{v}_t) \\
+ c_3 (a_{13} \mathbf{v}_1 + a_{23} \mathbf{v}_2 + a_{33} \mathbf{v}_3 + \cdots + a_{t3} \mathbf{v}_t) \\
+ \cdots \\
+ c_m (a_{1m} \mathbf{v}_1 + a_{2m} \mathbf{v}_2 + a_{3m} \mathbf{v}_3 + \cdots + a_{tm} \mathbf{v}_t) \\
= c_1 a_{11} \mathbf{v}_1 + c_1 a_{21} \mathbf{v}_2 + c_1 a_{31} \mathbf{v}_3 + \cdots + c_1 a_{1t} \mathbf{v}_t \\
+ c_2 a_{12} \mathbf{v}_1 + c_2 a_{22} \mathbf{v}_2 + c_2 a_{32} \mathbf{v}_3 + \cdots + c_2 a_{1t} \mathbf{v}_t \\
+ c_3 a_{13} \mathbf{v}_1 + c_3 a_{23} \mathbf{v}_2 + c_3 a_{33} \mathbf{v}_3 + \cdots + c_3 a_{1t} \mathbf{v}_t \\
+ \cdots \\
+ c_m a_{1m} \mathbf{v}_1 + c_m a_{2m} \mathbf{v}_2 + c_m a_{3m} \mathbf{v}_3 + \cdots + c_m a_{1t} \mathbf{v}_t \\
= \left( c_1 a_{11} + c_2 a_{12} + c_3 a_{13} + \cdots + c_m a_{1m} \right) \mathbf{v}_1 \\
+ \left( c_1 a_{21} + c_2 a_{22} + c_3 a_{23} + \cdots + c_m a_{2m} \right) \mathbf{v}_2 \\
+ \left( c_1 a_{31} + c_2 a_{32} + c_3 a_{33} + \cdots + c_m a_{3m} \right) \mathbf{v}_3 \\
+ \cdots \\
+ \left( c_1 a_{1t} + c_2 a_{1t} + c_3 a_{1t} + \cdots + c_m a_{1t} \right) \mathbf{v}_t \\
= \left( a_{11} c_1 + a_{12} c_2 + a_{13} c_3 + \cdots + a_{1t} c_m \right) \mathbf{v}_1 \\
+ \left( a_{21} c_1 + a_{22} c_2 + a_{23} c_3 + \cdots + a_{2t} c_m \right) \mathbf{v}_2 \\
+ \left( a_{31} c_1 + a_{32} c_2 + a_{33} c_3 + \cdots + a_{3t} c_m \right) \mathbf{v}_3 \\
+ \cdots \\
+ \left( a_{1t} c_1 + a_{1t} c_2 + a_{1t} c_3 + \cdots + a_{1t} c_m \right) \mathbf{v}_t \\
= 0 \mathbf{v}_1 + 0 \mathbf{v}_2 + 0 \mathbf{v}_3 + \cdots + 0 \mathbf{v}_t \\
= 0 + 0 + 0 + \cdots + 0 \\
= 0 \\
\]

That does it. \( R \) has been undeniably shown to be a linearly dependent set. \( \blacksquare \)

The proof just given has some rather monstrous expressions in it, mostly owing to the double subscripts present. Now is a great opportunity to show the value of a more compact notation. We will rewrite the key steps of the previous proof using summation notation, resulting in a more economical presentation, and even greater insight into the key aspects of the proof. So here is an alternate proof — study it carefully.

**Proof (Alternate Proof of Theorem SSLD)** We want to prove that any set of \( t + 1 \) or more vectors from \( V \) is linearly dependent. So we will begin with a totally arbitrary set of vectors from \( V \), \( R = \{ \mathbf{u}_j \mid 1 \leq j \leq m \} \), where \( m > t \). We will now construct a nontrivial relation of linear dependence on \( R \).

Each vector \( \mathbf{u}_j, 1 \leq j \leq m \) can be written as a linear combination of \( \mathbf{v}_i, 1 \leq i \leq t \) since \( S \) is a spanning set of \( V \). This means there are scalars \( a_{ij}, 1 \leq i \leq t, 1 \leq j \leq m \),
so that

\[ \mathbf{u}_j = \sum_{i=1}^{t} a_{ij} \mathbf{v}_i \quad 1 \leq j \leq m \]

Now we form, unmotivated, the homogeneous system of \( t \) equations in the \( m \) variables, \( x_j, 1 \leq j \leq m \), where the coefficients are the just-discovered scalars \( a_{ij} \).

\[ \sum_{j=1}^{m} a_{ij} x_j = 0 \quad 1 \leq i \leq t \]

This is a homogeneous system with more variables than equations (our hypothesis is expressed as \( m > t \)), so by Theorem HMVEI \[65\] there are infinitely many solutions. Choose one of these solutions that is not trivial and denote it by \( x_j = c_j, 1 \leq j \leq m \). As a solution to the homogeneous system, we then have \( \sum_{j=1}^{m} a_{ij} c_j = 0 \) for \( 1 \leq i \leq t \). As a collection of nontrivial scalars, \( c_j, 1 \leq j \leq m \), will provide the nontrivial relation of linear dependence we desire,

\[ \sum_{j=1}^{m} c_j \mathbf{u}_j = \sum_{j=1}^{m} c_j \left( \sum_{i=1}^{t} a_{ij} \mathbf{v}_i \right) \quad S \text{ spans } V \]

\[ = \sum_{j=1}^{m} \sum_{i=1}^{t} c_j a_{ij} \mathbf{v}_i \quad \text{Property DVA} \[276\] \]

\[ = \sum_{i=1}^{t} \sum_{j=1}^{m} c_j a_{ij} \mathbf{v}_i \quad \text{Commutativity in } \mathbb{C} \]

\[ = \sum_{i=1}^{t} \sum_{j=1}^{m} a_{ij} c_j \mathbf{v}_i \quad \text{Commutativity in } \mathbb{C} \]

\[ = \sum_{i=1}^{t} \left( \sum_{j=1}^{m} a_{ij} c_j \right) \mathbf{v}_i \quad \text{Property DSA} \[276\] \]

\[ = \sum_{i=1}^{t} 0 \mathbf{v}_i \quad c_j \text{ as solution} \]

\[ = \sum_{i=1}^{t} 0 \quad \text{Theorem ZSSM} \[283\] \]

\[ = 0 \quad \text{Property Z} \[276\] \]

That does it. \( R \) has been undeniably shown to be a linearly dependent set.

Notice how the swap of the two summations is so much easier in the third step above, as opposed to all the rearranging and regrouping that takes place in the previous proof. In about half the space. And there are no ellipses (\ldots). Theorem SSLD \[331\] can be viewed as a generalization of Theorem MVSLD \[139\].

We know that \( \mathbb{C}^m \) has a basis with \( m \) vectors in it (Theorem SUVB \[318\]), so it is a set of \( m \) vectors that spans \( \mathbb{C}^m \). By Theorem SSLD \[331\], any set of more than \( m \) vectors from \( \mathbb{C}^m \) will be linearly dependent. But this is exactly the conclusion we have in
Theorem MVSLD [139]. Maybe this is not a total shock, as the proofs of both theorems rely heavily on Theorem HMVEI [65]. The beauty of Theorem SSLD [331] is that it applies in any vector space. We illustrate the generality of this theorem, and hint at its power, in the next example.

Example LDP4
Linearly dependent set in $P_4$

In Example SSP4 [313] we showed that

$$S = \{ x - 2, x^2 - 4x + 4, x^3 - 6x^2 + 12x - 8, x^4 - 8x^3 + 24x^2 - 32x + 16 \}$$

is a spanning set for $W = \{ p(x) \mid p \in P_4, \ p(2) = 0 \}$. So we can apply Theorem SSLD [331] to $W$ with $t = 4$. Here is a set of five vectors from $W$, as you may check by verifying that each is a polynomial of degree 4 or less and has $x = 2$ as a root,

$$T = \{ p_1, p_2, p_3, p_4, p_5 \} \subseteq W$$

where

$$p_1 = x^4 - 2x^3 + 2x^2 - 8x + 8$$
$$p_2 = -x^3 + 6x^2 - 5x - 6$$
$$p_3 = 2x^4 - 5x^3 + 5x^2 - 7x + 2$$
$$p_4 = -x^4 + 4x^3 - 7x^2 + 6x$$
$$p_5 = 4x^3 - 9x^2 + 5x - 6$$

By Theorem SSLD [331] we conclude that $T$ is linearly dependent, with no further computations.

Theorem SSLD [331] is indeed powerful, but our main purpose in proving it right now was to make sure that our definition of dimension (Definition D [331]) is well-defined. Here’s the theorem.

Theorem BIS
Bases have Identical Sizes

Suppose that $V$ is a vector space with a finite basis $B$ and a second basis $C$. Then $B$ and $C$ have the same size.

Proof Suppose that $C$ has more vectors than $B$. (Allowing for the possibility that $C$ is infinite, we can replace $C$ by a subset that has more vectors than $B$.) As a basis, $B$ is a spanning set for $V$ (Definition B [317]), so Theorem SSLD [331] says that $C$ is linearly dependent. However, this contradicts the fact that as a basis $C$ is linearly independent (Definition B [317]). So $C$ must also be a finite set, with size less than, or equal to, that of $B$.

Suppose that $B$ has more vectors than $C$. As a basis, $C$ is a spanning set for $V$ (Definition B [317]), so Theorem SSLD [331] says that $B$ is linearly dependent. However, this contradicts the fact that as a basis $B$ is linearly independent (Definition B [317]). So $C$ cannot be strictly smaller than $B$.

The only possibility left for the sizes of $B$ and $C$ is for them to be equal.

Theorem BIS [335] tells us that if we find one finite basis in a vector space, then they all have the same size. This (finally) makes Definition D [331] unambiguous.
Subsection DVS
Dimension of Vector Spaces

We can now collect the dimension of some common, and not so common, vector spaces.

**Theorem DCM**

**Dimension of \( \mathbb{C}^m \)**
The dimension of \( \mathbb{C}^m \) (Example VSCV 277) is \( m \). \( \square \)

**Proof** Theorem SUVB 318 provides a basis with \( m \) vectors. \( \blacksquare \)

**Theorem DP**

**Dimension of \( P_n \)**
The dimension of \( P_n \) (Example VSP 277) is \( n + 1 \). \( \square \)

**Proof** Example BP 318 provides two bases with \( n + 1 \) vectors. Take your pick. \( \blacksquare \)

**Theorem DM**

**Dimension of \( M_{mn} \)**
The dimension of \( M_{mn} \) (Example VSM 277) is \( mn \). \( \square \)

**Proof** Example BM 319 provides a basis with \( mn \) vectors. \( \blacksquare \)

**Example DSM22**

**Dimension of a subspace of \( M_{22} \)**
It should now be plausible that

\[
Z = \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \mid 2a + b + 3c + 4d = 0, -a + 3b - 5c - d = 0 \right\}
\]

is a subspace of the vector space \( M_{22} \) (Example VSM 277). (It is.) To find the dimension of \( Z \) we must first find a basis, though any old basis will do.

First concentrate on the conditions relating \( a, b, c \) and \( d \). They form a homogeneous system of two equations in four variables with coefficient matrix

\[
\begin{bmatrix}
2 & 1 & 3 & 4 \\
-1 & 3 & -5 & -1
\end{bmatrix}
\]

We can row-reduce this matrix to obtain

\[
\begin{bmatrix}
1 & 0 & 2 & 2 \\
0 & 1 & -1 & 0
\end{bmatrix}
\]

Rewrite the two equations represented by each row of this matrix, expressing the dependent variables \( (a \text{ and } b) \) in terms of the free variables \( (c \text{ and } d) \), and we obtain,

\[
a = -2c - 2d \\
b = c
\]
We can now write a typical entry of $Z$ strictly in terms of $c$ and $d$, and we can decompose the result,

\[
\begin{bmatrix}
  a & b \\
  c & d
\end{bmatrix} = \begin{bmatrix}
  -2c - 2d & c \\
  c & -2d
\end{bmatrix} = \begin{bmatrix}
  -2c & c \\
  c & 0
\end{bmatrix} + \begin{bmatrix}
  -2d & 0 \\
  0 & d
\end{bmatrix} = c \begin{bmatrix}
  -2 & 1 \\
  1 & 0
\end{bmatrix} + d \begin{bmatrix}
  -2 & 0 \\
  0 & 1
\end{bmatrix}
\]

this equation says that an arbitrary matrix in $Z$ can be written as a linear combination of the two vectors in

\[S = \left\{ \begin{bmatrix}
  -2 & 1 \\
  1 & 0
\end{bmatrix}, \begin{bmatrix}
  -2 & 0 \\
  0 & 1
\end{bmatrix} \right\}\]

so we know that

\[Z = S_p(S) = S_p\left(\left\{ \begin{bmatrix}
  -2 & 1 \\
  1 & 0
\end{bmatrix}, \begin{bmatrix}
  -2 & 0 \\
  0 & 1
\end{bmatrix} \right\}\right)\]

Are these two matrices (vectors) also linearly independent? Begin with a relation of linear dependence on $S$,

\[a_1 \begin{bmatrix}
  -2 & 1 \\
  1 & 0
\end{bmatrix} + a_2 \begin{bmatrix}
  -2 & 0 \\
  0 & 1
\end{bmatrix} = O\]

From the equality of the two entries in the last row, we conclude that $a_1 = 0, a_2 = 0$. Thus the only possible relation of linear dependence is the trivial one, and therefore $S$ is linearly independent (Definition LI 309). So $S$ is a basis for $V$ (Definition B 317). Finally, we can conclude that $\dim (Z) = 2$ (Definition D 331) since $S$ has two elements. $\D$

**Example DSP4**

**Dimension of a subspace of $P_4$**

In Example BSP4 319 we showed that

\[S = \{ x - 2, x^2 - 4x + 4, x^3 - 6x^2 + 12x - 8, x^4 - 8x^3 + 24x^2 - 32x + 16 \}\]

is a basis for $W = \{ p(x) \mid p \in P_4, p(2) = 0 \}$. Thus, the dimension of $W$ is four, $\dim (W) = 4$. $\D$

It is possible for a vector space to have no finite bases, in which case we say it has infinite dimension. Many of the best examples of this are vector spaces of functions, which lead to constructions like Hilbert spaces. We will focus exclusively on finite-dimensional vector spaces. OK, one example, and then we will focus exclusively on finite-dimensional vector spaces.

**Example VSPUD**

**Vector space of polynomials with unbounded degree**

Define the set $P$ by

\[P = \{ p \mid p(x) \text{ is a polynomial in } x \}\]

Our operations will be the same as those defined for $P_n$ (Example VSP 277).

With no restrictions on the possible degrees of our polynomials, any finite set that is a candidate for spanning $P$ will come up short. Suppose $S$ is a potential finite spanning set and let $m$ be the maximum degree of all the polynomials in $S$. If $q$ is a polynomial
of degree \( m + 1 \), then it will be impossible to form a linear combination that equals \( q \) by using elements of \( S \). So no finite set can span \( P \) and no finite bases exist. Thus, \( \dim(P) = \infty \). 

**Subsection RNM**  
**Rank and Nullity of a Matrix**

For any matrix, we have seen that we can associate several subspaces — the null space (Theorem NSMS [296]), the column space (Theorem RMS [302]) and the row space (Theorem RSMS [303]). As vector spaces, each of these has a dimension, and for the null space and column space, they are important enough to warrant names.

**Definition NOM**  
**Nullity Of a Matrix**

Suppose that \( A \) is an \( m \times n \) matrix. Then the **nullity** of \( A \) is the dimension of the null space of \( A \), \( n(A) = \dim(N(A)) \).

**Definition ROM**  
**Rank Of a Matrix**

Suppose that \( A \) is an \( m \times n \) matrix. Then the **rank** of \( A \) is the dimension of the column space of \( A \), \( r(A) = \dim(C(A)) \).

**Example RNM**  
**Rank and nullity of a matrix**

Let’s compute the rank and nullity of

\[
A = \begin{bmatrix}
2 & -4 & -1 & 3 & 2 & 1 & -4 \\
1 & -2 & 0 & 0 & 4 & 0 & 1 \\
-2 & 4 & 1 & 0 & -5 & -4 & -8 \\
1 & -2 & 1 & 1 & 6 & 1 & -3 \\
2 & -4 & -1 & 1 & 4 & -2 & -1 \\
-1 & 2 & 3 & -1 & 6 & 3 & -1
\end{bmatrix}
\]

To do this, we will first row-reduce the matrix since that will help us determine bases for the null space and column space.

\[
\begin{bmatrix}
1 & -2 & 0 & 0 & 4 & 0 & 1 \\
0 & 0 & 1 & 0 & 3 & 0 & -2 \\
0 & 0 & 0 & 1 & -1 & 0 & -3 \\
0 & 0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

From this row-equivalent matrix in reduced row-echelon form we record \( D = \{1, 3, 4, 6\} \) and \( F = \{2, 5, 7\} \).

For each index in \( D \), Theorem BCSOC [238] creates a single basis vector. In total the basis will have 4 vectors, so the column space of \( A \) will have dimension 4 and we write \( r(A) = 4 \).
For each index in \( F \), Theorem BNS \[141\] creates a single basis vector. In total the basis will have 3 vectors, so the null space of \( A \) will have dimension 3 and we write \( n(A) = 3 \).

There were no accidents or coincidences in the previous example — with the row-reduced version of a matrix in hand, the rank and nullity are easy to compute.

**Theorem CRN**
**Computing Rank and Nullity**
Suppose that \( A \) is an \( m \times n \) matrix and \( B \) is a row-equivalent matrix in reduced row-echelon form with \( r \) nonzero rows. Then \( r(A) = r \) and \( n(A) = n - r \).

**Proof** Theorem BCSOC \[238\] provides a basis for the column space by choosing columns of \( A \) that correspond to the dependent variables in a description of the solutions to \( LS(A,0) \). In the analysis of \( B \), there is one dependent variable for each leading 1, one per nonzero row, or one per pivot column. So there are \( r \) column vectors in a basis for \( C(A) \).

Theorem BNS \[141\] provide a basis for the null space by creating basis vectors of the null space of \( A \) from entries of \( B \), one for each independent variable, one per column with out a leading 1. So there are \( n - r \) column vectors in a basis for \( n(A) \).

Every archetype (Chapter A \[559\]) that involves a matrix lists its rank and nullity. You may have noticed as you studied the archetypes that the larger the column space is the smaller the null space is. A simple corollary states this trade-off succinctly.

**Theorem RPNC**
**Rank Plus Nullity is Columns**
Suppose that \( A \) is an \( m \times n \) matrix. Then \( r(A) + n(A) = n \).

**Proof** Let \( r \) be the number of nonzero rows in a row-equivalent matrix in reduced row-echelon form. By Theorem CRN \[339\],

\[
r(A) + n(A) = r + (n - r) = n
\]

When we first introduced \( r \) as our standard notation for the number of nonzero rows in a matrix in reduced row-echelon form you might have thought \( r \) stood for “rows.” Not really — it stands for “rank”!

**Subsection RNNSM**
**Rank and Nullity of a NonSingular Matrix**

Let’s take a look at the rank and nullity of a square matrix.

**Example RNSM**
Rank and nullity of a square matrix
The matrix

\[
E = \begin{bmatrix}
0 & 4 & -1 & 2 & 2 & 3 & 1 \\
2 & -2 & 1 & -1 & 0 & -4 & -3 \\
-2 & -3 & 9 & -3 & 9 & -1 & 9 \\
-3 & -4 & 9 & 4 & -1 & 6 & -2 \\
-3 & -4 & 6 & -2 & 5 & 9 & -4 \\
9 & -3 & 8 & -2 & -4 & 2 & 4 \\
8 & 2 & 2 & 9 & 3 & 0 & 9
\end{bmatrix}
\]

is row-equivalent to the matrix in reduced row-echelon form,

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

With \( n = 7 \) columns and \( r = 7 \) nonzero rows, Theorem CRN \[339\] tells us the rank is \( r(E) = 7 \) and the nullity is \( n(E) = 7 - 7 = 0 \).

The value of either the nullity or the rank are enough to characterize a nonsingular matrix.

**Theorem RNNSM**

**Rank and Nullity of a NonSingular Matrix**

Suppose that \( A \) is a square matrix of size \( n \). The following are equivalent.

1. \( A \) is nonsingular.
2. The rank of \( A \) is \( n \), \( r(A) = n \).
3. The nullity of \( A \) is zero, \( n(A) = 0 \).

**Proof**

(1 \( \Rightarrow \) 2) Theorem CSNSM \[241\] says that if \( A \) is nonsingular then \( \mathcal{C}(A) = \mathbb{C}^n \). If \( \mathcal{C}(A) = \mathbb{C}^n \), then the column space has dimension \( n \) by Theorem DCM \[336\], so the rank of \( A \) is \( n \).

(2 \( \Rightarrow \) 3) Suppose \( r(A) = n \). Then Theorem RPNC \[339\] gives

\[
\begin{align*}
n(A) &= n - r(A) \\
&= n - n \\
&= 0
\end{align*}
\]

(3 \( \Rightarrow \) 1) Suppose \( n(A) = 0 \), so a basis for the null space of \( A \) is the empty set. This implies that \( \mathcal{N}(A) = \{0\} \) and Theorem NSTNS \[78\] says \( A \) is nonsingular.

With a new equivalence for a nonsingular matrix, we can update our list of equivalences (Theorem NSME5 \[323\]) which now becomes a list requiring into double digits to number.
Theorem NSME6
NonSingular Matrix Equivalences, Round 6
Suppose that $A$ is a square matrix of size $n$. The following are equivalent.

1. $A$ is nonsingular.
2. $A$ row-reduces to the identity matrix.
3. The null space of $A$ contains only the zero vector, $N(A) = \{0\}$.
4. The linear system $LS(A, b)$ has a unique solution for every possible choice of $b$.
5. The columns of $A$ are a linearly independent set.
6. $A$ is invertible.
7. The column space of $A$ is $\mathbb{C}^n$, $C(A) = \mathbb{C}^n$.
8. The columns of $A$ are a basis for $\mathbb{C}^n$.
9. The rank of $A$ is $n$, $r(A) = n$.
10. The nullity of $A$ is zero, $n(A) = 0$.

Subsection READ
Reading Questions

1. What is the dimension of the vector space $P_6$, the set of all polynomials of degree 6 or less?
2. How are the rank and nullity of a matrix related?
3. Explain why we might say that a nonsingular matrix has “full rank.”
Subsection EXC
Exercises

C20  The archetypes listed below are matrices, or systems of equations with coefficient matrices. For each, compute the nullity and rank of the matrix. This information is listed for each archetype (along with the number of columns in the matrix, so as to illustrate Theorem RPNC [339]), and notice how it could have been computed immediately after the determination of the sets $D$ and $F$ associated with the reduced row-echelon form of the matrix.

Archetype A 563
Archetype B 568
Archetype C 573
Archetype D 577
Archetype E 581
Archetype F 585
Archetype G 590
Archetype H 594
Archetype I 599
Archetype J 604
Archetype K 609
Archetype L 613
Contributed by Robert Beezer

M20  $M_{22}$ is the vector space of $2 \times 2$ matrices. Let $S_{22}$ denote the set of all $2 \times 2$ symmetric matrices. That is

$$S_{22} = \{ A \in M_{22} \mid A^t = A \}$$

(a) Show that $S_{22}$ is a subspace of $M_{22}$.
(b) Exhibit a basis for $S_{22}$ and prove that it has the required properties.
(c) What is the dimension of $S_{22}$?
Contributed by Robert Beezer  Solution 345
M20 Contributed by Robert Beezer Statement 343
(a) We will use the three criteria of Theorem TSS 293. The zero vector of $M_{22}$ is the zero matrix, $O$ (Definition ZM 182), which is a symmetric matrix. So $S_{22}$ is not empty, since $O \in S_{22}$.

Suppose that $A$ and $B$ are two matrices in $S_{22}$. Then we know that $A^t = A$ and $B^t = B$. We want to know if $A + B \in S_{22}$, so test $A + B$ for membership,

$$
(A + B)^t = A^t + B^t = A + B
$$
Theorem TMA 184

So $A + B$ is symmetric and qualifies for membership in $S_{22}$.

Suppose that $A \in S_{22}$ and $\alpha \in \mathbb{C}$. Is $\alpha A \in S_{22}$? We know that $A^t = A$. Now check that,

$$
\alpha A^t = \alpha A^t = \alpha A
$$
Theorem TMSM 184

So $\alpha A$ is also symmetric and qualifies for membership in $S_{22}$.

With the three criteria of Theorem TSS 293 fulfilled, we see that $S_{22}$ is a subspace of $M_{22}$.

(b) An arbitrary matrix from $S_{22}$ can be written as $\begin{bmatrix} a & b \\ b & d \end{bmatrix}$. We can express this matrix as

$$
\begin{bmatrix} a & b \\ b & d \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & b \\ b & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}
$$

$$
= a \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + b \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + d \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}
$$

this equation says that the set

$$
T = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}
$$

spans $S_{22}$. Is it also linearly independent?

Write a relation of linear dependence on $S$,

$$
O = a_1 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + a_2 \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + a_3 \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}
$$

$$
\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_2 & a_3 \end{bmatrix}
$$

The equality of these two matrices (Definition ME 179) tells us that $a_1 = a_2 = a_3 = 0$, and the only relation of linear dependence on $T$ is trivial. So $T$ is linearly independent, and hence is a basis of $S_{22}$.

(c) The basis $T$ found in part (b) has size 3. So by Definition D 331, dim ($S_{22}$) = 3.
Once the dimension of a vector space is known, then the determination of whether or not a set of vectors is linearly independent, or if it spans the vector space, can often be much easier. In this section we will state a workhorse theorem and then apply it to the column space and row space of a matrix. It will also help us describe a super-basis for $\mathbb{C}^m$.

Subsection GT
Goldilocks’ Theorem

We begin with a useful theorem that we will need later, and in the proof of the main theorem in this subsection. This theorem says that we can extend linearly independent sets, one vector at a time, by adding vectors from outside the span of the linearly independent set, all the while preserving the linear independence of the set.

**Theorem ELIS**
Extending Linearly Independent Sets
Suppose $V$ is vector space and $S$ is a linearly independent set of vectors from $V$. Suppose $w$ is a vector such that $w \notin Sp(S)$. Then the set $S' = S \cup \{w\}$ is linearly independent.

**Proof** Suppose $S = \{v_1, v_2, v_3, \ldots, v_m\}$ and begin with a relation of linear dependence on $S'$,

$$a_1v_1 + a_2v_2 + a_3v_3 + \cdots + a_mv_m + a_{m+1}w = 0.$$

There are two cases to consider. First suppose that $a_{m+1} = 0$. Then the relation of linear dependence on $S'$ becomes

$$a_1v_1 + a_2v_2 + a_3v_3 + \cdots + a_mv_m = 0.$$

and by the linear independence of the set $S$, we conclude that $a_1 = a_2 = a_3 = \cdots = a_m = 0$. So all of the scalars in the relation of linear dependence on $S'$ are zero.

In the second case, suppose that $a_{m+1} \neq 0$. Then the relation of linear dependence on $S'$ becomes

$$a_{m+1}w = -a_1v_1 - a_2v_2 - a_3v_3 - \cdots - a_mv_m$$

$$w = -\frac{a_1}{a_{m+1}}v_1 - \frac{a_2}{a_{m+1}}v_2 - \frac{a_3}{a_{m+1}}v_3 - \cdots - \frac{a_m}{a_{m+1}}v_m$$

This equation expresses $w$ as a linear combination of the vectors in $S$, contrary to the assumption that $w \notin Sp(S)$, so this case leads to a contradiction.

The first case yielded only a trivial relation of linear dependence on $S'$ and the second case led to a contradiction. So $S'$ is a linearly independent set since any relation of linear dependence is trivial. 

\[ \square \]
In the story *Goldilocks and the Three Bears*, the young girl Goldilocks visits the empty house of the three bears while out walking in the woods. One bowl of porridge is too hot, the other too cold, the third is just right. One chair is too hard, one too soft, the third is just right. So it is with sets of vectors — some are too big (linearly dependent), some are too small (they don’t span), and some are just right (bases). Here’s Goldilocks’ Theorem.

**Theorem G**

**Goldilocks**

Suppose that $V$ is a vector space of dimension $t$. Let $S = \{v_1, v_2, \ldots, v_m\}$ be a set of vectors from $V$. Then

1. If $m > t$, then $S$ is linearly dependent.
2. If $m < t$, then $S$ does not span $V$.
3. If $m = t$ and $S$ is linearly independent, then $S$ spans $V$.
4. If $m = t$ and $S$ spans $V$, then $S$ is linearly independent. $\blacksquare$

**Proof** Let $B$ be a basis of $V$. Since $\dim (V) = t$, Definition B [317] and Theorem BIS [335] imply that $B$ is a linearly independent set of $t$ vectors that spans $V$.

1. Suppose to the contrary that $S$ is linearly independent. Then $B$ is a smaller set of vectors that spans $V$. This contradicts Theorem SSLD [331].
2. Suppose to the contrary that $S$ does span $V$. Then $B$ is a larger set of vectors that is linearly independent. This contradicts Theorem SSLD [331].
3. Suppose to the contrary that $S$ does not span $V$. Then we can choose a vector $w$ such that $w \in V$ and $w \not\in Sp(S)$. By Theorem ELIS [347], the set $S' = S \cup \{w\}$ is again linearly independent. Then $S'$ is a set of $m + 1 = t + 1$ vectors that are linearly independent, while $B$ is a set of $t$ vectors that span $V$. This contradicts Theorem SSLD [331].
4. Suppose to the contrary that $S$ is linearly dependent. Then by Theorem DLDS [151] (which can be upgraded, with no changes in the proof, to the setting of a general vector space), there is a vector in $S$, say $v_k$ that is equal to a linear combination of the other vectors in $S$. Let $S'' = S \setminus \{v_k\}$, the set of “other” vectors in $S$. Then it is easy to show that $V = Sp(S) = Sp(S'')$. So $S''$ is a set of $m - 1 = t - 1$ vectors that spans $V$, while $B$ is a set of $t$ linearly independent vectors in $V$. This contradicts Theorem SSLD [331]. $\blacksquare$

There is a tension in the construction of basis. Make a set too big and you will end up with relations of linear dependence among the vectors. Make a set too small and you will not have enough raw material to span the entire vector space. Make a set just the right size (the dimension) and you only need to have linear independence or spanning, and you get the other property for free. These roughly-stated ideas are made precise by Theorem G [348].

The structure and proof of this theorem also deserve comment. The hypotheses seem innocuous. We presume we know the dimension of the vector space in hand, then we
mostly just look at the size of the set $S$. From this we get big conclusions about spanning and linear independence. Each of the four proofs relies on ultimately contradicting Theorem DLDS [151], so in a way we could think of this entire theorem as a corollary of Theorem DLDS [151]. The proofs of the third and fourth parts parallel each other in style (add $w$, toss $v_k$) and then turn on Theorem ELIS [347] before contradicting Theorem DLDS [151].

Theorem G [348] is useful in both concrete examples and as a tool in other proofs. We will use it often to bypass verifying linear independence or spanning.

**Example BPR**

**Bases for $P_n$, reprised**

In Example BP [318] we claimed that

$$B = \{1, x, x^2, x^3, \ldots, x^n\}$$

$$C = \{1, 1 + x, 1 + x + x^2, 1 + x + x^2 + x^3, \ldots, 1 + x + x^2 + x^3 + \cdots + x^n\}.$$

were both bases for $P_n$ (Example VSP [277]). Suppose we had first verified that $B$ was a basis, so we would then know that dim $(P_n) = n + 1$. The size of $C$ is $n + 1$, the right size to be a basis. We could then verify that $C$ is linearly independent. We would not have to make any special efforts to prove that $C$ spans $P_n$, since Theorem G [348] would allow us to conclude this property of $C$ directly. Then we would be able to say that $C$ is a basis of $P_n$ also.

**Example BDM22**

**Basis by dimension in $M_{22}$**

In Example DSM22 [336] we showed that

$$B = \left\{ \begin{bmatrix} -2 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} -2 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

is a basis for the subspace $Z$ of $M_{22}$ (Example VSM [277]) given by

$$Z = \left\{ \begin{bmatrix} a & b \\ c & d \end{bmatrix} \ \middle| \ \begin{array}{c} 2a + b + 3c + 4d = 0, \\
-a + 3b - 5c - d = 0 \end{array} \right\}$$

This tells us that dim $(Z) = 2$. In this example we will find another basis. We can construct two new matrices in $Z$ by forming linear combinations of the matrices in $B$.

$$2 \begin{bmatrix} -2 & 1 \\ 1 & 0 \end{bmatrix} + (-3) \begin{bmatrix} -2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2 & -3 \end{bmatrix}$$

$$3 \begin{bmatrix} -2 & 1 \\ 1 & 0 \end{bmatrix} + 1 \begin{bmatrix} -2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} -8 & 3 \\ 3 & 1 \end{bmatrix}$$

Then the set

$$C = \left\{ \begin{bmatrix} 2 & 2 \\ 2 & -3 \end{bmatrix}, \begin{bmatrix} -8 & 3 \\ 3 & 1 \end{bmatrix} \right\}$$

has the right size to be a basis of $Z$. Let’s see if it is a linearly independent set. The relation of linear dependence

$$a_1 \begin{bmatrix} 2 & 2 \\ 2 & -3 \end{bmatrix} + a_2 \begin{bmatrix} -8 & 3 \\ 3 & 1 \end{bmatrix} = \mathcal{O}$$

$$\begin{bmatrix} 2a_1 - 8a_2 & 2a_1 + 3a_2 \\ 2a_1 + 3a_2 & -3a_1 + a_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$
leads to the homogeneous system of equations whose coefficient matrix
\[
\begin{bmatrix}
2 & -8 \\
2 & 3 \\
2 & 3 \\
-3 & 1 \\
\end{bmatrix}
\]
row-reduces to
\[
\begin{bmatrix}
1 & 0 \\
0 & 1 \\
0 & 0 \\
0 & 0 \\
\end{bmatrix}
\]
So with \(a_1 = a_2 = 0\) as the only solution, the set is linearly independent. Now we can apply Theorem G \([348]\) to see that \(C\) also spans \(Z\) and therefore is a second basis for \(Z\).

Example SVP4
Sets of vectors in \(P_4\)
In Example BSP4 \([319]\) we showed that
\[
B = \{x - 2, x^2 - 4x + 4, x^3 - 6x^2 + 12x - 8, x^4 - 8x^3 + 24x^2 - 32x + 16\}
\]
is a basis for \(W = \{p(x) \mid p \in P_4, p(2) = 0\}\). So \(\dim(W) = 4\).

The set
\[
\{3x^2 - 5x - 2, 2x^2 - 7x + 6, x^3 - 2x^2 + x - 2\}
\]
is a subset of \(W\) (check this) and it happens to be linearly independent (check this, too). However, by Theorem G \([348]\) it cannot span \(W\).

The set
\[
\{3x^2 - 5x - 2, 2x^2 - 7x + 6, x^3 - 2x^2 + x - 2, -x^4 + 2x^3 + 5x^2 - 10x, x^4 - 16\}
\]
is another subset of \(W\) (check this) and Theorem G \([348]\) tells us that it must be linearly dependent.

The set
\[
\{x - 2, x^2 - 2x, x^3 - 2x^2, x^4 - 2x^3\}
\]
is a third subset of \(W\) (check this) and is linearly independent (check this). Since it has the right size to be a basis, and is linearly independent, Theorem G \([348]\) tells us that it also spans \(W\), and therefore is a basis of \(W\).

The final theorem of this subsection is often a useful tool for establishing the equality of two sets that are subspaces. Notice that the hypotheses include the equality of two integers (dimensions) while the conclusion is the equality of two sets (subspaces). It is the extra “structure” of a vector space and its dimension that makes this leap possible.

**Theorem EDYES**
**Equal Dimensions Yields Equal Subspaces**
Suppose that \(U\) and \(V\) are subspaces of the vector space \(W\), such that \(U \subseteq V\) and \(\dim(U) = \dim(V)\). Then \(U = V\).
Proof Suppose to the contrary that \( U \neq V \). Since \( U \subseteq V \), there must be a vector \( v \in V \) and \( v \not\in U \). Let \( B = \{u_1, u_2, u_3, \ldots, u_t\} \) be a basis for \( U \). Then, by Theorem ELIS 347, the set \( C = B \cup \{v\} = \{u_1, u_2, u_3, \ldots, u_t, v\} \) is a linearly independent set of \( t+1 \) vectors in \( V \). However, by hypothesis, \( V \) has the same dimension as \( U \) (namely \( t \)) and therefore Theorem G 348 says that \( C \) is too big to be linearly independent. This contradiction shows that \( U = V \).  

Subsection RT  
Ranks and Transposes

With Theorem G 348 in our arsenal, we prove one of the most surprising theorems about matrices.

Theorem RMRT  
Rank of a Matrix is the Rank of the Transpose

Suppose \( A \) is an \( m \times n \) matrix. Then \( r(A) = r(A^t) \).

Proof We will need a bit of notation before we really get rolling. Write the columns of \( A \) as individual vectors, \( A_j, 1 \leq j \leq n \), and write the rows of \( A \) as individual column vectors \( R_i, 1 \leq i \leq m \). Pictorially then,  
\[
A = [A_1|A_2|A_3|\ldots|A_n] \quad A^t = [R_1|R_2|R_3|\ldots|R_m]
\]

Let \( d \) denote the rank of \( A \), i.e. \( d = r(A) = \dim(C(A)) \). Let \( C = \{v_1, v_2, v_3, \ldots, v_d\} \subseteq \mathbb{C}^m \) be a basis for \( C(A) \).

Every column of \( A \) is an element of \( C(A) \) and \( C \) is a spanning set for \( C(A) \), so there must be scalars, \( b_{ij}, 1 \leq i \leq d, 1 \leq j \leq n \) such that  
\[
A_j = b_{1j}v_1 + b_{2j}v_2 + b_{3j}v_3 + \cdots + b_{dj}v_d
\]

Define \( V \) to be the \( m \times d \) matrix whose columns are the vectors \( v_i, 1 \leq i \leq d \). Let \( B \) be the \( d \times n \) matrix whose entries are the scalars, \( b_{ij} \). More precisely, \( [B]_{ij} = b_{ij}, 1 \leq i \leq d, 1 \leq j \leq n \). Then the previous equation expresses column \( j \) of \( A \) as a linear combination of the columns of \( V \), where the scalars come from column \( j \) of \( B \). Let \( B_j \) denote column \( j \) of \( B \) and then we are in a position to use Definition MVP 187 to write  
\[
A_j = V B_j \quad 1 \leq j \leq n
\]

Since column \( j \) of \( A \) is the product of the matrix \( V \) with column \( j \) of \( B \), Definition MM 191 tells us that \( A = VB \). We are now in position to do all of the hard work in this proof — take the transpose of both sides of this equation.

\[
B^t V^t = (V B)^t \quad \text{Theorem MMT 198}
\]

\[
= A^t
\]

\[
= [R_1|R_2|R_3|\ldots|R_m]
\]

So the rows of \( A \), expressed as the columns \( R_i \), are the result of the matrix product \( B^t V^t \). By Definition MM 191, \( R_i \) is equal to the product of the \( n \times d \) matrix \( B^t \) with
column \( i \) of \( V^t \). Then applying [Definition MVP 187], we see that each row of \( A \) is a linear combination of the \( d \) columns of \( B^t \). This is the key observation in this proof.

Since each row of \( A \) is a linear combination of the \( d \) columns of \( B^t \), and the rows of \( A \) are a spanning set for the row space of \( A \), \( \mathcal{R}(A) \), we can conclude that the \( d \) columns of \( B^t \) are a spanning set for \( \mathcal{R}(A) \). Since a basis of the row space of \( A \) is linearly independent, [Theorem SSLD 331] tells us that the size of such a basis cannot exceed the size of a spanning set. So in this case, the dimension of the row space cannot exceed \( d \). Then,

\[
\begin{align*}
  r(A^t) & = \dim (\mathcal{C}(A^t)) \\
  & = \dim (\mathcal{R}(A)) \\
  & \leq d \\
  & = r(A)
\end{align*}
\]

so \( r(A^t) \leq r(A) \).

This relationship only assumed that \( A \) is a matrix. It applies equally well to \( A^t \), so

\[
  r(A) = r\left( (A^t)^t \right) \leq r(A^t)
\]

These two inequalities together imply that \( r(A) = r(A^t) \).

This says that the row space and the column space of a matrix have the same dimension, which should be very surprising. It does not say that column space and the row space are identical. Indeed, if the matrix is not square, then the sizes (number of slots) of the vectors in each space are different, so the sets are not even comparable.

It is not hard to construct by yourself examples of matrices that illustrate [Theorem RMRT 351], since it applies equally well to any matrix. Grab a matrix, row-reduce it, count the nonzero rows or the leading 1’s. That’s the rank. Transpose the matrix, row-reduce that, count the nonzero rows or the leading 1’s. That’s the rank of the transpose. The theorem says the two will be equal. Here’s an example anyway.

**Example RRTI**

**Rank, rank of transpose, Archetype I**

Archetype I 599 has a \( 4 \times 7 \) coefficient matrix which row-reduces to

\[
\begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

so the rank is 3. Row-reducing the transpose yields

\[
\begin{bmatrix}
1 & 0 & 0 & -31/7 \\
0 & 1 & 0 & 12/7 \\
0 & 0 & 1 & 13/7 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

demonstrating that the rank of the transpose is also 3.
We learned about orthogonal sets of vectors in $\mathbb{C}^m$ back in Section O [165], and we also learned that orthogonal sets are automatically linearly independent (Theorem OSLI [172]). When an orthogonal set also spans a subspace of $\mathbb{C}^m$, then the set is a basis. And when the set is orthonormal, then the set is an incredibly nice basis. We will back up this claim with a theorem, but first consider how you might manufacture such a set.

Suppose that $W$ is a subspace of $\mathbb{C}^m$ with basis $B$. Then $B$ spans $W$ and is a linearly independent set of nonzero vectors. We can apply the Gram-Schmidt Procedure (Theorem GSPCV [173]) and obtain a linearly independent set $T$ such that $S_p(T) = S_p(B) = W$ and $T$ is orthogonal. In other words, $T$ is a basis for $W$, and is an orthogonal set. By scaling each vector of $T$ to norm 1, we can convert $T$ into an orthonormal set, without destroying the properties that make it a basis of $W$. In short, we can convert any basis into an orthonormal basis. Example GSTV [174], followed by Example ONTV [175], illustrates this process.

Orthogonal matrices (Definition OM [226]) are another good source of orthonormal bases (and vice versa). Suppose that $Q$ is an orthogonal matrix of size $n$. Then the $n$ columns of $Q$ form an orthonormal set (Theorem COMOS [227]) that is therefore linearly independent (Theorem OSLI [172]). Since $Q$ is invertible (Theorem OMI [227]), we know $Q$ is nonsingular (Theorem NSI [225]), and then the columns of $Q$ span $\mathbb{C}^n$ (Theorem CSNSM [241]). So the columns of an orthogonal matrix of size $n$ are an orthonormal basis for $\mathbb{C}^n$.

Why all the fuss about orthonormal bases? Theorem VRRE [324] told us that any vector in a vector space could be written, uniquely, as a linear combination of basis vectors. For an orthonormal basis, finding the scalars for this linear combination is extremely easy, and this is the content of the next theorem. Furthermore, with vectors written this way (as linear combinations of the elements of an orthonormal set) certain computations and analysis become much easier. Here’s the promised theorem.

**Theorem COB**

**Coordinates and Orthonormal Bases**

Suppose that $B = \{v_1, v_2, v_3, \ldots, v_p\}$ is an orthonormal basis of the subspace $W$ of $\mathbb{C}^m$. For any $w \in W$,

$$w = \langle w, v_1 \rangle v_1 + \langle w, v_2 \rangle v_2 + \langle w, v_3 \rangle v_3 + \cdots + \langle w, v_p \rangle v_p$$

**Proof** Because $B$ is a basis of $W$, Theorem VRRE [324] tells us that we can write $w$ uniquely as a linear combination of the vectors in $B$. So it is not this aspect of the conclusion that makes this theorem interesting. What is interesting is that the particular scalars are so easy to compute. No need to solve big systems of equations — just do an inner product of $w$ with $v_i$ to arrive at the coefficient of $v_i$ in the linear combination.

So begin the proof by writing $w$ as a linear combination of the vectors in $B$, using unknown scalars,

$$w = a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_p v_p$$
and compute,
\[
\langle w, v_i \rangle = \left\langle \sum_{k=1}^{p} a_k v_k, v_i \right\rangle
\]
\[
= \sum_{k=1}^{p} \langle a_k v_k, v_i \rangle \tag{Theorem IPVA 167}
\]
\[
= \sum_{k=1}^{p} a_k \langle v_k, v_i \rangle \tag{Theorem IPSM 168}
\]
\[
= a_i \langle v_i, v_i \rangle + \sum_{k \neq i} a_k \langle v_k, v_i \rangle \tag{Isolate term with k = i}
\]
\[
= a_i(1) + \sum_{k \neq i} a_k(0) \tag{T orthonormal}
\]

So the (unique) scalars for the linear combination are indeed the inner products advertised in the conclusion of the theorem’s statement.

Example CROB4
Coordination relative to an orthonormal basis, \( \mathbb{C}^4 \)
The set
\[
\{x_1, x_2, x_3, x_4\} = \left\{ \begin{bmatrix} 1 + i \\ 1 \\ 1 - i \\ i \end{bmatrix}, \begin{bmatrix} 1 + 5i \\ 6 + 5i \\ -7 - i \\ 1 - 6i \end{bmatrix}, \begin{bmatrix} -7 + 34i \\ -8 - 23i \\ -10 + 22i \\ 30 + 13i \end{bmatrix}, \begin{bmatrix} -2 - 4i \\ 6 + i \\ 4 + 3i \\ 6 - i \end{bmatrix} \right\}
\]
was proposed, and partially verified, as an orthogonal set in Example AOS [171]. Let’s scale each vector to norm 1, so as to form an orthonormal basis of \( \mathbb{C}^4 \). (Notice that by Theorem OSLI [172] the set is linearly independent. Since we know the dimension of \( \mathbb{C}^4 \) is 4, Theorem G [348] tells us the set is just the right size to be a basis of \( \mathbb{C}^4 \).) The norms of these vectors are,
\[
\|x_1\| = \sqrt{6}, \quad \|x_2\| = \sqrt{174}, \quad \|x_3\| = \sqrt{3451}, \quad \|x_4\| = \sqrt{119}
\]
So an orthonormal basis is
\[
B = \{v_1, v_2, v_3, v_4\}
\]
\[
= \left\{ \frac{1}{\sqrt{6}} \begin{bmatrix} 1 + i \\ 1 \\ 1 - i \\ i \end{bmatrix}, \frac{1}{\sqrt{174}} \begin{bmatrix} 1 + 5i \\ 6 + 5i \\ -7 - i \\ 1 - 6i \end{bmatrix}, \frac{1}{\sqrt{3451}} \begin{bmatrix} -7 + 34i \\ -8 - 23i \\ -10 + 22i \\ 30 + 13i \end{bmatrix}, \frac{1}{\sqrt{119}} \begin{bmatrix} -2 - 4i \\ 6 + i \\ 4 + 3i \\ 6 - i \end{bmatrix} \right\}
\]

Now, choose any vector from \( \mathbb{C}^4 \), say \( w = \begin{bmatrix} 2 \\ -3 \\ 1 \\ 4 \end{bmatrix} \), and compute
\[
\langle w, v_1 \rangle = \frac{-5i}{\sqrt{6}}, \quad \langle w, v_2 \rangle = \frac{-19 + 30i}{\sqrt{174}}, \quad \langle w, v_3 \rangle = \frac{120 - 211i}{\sqrt{3451}}, \quad \langle w, v_4 \rangle = \frac{6 + 12i}{\sqrt{119}}
\]
Theorem COB guarantees that
\[
\begin{bmatrix}
2 \\
-3 \\
1 \\
4
\end{bmatrix} = -\frac{5i}{\sqrt{6}} \begin{bmatrix}
1 + i \\
1 - i
\end{bmatrix} + 19 + 30i \sqrt{6} \begin{bmatrix}
1 + 5i \\
-7 - i
\end{bmatrix} + 120 - 211i \sqrt{3451} \begin{bmatrix}
-7 + 34i \\
-8 - 23i
\end{bmatrix} + 6 + 12i \sqrt{119} \begin{bmatrix}
-2 - 4i \\
6 + i
\end{bmatrix}
\]
as you might want to check (if you have unlimited patience).

A slightly less intimidating example follows, in three dimensions and with just real numbers.

**Example CROB3**

*Coordinatization relative to an orthonormal basis, C^3*

The set
\[
\{x_1, x_2, x_3\} = \left\{ \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} \right\}
\]
is a linearly independent set, which the Gram-Schmidt Process converts to an orthogonal set, and which can then be converted to the orthonormal set,
\[
\{v_1, v_2, v_3\} = \left\{ \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}, \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}, \frac{1}{\sqrt{3}} \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix} \right\}
\]
which is therefore an orthonormal basis of C^3. With three vectors in C^3, all with real number entries, the inner product (Definition IP) reduces to the usual “dot product” (or scalar product) and the orthogonal pairs of vectors can be interpreted as perpendicular pairs of directions. So the vectors in \( \vec{B} \) serve as replacements for our usual 3-D axes, or the usual 3-D unit vectors \( \vec{i}, \vec{j} \) and \( \vec{k} \). We would like to decompose arbitrary vectors into “components” in the directions of each of these basis vectors. It is Theorem COB that tells us how to do this.

Suppose that we choose \( \mathbf{w} = \begin{bmatrix} 2 \\ -1 \\ 5 \end{bmatrix} \). Compute
\[
\langle \mathbf{w}, \mathbf{v}_1 \rangle = \frac{5}{\sqrt{6}}, \quad \langle \mathbf{w}, \mathbf{v}_2 \rangle = \frac{3}{\sqrt{2}}, \quad \langle \mathbf{w}, \mathbf{v}_3 \rangle = \frac{8}{\sqrt{3}}
\]
then Theorem COB guarantees that
\[
\begin{bmatrix}
2 \\
-1 \\
5
\end{bmatrix} = \frac{5}{\sqrt{6}} \begin{bmatrix}
1 \\
2 \\
1
\end{bmatrix} + \frac{3}{\sqrt{2}} \begin{bmatrix}
-1 \\
0 \\
1
\end{bmatrix} + \frac{8}{\sqrt{3}} \begin{bmatrix}
1 \\
-1 \\
1
\end{bmatrix}
\]
which you should be able to check easily, even if you do not have much patience.
1. Why does Theorem G 348 have the title it does?

2. What is so surprising about Theorem RMRT 351?

3. Why is an orthonormal basis desirable?
Subsection EXC
Exercises

C10 Example SVP4 leaves several details for the reader to check. Verify these five claims.
Contributed by Robert Beezer

T15 Suppose that $A$ is an $m \times n$ matrix and let $\min(m, n)$ denote the minimum of $m$ and $n$. Prove that $r(A) \leq \min(m, n)$.
Contributed by Robert Beezer

T20 Suppose that $A$ is an $m \times n$ matrix and $b \in \mathbb{C}^m$. Prove that the linear system $\mathcal{L}(A, b)$ is consistent if and only if $r(A) = r([A \mid b])$.
Contributed by Robert Beezer

T25 Suppose that $V$ is a vector space with finite dimension. Let $W$ be any subspace of $V$. Prove that $W$ has finite dimension.
Contributed by Robert Beezer

T60 Suppose that $W$ is a vector space with dimension 5, and $U$ and $V$ are subspaces of $W$, each of dimension 3. Prove that $U \cap V$ contains a non-zero vector. State a more general result.
Contributed by Joe Riegsecker

Solution
Subsection PD.SOL
Solutions

T20 Contributed by Robert Beezer Statement 357

(⇒) Suppose first that $\mathcal{L}S(A, b)$ is consistent. Then by Theorem CSCS [236], $b \in \mathcal{C}(A)$. This means that $\mathcal{C}(A) = \mathcal{C}([A | b])$ and so it follows that $r(A) = r([A | b])$.

(⇐) Adding a column to a matrix will only increase the size of its column space, so in all cases, $\mathcal{C}(A) \subseteq \mathcal{C}([A | b])$. However, if we assume that $r(A) = r([A | b])$, then by Theorem EDYES [350] we conclude that $\mathcal{C}(A) = \mathcal{C}([A | b])$. Then $b \in \mathcal{C}([A | b]) = \mathcal{C}(A)$ so by Theorem CSCS [236], $\mathcal{L}S(A, b)$ is consistent.

T60 Contributed by Robert Beezer Statement 357

Let $\{u_1, u_2, u_3\}$ and $\{v_1, v_2, v_3\}$ be bases for $U$ and $V$ (respectively). Then, the set $\{u_1, u_2, u_3, v_1, v_2, v_3\}$ is linearly dependent, since Theorem G [348] says we cannot have 6 linearly independent vectors in a vector space of dimension 5. So we can assert that there is a non-trivial relation of linear dependence,

$$a_1u_1 + a_2u_2 + a_3u_3 + b_1v_1 + b_2v_2 + b_3v_3 = 0$$

where $a_1, a_2, a_3$ and $b_1, b_2, b_3$ are not all zero.

We can rearrange this equation as

$$a_1u_1 + a_2u_2 + a_3u_3 = -b_1v_1 - b_2v_2 - b_3v_3$$

This is an equality of two vectors, so we can give this common vector a name, say $w$,

$$w = a_1u_1 + a_2u_2 + a_3u_3 = -b_1v_1 - b_2v_2 - b_3v_3$$

This is the desired non-zero vector, as we will now show.

First, since $w = a_1u_1 + a_2u_2 + a_3u_3$, we can see that $w \in U$. Similarly, $w = -b_1v_1 - b_2v_2 - b_3v_3$, so $w \in V$. This establishes that $w \in U \cap V$.

Is $w \neq 0$? Suppose not, in other words, suppose $w = 0$. Then

$$0 = w = a_1u_1 + a_2u_2 + a_3u_3$$

Because $\{u_1, u_2, u_3\}$ is a basis for $U$, it is a linearly independent set and the relation of linear dependence above means we must conclude that $a_1 = a_2 = a_3 = 0$. By a similar process, we would conclude that $b_1 = b_2 = b_3 = 0$. But this is a contradiction since $a_1, a_2, a_3, b_1, b_2, b_3$ were chosen so that some were nonzero. So $w \neq 0$.

How does this generalize? All we really needed was the original relation of linear dependence that resulted because we had “too many” vectors in $W$. A more general statement would be: Suppose that $W$ is a vector space with dimension $n$, $U$ is a subspace of dimension $p$ and $V$ is a subspace of dimension $q$. If $p + q > n$, then $U \cap V$ contains a non-zero vector.
D: Determinants

Section DM
Determinants of Matrices

The determinant is a function that takes a square matrix as an input and produces a scalar as an output. So unlike a vector space, it is not an algebraic structure. However, it has many beneficial properties for studying vector spaces, matrices and systems of equations, so it is hard to ignore (though some have tried). While the properties of a determinant can be very useful, they are also complicated to prove. We’ll begin with a definition, do some computations and then establish some properties. The definition of the determinant function is recursive, that is, the determinant of a large matrix is defined in terms of the determinant of smaller matrices. To this end, we will make a few definitions.

Definition SM
SubMatrix
Suppose that $A$ is an $m \times n$ matrix. Then the submatrix $A_{ij}$ is the $(m - 1) \times (n - 1)$ matrix obtained from $A$ by removing row $i$ and column $j$.

Example SS
Some submatrices
For the matrix

$$A = \begin{bmatrix} 1 & -2 & 3 & 9 \\ 4 & -2 & 0 & 1 \\ 3 & 5 & 2 & 1 \end{bmatrix}$$

we have the submatrices

$$A_{23} = \begin{bmatrix} 1 & -2 & 9 \\ 3 & 5 & 1 \end{bmatrix} \quad A_{31} = \begin{bmatrix} -2 & 3 & 9 \\ -2 & 0 & 1 \end{bmatrix}$$

Definition DM
Determinant
Suppose $A$ is a square matrix. Then its determinant, $\det(A) = |A|$, is an element of $\mathbb{C}$ defined recursively by:

If $A = [a]$ is a $1 \times 1$ matrix, then $\det(A) = a$. 

361
If \( A \) is a matrix of size \( n \) with \( n \geq 2 \), then
\[
\det (A) = [A]_{11} \det (A_{11}) - [A]_{12} \det (A_{12}) + [A]_{13} \det (A_{13}) - \cdots + (-1)^{n+1} [A]_{1n} \det (A_{1n})
\]

So to compute the determinant of a \( 5 \times 5 \) matrix we must build 5 submatrices, each of size 4. To compute the determinants of each the \( 4 \times 4 \) matrices we need to create 4 submatrices each, these now of size 3 and so on. To compute the determinant of a \( 10 \times 10 \) matrix would require computing the determinant of \( 10! = 10 \times 9 \times 8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 = 3,628,800 \) \( 1 \times 1 \) matrices. Fortunately there are better ways. However this does suggest an excellent computer programming exercise to write a recursive procedure to compute a determinant.

Let’s compute the determinant of a reasonable sized matrix by hand.

**Example D33M**

**Determinant of a \( 3 \times 3 \) matrix**

Suppose that we have the \( 3 \times 3 \) matrix
\[
A = \begin{bmatrix}
3 & 2 & -1 \\
4 & 1 & 6 \\
-3 & -1 & 2
\end{bmatrix}
\]

Then
\[
\det (A) = |A| = \begin{vmatrix}
3 & 2 & -1 \\
4 & 1 & 6 \\
-3 & -1 & 2
\end{vmatrix}
= 3 \begin{vmatrix}
1 & 6 \\
-1 & 2
\end{vmatrix} - 2 \begin{vmatrix}
4 & 6 \\
-3 & 2
\end{vmatrix} + (-1) \begin{vmatrix}
4 & 1 \\
-3 & -1
\end{vmatrix}
= 3 (1(2) - 6(-1)) - 2 (4(2) - 6(-3)) - (4(-1) - 1(-3))
= 24 - 52 + 1
= -27
\]

In practice it is a bit silly to decompose a \( 2 \times 2 \) matrix down into a couple of \( 1 \times 1 \) matrices and then compute the exceedingly easy determinant of these puny matrices. So here is a simple theorem.

**Theorem DMST**

**Determinant of Matrices of Size Two**

Suppose that \( A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \). Then \( \det (A) = ad - bc \)

**Proof** Applying Definition DM [361],
\[
\begin{vmatrix} a & b \\ c & d \end{vmatrix} = a |d| - b |c| = ad - bc
\]

Do you recall seeing the expression \( ad - bc \) before? (Hint: Theorem TTMI [210])
Subsection CD
Computing Determinants

For any given matrix, there are a variety of ways to compute the determinant, by “expanding” about any row or column. The determinants of the submatrices used in these computations are used so often that they have their own names. The first is the determinant of a submatrix, the second differs only by a sign.

**Definition MIM**
**Minor In a Matrix**
Suppose $A$ is an $n \times n$ matrix and $A_{ij}$ is the $(n-1) \times (n-1)$ submatrix formed by removing row $i$ and column $j$. Then the **minor** for $A$ at location $i,j$ is the determinant of the submatrix, $M_{A,ij} = \det (A_{ij})$.

**Definition CIM**
**Cofactor In a Matrix**
Suppose $A$ is an $n \times n$ matrix and $A_{ij}$ is the $(n-1) \times (n-1)$ submatrix formed by removing row $i$ and column $j$. Then the **cofactor** for $A$ at location $i,j$ is the signed determinant of the submatrix, $C_{A,ij} = (-1)^{i+j} \det (A_{ij})$.

**Example MC**
**Minors and cofactors**
For the matrix,
\[
A = \begin{bmatrix}
2 & 4 & 2 & 1 \\
-1 & 2 & 3 & -1 \\
3 & 1 & 0 & 5 \\
3 & 6 & 3 & 2
\end{bmatrix}
\]
we have minors
\[
M_{A,4,2} = \begin{vmatrix}
2 & 2 & 1 \\
-1 & 3 & -1 \\
3 & 0 & 5
\end{vmatrix} = 2(15) - 2(-2) + 1(-9) = 25
\]
\[
M_{A,3,4} = \begin{vmatrix}
2 & 4 & 2 \\
-1 & 2 & 3 \\
3 & 6 & 3
\end{vmatrix} = 2(-12) - 4(-12) + 2(-12) = 0
\]
and so two cofactors are
\[
C_{A,4,2} = (-1)^{4+2} M_{A,4,2} = (1)(25) = 25
\]
\[
C_{A,3,4} = (-1)^{3+4} M_{A,3,4} = (-1)(0) = 0
\]
A third cofactor is
\[
C_{A,1,2} = (-1)^{1+2} M_{A,1,2} = (-1) \begin{vmatrix}
-1 & 3 & -1 \\
3 & 0 & 5 \\
3 & 3 & 2
\end{vmatrix} = (-1)((-1)(-15) - (3)(-9) + (-1)(9)) = -33
\]
With this notation in hand, we can state

**Theorem DERC**

**Determinant Expansion about Rows and Columns**

Suppose that $A$ is a square matrix of size $n$. Then

$$
\det(A) = a_{i1}C_{A,i1} + a_{i2}C_{A,i2} + a_{i3}C_{A,i3} + \cdots + a_{in}C_{A,in} \quad 1 \leq i \leq n
$$

which is known as **expansion** about row $i$, and

$$
\det(A) = [A]_{1j}C_{A,1j} + [A]_{2j}C_{A,2j} + [A]_{3j}C_{A,3j} + \cdots + [A]_{nj}C_{A,nj} \quad 1 \leq j \leq n
$$

which is known as **expansion** about column $j$.

**Proof**  TODO  ■

That the determinant of an $n \times n$ matrix can be computed in $2^n$ different (albeit similar) ways is nothing short of remarkable. For the doubters among us, we will do an example, computing a $4 \times 4$ matrix in two different ways.

**Example TCSD**

**Two computations, same determinant**

Let

$$
A = \begin{bmatrix}
-2 & 3 & 0 & 1 \\
9 & -2 & 0 & 1 \\
1 & 3 & -2 & -1 \\
4 & 1 & 2 & 6 \\
\end{bmatrix}
$$

Then expanding about the fourth row (Theorem DERC 364 with $i = 4$) yields,

$$
\begin{align*}
\det(A) &= (4)(-1)^{4+1} \left| \begin{array}{ccc}
3 & 0 & 1 \\
-2 & 0 & 1 \\
3 & -2 & -1 \\
\end{array} \right| + (1)(-1)^{4+2} \left| \begin{array}{ccc}
9 & 0 & 1 \\
1 & -2 & -1 \\
\end{array} \right| \\
&\quad + (2)(-1)^{4+3} \left| \begin{array}{ccc}
-2 & 3 & 1 \\
9 & -2 & 1 \\
1 & 3 & -1 \\
\end{array} \right| + (6)(-1)^{4+4} \left| \begin{array}{ccc}
-2 & 3 & 0 \\
9 & -2 & 0 \\
1 & 3 & -2 \\
\end{array} \right| \\
&= (-4)(10) + (1)(-22) + (-2)(61) + 6(46) = 92
\end{align*}
$$

while expanding about column 3 (Theorem DERC 364 with $j = 3$) gives

$$
\begin{align*}
\det(A) &= (0)(-1)^{1+3} \left| \begin{array}{ccc}
9 & -2 & 1 \\
1 & 3 & -1 \\
4 & 1 & 6 \\
\end{array} \right| + (0)(-1)^{2+3} \left| \begin{array}{ccc}
1 & 3 & -1 \\
4 & 1 & 6 \\
\end{array} \right| \\
&\quad + (-2)(-1)^{3+3} \left| \begin{array}{ccc}
-2 & 3 & 1 \\
9 & -2 & 1 \\
4 & 1 & 6 \\
\end{array} \right| + (2)(-1)^{4+3} \left| \begin{array}{ccc}
-2 & 3 & 1 \\
9 & -2 & 1 \\
1 & 3 & -1 \\
\end{array} \right| \\
&= 0 + 0 + (-2)(-107) + (-2)(61) = 92
\end{align*}
$$

Notice how much easier the second computation was. By choosing to expand about the third column, we have two entries that are zero, so two $3 \times 3$ determinants need not be computed at all!

©
When a matrix has all zeros above (or below) the diagonal, exploiting the zeros by expanding about the proper row or column makes computing a determinant insanely easy.

**Example DUTM**

**Determinant of an upper-triangular matrix**

Suppose that $T=$

$$
\begin{bmatrix}
2 & 3 & -1 & 3 & 3 \\
0 & -1 & 5 & 2 & -1 \\
0 & 0 & 3 & 9 & 2 \\
0 & 0 & 0 & -1 & 3 \\
0 & 0 & 0 & 0 & 5
\end{bmatrix}
$$

We will compute the determinant of this $5 \times 5$ matrix by consistently expanding about the first column for each submatrix that arises and does not have a zero entry multiplying it.

$$
\det (T) = 2\left|\begin{array}{ccccc}
-1 & 5 & 2 & -1 \\
0 & 3 & 9 & 2 \\
0 & 0 & -1 & 3 \\
0 & 0 & 0 & 5
\end{array}\right|
\]

$$
= 2(-1)^{1+1}\left|\begin{array}{ccc}
3 & 9 & 2 \\
0 & -1 & 3 \\
0 & 0 & 5
\end{array}\right|
\]

$$
= 2(-1)(-1)^{1+1}\left|\begin{array}{cc}
-1 & 3 \\
0 & 5
\end{array}\right|
\]

$$
= 2(-1)(3)(-1)(-1)^{1+1}|5|
\]

$$
= 2(-1)(3)(-1)(5) = 30
\]

---

**Subsection PD**

**Properties of Determinants**

The determinant is of some interest by itself, but it is of the greatest use when employed to determine properties of matrices. To that end, we list some theorems here. Unfortunately, mostly without proof at the moment.

**Theorem DT**

**Determinant of the Transpose**

Suppose that $A$ is a square matrix. Then $\det (A^t) = \det (A)$. □
Proof We will prove this result by induction on the size of the matrix. For a matrix of size 1, the transpose and the matrix itself are equal, so matter what the definition of a determinant might be, their determinants are equal.

Now suppose the theorem is true for matrices of size \( n - 1 \). By Theorem DERC \[364\] we can write the determinant as a product of entries from the first row with their cofactors and then sum these products. These cofactors are signed determinants of matrices of size \( n - 1 \), which by the induction hypothesis, are equal to the determinant of their transposes, and commutativity in the sum in the exponent of \(-1\) means the cofactor is equal to a cofactor of the transpose.

\[
\det (A) = [A]_{11} C_{A,11} + [A]_{12} C_{A,12} + \cdots + [A]_{1n} C_{A,1n} = [A^t]_{11} C_{A^t,11} + [A^t]_{12} C_{A^t,12} + \cdots + [A^t]_{1n} C_{A^t,1n}
\]

Theorem DERC \[364\], row 1

\[
= [A^t]_{11} C_{A^t,11} + [A^t]_{21} C_{A^t,21} + \cdots + [A^t]_{n1} C_{A^t,n1}
\]

Definition TM \[182\]

\[
= [A^t]_{11} C_{A^t,11} + [A^t]_{21} C_{A^t,21} + \cdots + [A^t]_{n1} C_{A^t,n1} = \det (A^t)
\]

Theorem DERC \[364\], column 1 □

Theorem DRMM Determinant Respects Matrix Multiplication
Suppose that \( A \) and \( B \) are square matrices of size \( n \). Then \( \det (AB) = \det (A) \det (B) \).

Proof TODO: □

Its an amazing thing that matrix multiplication and the determinant interact this way. Might it also be true that \( \det (A + B) = \det (A) + \det (B) \)?

Theorem SMZD Singular Matrices have Zero Determinants
Let \( A \) be a square matrix. Then \( A \) is singular if and only if \( \det (A) = 0 \).

Proof TODO: □

For the case of \( 2 \times 2 \) matrices you might compare the application of Theorem SMZD \[366\] with the combination of the results stated in Theorem DMST \[362\] and Theorem TTMI \[210\].

Example ZNDAB Zero and nonzero determinant, Archetypes A and B
The coefficient matrix in Archetype A \[563\] has a zero determinant (check this!) while the coefficient matrix Archetype B \[568\] has a nonzero determinant (check this, too). These matrices are singular and nonsingular, respectively. This is exactly what Theorem SMZD \[366\] says, and continues our list of contrasts between these two archetypes. □

Since Theorem SMZD \[366\] is an equivalence (Technique E \[52\]) we can expand on our growing list of equivalences about nonsingular matrices.

Theorem NSME7 NonSingular Matrix Equivalences, Round 7
Suppose that \( A \) is a square matrix of size \( n \). The following are equivalent.
1. $A$ is nonsingular.

2. $A$ row-reduces to the identity matrix.

3. The null space of $A$ contains only the zero vector, $\mathcal{N}(A) = \{0\}$.

4. The linear system $\mathcal{L}(A, b)$ has a unique solution for every possible choice of $b$.

5. The columns of $A$ are a linearly independent set.

6. $A$ is invertible.

7. The column space of $A$ is $\mathbb{C}^n$, $\mathcal{C}(A) = \mathbb{C}^n$.

8. The columns of $A$ are a basis for $\mathbb{C}^n$.

9. The rank of $A$ is $n$, $r(A) = n$.

10. The nullity of $A$ is zero, $n(A) = 0$.

11. The determinant of $A$ is nonzero, $\det(A) \neq 0$.

**Proof** Theorem SMZD [366] says $A$ is singular if and only if $\det(A) = 0$. If we negate each of these statements, we arrive at two contrapositives that we can combine as the equivalence, $A$ is nonsingular if and only if $\det(A) \neq 0$. This allows us to add a new statement to the list.

Computationally, row-reducing a matrix is the most efficient way to determine if a matrix is nonsingular, though the effect of using division in a computer can lead to round-off errors that confuse small quantities with critical zero quantities. Conceptually, the determinant may seem the most efficient way to determine if a matrix is nonsingular. The definition of a determinant uses just addition, subtraction and multiplication, so division is never a problem. And the final test is easy: is the determinant zero or not? However, the number of operations involved in computing a determinant very quickly becomes so excessive as to be impractical.

**Subsection READ**

**Reading Questions**

1. Compute the determinant of the matrix

$$
\begin{bmatrix}
2 & 3 & -1 \\
3 & 8 & 2 \\
-4 & 1 & 3
\end{bmatrix}
$$

2. What is our latest addition to the NSMExx series of theorems?

3. What is amazing about the interaction between matrix multiplication and the determinant?
Subsection EXC Exercises

C25 Doing the computations by hand, find the determinant of the matrix below. Is the matrix singular or nonsingular?

\[
\begin{bmatrix}
3 & -1 & 4 \\
2 & 5 & 1 \\
2 & 0 & 6 \\
\end{bmatrix}
\]

Contributed by Robert Beezer Solution

C30 Each of the archetypes below is a system of equations with a square coefficient matrix, or is a square matrix itself. Compute the determinant of each matrix, noting how Theorem SMZD indicates when the matrix is singular or nonsingular.

Archetype A 563
Archetype B 568
Archetype C 585
Archetype D 609
Archetype E 613

Contributed by Robert Beezer

M20 Construct a 3 \times 3 nonsingular matrix and call it \( A \). Then, for each entry of the matrix, compute the corresponding cofactor, and create a new 3 \times 3 matrix full of these cofactors by placing the cofactor of an entry in the same location as the entry it was based on. Once complete, call this matrix \( C \). Compute \( AC^t \). Any observations? Repeat with a new matrix, or perhaps with a 4 \times 4 matrix.

Contributed by Robert Beezer Solution

M30 Construct an example to show that the following statement is not true for all square matrices \( A \) and \( B \) of the same size: \( \det (A + B) = \det (A) + \det (B) \).

Contributed by Robert Beezer
Subsection SOL
Solutions

C25 Contributed by Robert Beezer  Statement 369
We can expand about any row or column, so the zero entry in the middle of the last row is attractive. Let’s expand about column 2. By Theorem DERC 364 you will get the same result by expanding about a different row or column. We will use Theorem DMST 362 twice.

$$\begin{vmatrix} 3 & -1 & 4 \\ 2 & 5 & 1 \\ 2 & 0 & 6 \end{vmatrix} = (-1)(-1)^{1+2} \begin{vmatrix} 2 & 1 \\ 2 & 6 \end{vmatrix} + (5)(-1)^{2+2} \begin{vmatrix} 3 & 4 \\ 2 & 6 \end{vmatrix} + (0)(-1)^{3+2} \begin{vmatrix} 3 & 4 \\ 2 & 1 \end{vmatrix}$$

$$= (1)(10) + (5)(10) + 0 = 60$$

With a nonzero determinant, Theorem SMZD 366 tells us that the matrix is nonsingular.

M20 Contributed by Robert Beezer  Statement 369
The result of these computations should be a matrix with the value of det(A) in the diagonal entries and zeros elsewhere. The suggestion of using a nonsingular matrix was only so that it was obvious that the value of the determinant appears on the diagonal.

This provides a method for computing the inverse of a nonsingular matrix. Check that $\frac{1}{\det(A)} C^t = A^{-1}$.

TODO: this solution needs some unstated theorems to explain the result.
Section EE
Eigenvalues and Eigenvectors

When we have a square matrix of size \( n \), \( A \), and we multiply it by a vector from \( \mathbb{C}^n \), \( x \), to form the matrix-vector product (Definition MVP [187]), the result is another vector in \( \mathbb{C}^n \). So we can adopt a functional view of this computation — the act of multiplying by a square matrix is a function that converts one vector \( (x) \) into another one \( (Ax) \) of the same size. For some vectors, this seemingly complicated computation is really no more complicated than scalar multiplication. The vectors vary according to the choice of \( A \), so the question is to determine, for an individual choice of \( A \), if there are any such vectors, and if so, which ones. It happens in a variety of situations that these vectors (and the scalars that go along with them) are of special interest.

Subsection EEM
Eigenvalues and Eigenvectors of a Matrix

Definition EEM
Eigenvalues and Eigenvectors of a Matrix
Suppose that \( A \) is a square matrix of size \( n \), \( x \neq 0 \) is a vector from \( \mathbb{C}^n \), and \( \lambda \) is a scalar from \( \mathbb{C} \) such that

\[ Ax = \lambda x \]

Then we say \( x \) is an eigenvector of \( A \) with eigenvalue \( \lambda \).

Before going any further, perhaps we should convince you that such things ever happen at all. Believe the next example, but do not concern yourself with where the pieces come from. We will have methods soon enough to be able to discover these eigenvectors ourselves.

Example SEE
Some eigenvalues and eigenvectors
Consider the matrix
\[
A = \begin{bmatrix}
204 & 98 & -26 & -10 \\
-280 & -134 & 36 & 14 \\
716 & 348 & -90 & -36 \\
-472 & -232 & 60 & 28
\end{bmatrix}
\]
and the vectors
\[
x = \begin{bmatrix} 1 \\ -1 \\ 2 \\ 5 \end{bmatrix}, \quad y = \begin{bmatrix} -3 \\ 4 \\ -10 \\ 4 \end{bmatrix}, \quad z = \begin{bmatrix} -3 \\ 7 \\ 0 \\ 8 \end{bmatrix}, \quad w = \begin{bmatrix} 1 \\ -1 \\ 4 \\ 0 \end{bmatrix}
\]
Then
\[
Ax = \begin{bmatrix}
204 & 98 & -26 & -10 \\
-280 & -134 & 36 & 14 \\
716 & 348 & -90 & -36 \\
-472 & -232 & 60 & 28
\end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 2 \\ 5 \end{bmatrix} = 4 \begin{bmatrix} 1 \\ -4 \\ 2 \\ 5 \end{bmatrix} = 4x
\]
so \(x\) is an eigenvector of \(A\) with eigenvalue \(\lambda = 4\). Also,
\[
Ay = \begin{bmatrix}
204 & 98 & -26 & -10 \\
-280 & -134 & 36 & 14 \\
716 & 348 & -90 & -36 \\
-472 & -232 & 60 & 28
\end{bmatrix} \begin{bmatrix} -3 \\ 4 \\ -10 \\ 4 \end{bmatrix} = 0 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 4 \end{bmatrix} = 0y
\]
so \(y\) is an eigenvector of \(A\) with eigenvalue \(\lambda = 0\). Also,
\[
Az = \begin{bmatrix}
204 & 98 & -26 & -10 \\
-280 & -134 & 36 & 14 \\
716 & 348 & -90 & -36 \\
-472 & -232 & 60 & 28
\end{bmatrix} \begin{bmatrix} -3 \\ 7 \\ 0 \\ 8 \end{bmatrix} = 2 \begin{bmatrix} -3 \\ 7 \\ 0 \\ 8 \end{bmatrix} = 2z
\]
so \(z\) is an eigenvector of \(A\) with eigenvalue \(\lambda = 2\). Also,
\[
Aw = \begin{bmatrix}
204 & 98 & -26 & -10 \\
-280 & -134 & 36 & 14 \\
716 & 348 & -90 & -36 \\
-472 & -232 & 60 & 28
\end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 4 \\ 0 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ -2 \\ 8 \\ 0 \end{bmatrix} = 2w
\]
so \(w\) is an eigenvector of \(A\) with eigenvalue \(\lambda = 2\).

So we have demonstrated four eigenvectors of \(A\). Are there more? Yes, any nonzero scalar multiple of an eigenvector is again an eigenvector. In this example, set \(u = 30x\). Then
\[
Au = A(30x) = 30Ax = 30(4x) = 4(30x) = 4u
\]
so that \(u\) is also an eigenvector of \(A\) for the same eigenvalue, \(\lambda = 4\).
The vectors \( z \) and \( w \) are both eigenvectors of \( A \) for the same eigenvalue \( \lambda = 2 \), yet this is not as simple as the two vectors just being scalar multiples of each other (they aren’t). Look what happens when we add them together, to form \( v = z + w \), and multiply by \( A \),

\[
Av = A(z + w) = Az + Aw = 2z + 2w = 2(z + w) = 2v
\]

so that \( v \) is also an eigenvector of \( A \) for the eigenvalue \( \lambda = 2 \). So it would appear that the set of eigenvectors that are associated with a fixed eigenvalue is closed under the vector space operations of \( \mathbb{C}^n \). Hmm.

The vector \( y \) is an eigenvector of \( A \) for the eigenvalue \( \lambda = 0 \), so we can use Theorem ZSSM to write \( Ay = 0y = 0 \). But this also means that \( y \in \mathcal{N}(A) \). There would appear to be a connection here also.

Example SEE hints at a number of intriguing properties, and there are many more. We will explore the general properties of eigenvalues and eigenvectors in Section PEE, but in this section we will concern ourselves with the question of actually computing eigenvalues and eigenvectors. First we need a bit of background material on polynomials and matrices.

Subsection PM
Polynomials and Matrices

A polynomial is a combination of powers, multiplication by scalar coefficients, and addition (with subtraction just being the inverse of addition). We never have occasion to divide in a polynomial. So it is with matrices. We can add and subtract, we can multiply by scalars, and we can form powers by repeated uses of matrix multiplication. We do not normally divide matrices (though sometimes we can multiply by an inverse). If a matrix is square, all the operations of a polynomial will preserve the size of the matrix. We’ll demonstrate with an example,

Example PM
Polynomial of a matrix

Let

\[
p(x) = 14 + 19x - 3x^2 - 7x^3 + x^4
\]

\[
D = \begin{bmatrix}
-1 & 3 & 2 \\
1 & 0 & -2 \\
-3 & 1 & 1
\end{bmatrix}
\]
and we will compute \( p(D) \). First, the necessary powers of \( D \). Notice that \( D^0 \) is defined to be the multiplicative identity, \( I_3 \), as will be the case in general.

\[
\begin{align*}
D^0 &= I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
D^1 &= D = \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} \\
D^2 &= DD^1 = \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} = \begin{bmatrix} -2 & -1 & -6 \\ 5 & 1 & 0 \\ 1 & -8 & -7 \end{bmatrix} \\
D^3 &= DD^2 = \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} \begin{bmatrix} -2 & -1 & -6 \\ 5 & 1 & 0 \\ 1 & -8 & -7 \end{bmatrix} = \begin{bmatrix} 19 & -12 & -8 \\ -4 & 15 & 8 \\ 12 & -4 & 11 \end{bmatrix} \\
D^4 &= DD^3 = \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} \begin{bmatrix} 19 & -12 & -8 \\ -4 & 15 & 8 \\ 12 & -4 & 11 \end{bmatrix} = \begin{bmatrix} -7 & 49 & 54 \\ -5 & -4 & -30 \\ -49 & 47 & 43 \end{bmatrix}
\end{align*}
\]

Then
\[
p(D) = 14 + 19D - 3D^2 - 7D^3 + D^4 \\
= 14 \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + 19 \begin{bmatrix} -1 & 3 & 2 \\ 1 & 0 & -2 \\ -3 & 1 & 1 \end{bmatrix} - 3 \begin{bmatrix} -2 & -1 & -6 \\ 5 & 1 & 0 \\ 1 & -8 & -7 \end{bmatrix} \\
- 7 \begin{bmatrix} 19 & -12 & -8 \\ -4 & 15 & 8 \\ 12 & -4 & 11 \end{bmatrix} + \begin{bmatrix} -7 & 49 & 54 \\ -5 & -4 & -30 \\ -49 & 47 & 43 \end{bmatrix}
= \begin{bmatrix} -139 & 193 & 166 \\ 27 & -98 & -124 \\ -193 & 118 & 20 \end{bmatrix}
\]

Notice that \( p(x) \) factors as
\[
p(x) = 14 + 19x - 3x^2 - 7x^3 + x^4 = (x - 2)(x - 7)(x + 1)^2
\]

Because \( A \) commutes with itself (\( AA = AA \)), we can use distributivity of matrix multiplication across matrix addition (Theorem MMDAA) without being careful with any of the matrix products, and just as easily evaluate \( p(D) \) using the factored form of \( p(x) \),
\[
p(x) = 14 + 19D - 3D^2 - 7D^3 + D^4 = (D - 2I_3)(D - 7I_3)(D + I_3)^2
\]
\[
= \begin{bmatrix} -3 & 3 & 2 \\ 1 & -2 & -2 \\ -3 & 1 & -1 \end{bmatrix} \begin{bmatrix} -8 & 3 & 2 \\ 1 & -7 & -2 \\ -3 & 1 & -6 \end{bmatrix} \begin{bmatrix} 0 & 3 & 2 \\ 1 & 1 & -2 \\ -3 & 1 & 2 \end{bmatrix}^2
= \begin{bmatrix} -139 & 193 & 166 \\ 27 & -98 & -124 \\ -193 & 118 & 20 \end{bmatrix}
\]
This example is not meant to be too profound. It is meant to show you that it is natural to evaluate a polynomial with a matrix, and that the factored form of the polynomial is as good as (or maybe better than) the expanded form. And do not forget that constant terms in polynomials are really multiples of the identity matrix when we are evaluating the polynomial with a matrix.

Subsection EEE
Existence of Eigenvalues and Eigenvectors

Before we embark on computing eigenvalues and eigenvectors, we will prove that every matrix has at least one eigenvalue (and an eigenvector to go with it). Later, in Theorem MNEM, we will determine the maximum number of eigenvalues a matrix may have.

The determinant will be a powerful tool in Subsection EE.CEE when it comes time to compute eigenvalues. However, it is possible, with some more advanced machinery, to compute eigenvalues without ever making use of the determinant. Sheldon Axler does just that in his book, *Linear Algebra Done Right*. Here and now, we give Axler’s “determinant-free” proof that every matrix has an eigenvalue. The result is not too startling, but the proof is most enjoyable.

**Theorem EMHE**
Every Matrix Has an Eigenvalue

Suppose $A$ is a square matrix. Then $A$ has at least one eigenvalue.

**Proof** Suppose that $A$ has size $n$, and choose $x$ as any nonzero vector from $\mathbb{C}^n$. (Notice how much latitude we have in our choice of $x$. Only the zero vector is off-limits.) Consider the set

$$S = \{x, Ax, A^2x, A^3x, \ldots, A^nx\}$$

This is a set of $n + 1$ vectors from $\mathbb{C}^n$, so by Theorem MVSLD, $S$ is linearly dependent. Let $a_0, a_1, a_2, \ldots, a_n$ be a collection of $n + 1$ scalars from $\mathbb{C}$, not all zero, that provide a relation of linear dependence on $S$. In other words,

$$a_0x + a_1Ax + a_2A^2x + a_3A^3x + \cdots + a_nA^n x = 0$$

Some of the $a_i$ are nonzero. Suppose that just $a_0 \neq 0$, and $a_1 = a_2 = a_3 = \cdots = a_n = 0$. Then $a_0x = 0$ and by Theorem SMEZV, either $a_0 = 0$ or $x = 0$, which are both contradictions. So $a_i \neq 0$ for some $i \geq 1$. Let $m$ be the largest integer such that $a_m \neq 0$. From this discussion we know that $m \geq 1$. We can also assume that $a_m = 1$, for if not, replace each $a_i$ by $a_i/a_m$ to obtain scalars that serve equally well in providing a relation of linear dependence on $S$.

Define the polynomial

$$p(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + \cdots + a_mx^m$$

Because we have consistently used $\mathbb{C}$ as our set of scalars (rather than $\mathbb{R}$), we know that we can factor $p(x)$ into linear factors of the form $(x - b_i)$, where $b_i \in \mathbb{C}$. So there are
From the preceding equation, we know that
\[
k = k
\]
we take \( k = k \). Notice that by the definition of scalar, \( b \) scalars, \( b_1, b_2, b_3, \ldots, b_m \), from \( \mathbb{C} \) so that,
\[
p(x) = (x - b_m)(x - b_{m-1}) \cdots (x - b_3)(x - b_2)(x - b_1)
\]
Put it all together and
\[
0 = a_0x + a_1Ax + a_2A^2x + a_3A^3x + \cdots + a_nA^n x
\]
\[
= a_0x + a_1Ax + a_2A^2x + a_3A^3x + \cdots + a_mA^m x
\]
\[
= (a_0I_n + a_1A + a_2A^2 + a_3A^3 + \cdots + a_mA^m) x
\]
\[
= p(A)x
\]
\[
= (A - b_mI_n)(A - b_{m-1}I_n) \cdots (A - b_3I_n)(A - b_2I_n)(A - b_1I_n)x
\]
Let \( k \) be the smallest integer such that
\[
(A - b_kI_n)(A - b_{k-1}I_n) \cdots (A - b_3I_n)(A - b_2I_n)(A - b_1I_n)x = 0.
\]
From the preceding equation, we know that \( k \leq m \). Define the vector \( z \) by
\[
z = (A - b_{k-1}I_n) \cdots (A - b_3I_n)(A - b_2I_n)(A - b_1I_n)x
\]
Notice that by the definition of \( k \), the vector \( z \) must be nonzero. In the event that \( k = 1 \), we take \( z = x \), and \( z \) is still nonzero. Now
\[
(A - b_kI_n)z = (A - b_kI_n)(A - b_{k-1}I_n) \cdots (A - b_3I_n)(A - b_2I_n)(A - b_1I_n)x = 0
\]
which allows us to write
\[
Az = (A + 0)z
\]
\[
= (A - b_kI_n + b_kI_n)z
\]
\[
= (A - b_kI_n)z + b_kI_n z
\]
\[
= 0 + b_kI_n z
\]
\[
= b_kI_n z
\]
\[
= b_k z
\]
Since \( z \neq 0 \), this equation says that \( z \) is an eigenvector of \( A \) for the eigenvalue \( \lambda = b_k \) (Definition EEM 373), so we have shown that any square matrix \( A \) does have at least one eigenvalue. \( \blacksquare \)

The proof of Theorem EMHE 377 is constructive (it contains an unambiguous procedure that leads to an eigenvalue), but it is not meant to be practical. We will illustrate the theorem with an example, the purpose being to provide a companion for studying the proof and not to suggest this is the best procedure for computing an eigenvalue.

**Example CAEHW**

**Computing an eigenvalue the hard way**

This example illustrates the proof of Theorem EMHE 377, so will employ the same notation as the proof — look there for full explanations. It is not meant to be an example of a reasonable computational approach to finding eigenvalues and eigenvectors. OK, warnings in place, here we go.
Let
\[
A = \begin{bmatrix}
-7 & -1 & 11 & 0 & -4 \\
4 & 1 & 0 & 2 & 0 \\
-10 & -1 & 14 & 0 & -4 \\
8 & 2 & -15 & -1 & 5 \\
-10 & -1 & 16 & 0 & -6 \\
\end{bmatrix}
\]
and choose
\[
x = \begin{bmatrix}
3 \\
0 \\
3 \\
-5 \\
4 \\
\end{bmatrix}
\]
It is important to notice that the choice of \(x\) could be anything, so long as it is not the zero vector. We have not chosen \(x\) totally at random, but so as to make our illustration of the theorem as general as possible. You could replicate this example with your own choice and the computations are guaranteed to be reasonable, provided you have a computational tool that will factor a fifth degree polynomial for you.

The set
\[
S = \{x, Ax, A^2x, A^3x, A^4x, A^5x\}
\]
is guaranteed to be linearly dependent, as it has six vectors from \(\mathbb{C}^5\) (Theorem MVSLD [139]). We will search for a non-trivial relation of linear dependence by solving a homogeneous system of equations whose coefficient matrix has the vectors of \(S\) as columns through row operations.

\[
\begin{bmatrix}
3 & -4 & 6 & -10 & 18 & -34 \\
0 & 2 & -6 & 14 & -30 & 62 \\
3 & -4 & 6 & -10 & 18 & -34 \\
-5 & 4 & -2 & -2 & 10 & -26 \\
4 & -6 & 10 & -18 & 34 & -66 \\
\end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix}
1 & 0 & -2 & 6 & -14 & 30 \\
0 & 1 & -3 & 7 & -15 & 31 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]
There are four free variables for describing solutions to this homogeneous system, so we have our pick of solutions. The most expedient choice would be to set \(x_3 = 1\) and \(x_4 = x_5 = x_6 = 0\). However, we will again opt to maximize the generality of our illustration of Theorem EMHE [377] and choose \(x_3 = -8, x_4 = -3, x_5 = 1, x_6 = 0\). The leads to a solution with \(x_1 = 16, x_2 = 12\).

This relation of linear dependence then says that
\[
0 = 16x + 12Ax - 8A^2x - 3A^3x + A^4x + 0A^5x
\]
So we define \(p(x) = 16 + 12x - 8x^2 - 3x^3 + x^4\), and as advertised in the proof of Theorem EMHE [377], we have a polynomial of degree \(m = 4 > 1\) such that \(p(A)x = 0\).
Now we need to factor $p(x)$ over $\mathbb{C}$. If you made your own choice of $x$ at the start, this is where you might have a fifth degree polynomial, and where you might need to use a computational tool to find roots and factors. We have

$$p(x) = 16 + 12x - 8x^2 - 3x^3 + x^4 = (x - 4)(x + 2)(x - 2)(x + 1)$$

So we know that

$$0 = p(A)x = (A - 4I_5)(A + 2I_5)(A - 2I_5)(A + 1I_5)x$$

We apply one factor at a time, until we get the zero vector, so as to determine the value of $k$ described in the proof of Theorem EMHE [377],

$$ (A + 1I_5)x = \begin{bmatrix} -6 & -1 & 11 & 0 & -4 \\ 4 & 2 & 0 & 2 & 0 \\ -10 & -1 & 15 & 0 & -4 \\ 8 & 2 & -15 & 0 & 5 \\ -10 & -1 & 16 & 0 & -5 \end{bmatrix} \begin{bmatrix} 3 \\ 0 \\ 3 \\ -5 \\ 4 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ -1 \\ -5 \\ -2 \end{bmatrix}$$

$$ (A - 2I_5)(A + 1I_5)x = \begin{bmatrix} -9 & -1 & 11 & 0 & -4 \\ 4 & -1 & 0 & 2 & 0 \\ -10 & -1 & 12 & 0 & -4 \\ 8 & 2 & -15 & 0 & 5 \\ -10 & -1 & 16 & 0 & -8 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \\ -1 \\ -5 \\ -2 \end{bmatrix} = \begin{bmatrix} 4 \\ 2 \\ 4 \\ -1 \\ 8 \end{bmatrix}$$

$$ (A + 2I_5)(A - 2I_5)(A + 1I_5)x = \begin{bmatrix} -5 & -1 & 11 & 0 & -4 \\ 4 & 3 & 0 & 2 & 0 \\ -10 & -1 & 16 & 0 & -4 \\ 8 & 2 & -15 & 0 & 5 \\ -10 & -1 & 16 & 0 & -4 \end{bmatrix} \begin{bmatrix} 4 \\ -8 \\ 4 \\ 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

So $k = 3$ and

$$z = (A - 2I_5)(A + 1I_5)x = \begin{bmatrix} 4 \\ -8 \\ 4 \\ 4 \\ 8 \end{bmatrix}$$

is an eigenvector of $A$ for the eigenvalue $\lambda = -2$, as you can check by doing the computation $Ax$. If you work through this example with your own choice of the vector $x$ (strongly recommended) then the eigenvalue you will find may be different, but will be in the set $\{3, 0, 1, -1, -2\}$. ⊚

**Subsection CEE**

**Computing Eigenvalues and Eigenvectors**

Fortunately, we need not rely on the procedure of Theorem EMHE [377] each time we need an eigenvalue. It is the determinant, and specifically Theorem SMZD [366], that provide the main tool. First a key definition.
Definition CP
Characteristic Polynomial
Suppose that $A$ is a square matrix of size $n$. Then the characteristic polynomial of $A$ is the polynomial $p_A(x)$ defined by

$$p_A(x) = \det(A - xI_n)$$

Example CPMS3
Characteristic polynomial of a matrix, size 3
Consider

$$F = \begin{bmatrix} -13 & -8 & -4 \\ 12 & 7 & 4 \\ 24 & 16 & 7 \end{bmatrix}$$

Then

$$p_F(x) = \det(F - xI_3)$$

$$= \begin{vmatrix} -13 - x & -8 & -4 \\ 12 & 7 - x & 4 \\ 24 & 16 & 7 - x \end{vmatrix}$$

$$= (-13 - x) \begin{vmatrix} 7 - x & 4 \\ 16 & 7 - x \end{vmatrix} + (-8)(-1) \begin{vmatrix} 12 & 4 \\ 24 & 7 - x \end{vmatrix}$$

$$+ (-4) \begin{vmatrix} 12 & 7 - x \\ 24 & 16 \end{vmatrix}$$

$$= (-13 - x)((7 - x)(7 - x) - 4(16)) + (-8)(-1)(12(7 - x) - 4(24))$$

$$+ (-4)(12(16) - (7 - x)(24))$$

$$= 3 + 5x + x^2 - x^3$$

$$= -(x - 3)(x + 1)^2$$

The characteristic polynomial is our main computational tool for finding eigenvalues, and will sometimes be used to aid us in determining the properties of eigenvalues.

Theorem EMRCP
Eigenvalues of a Matrix are Roots of Characteristic Polynomials
Suppose $A$ is a square matrix. Then $\lambda$ is an eigenvalue of $A$ if and only if $p_A(\lambda) = 0$.

Proof
Suppose $A$ has size $n$.

$$p_A(\lambda) = 0$$

$$\iff \det(A - \lambda I_n) = 0$$

$$\iff A - \lambda I_n\text{ is singular}$$

$$\iff \text{there exists } x \neq 0 \text{ so that } (A - \lambda I_n)x = 0$$

$$\iff \text{there exists } x \neq 0 \text{ so that } Ax - \lambda I_n x = 0$$

$$\iff \text{there exists } x \neq 0 \text{ so that } Ax - \lambda x = 0$$

$$\iff \text{there exists } x \neq 0 \text{ so that } Ax = \lambda x$$

$$\iff \lambda \text{ is an eigenvalue of } A$$
Example EMS3
Eigenvalues of a matrix, size 3
In Example CPMS3 [381] we found the characteristic polynomial of

\[ F = \begin{bmatrix} -13 & -8 & -4 \\ 12 & 7 & 4 \\ 24 & 16 & 7 \end{bmatrix} \]

to be \( p_F(x) = -(x - 3)(x + 1)^2 \). Factored, we can find all of its roots easily, they are \( x = 3 \) and \( x = -1 \). By Theorem EMRCP [381], \( \lambda = 3 \) and \( \lambda = -1 \) are both eigenvalues of \( F \), and these are the only eigenvalues of \( F \). We’ve found them all.

Let us now turn our attention to the computation of eigenvectors.

Definition EM
Eigenvalue of a Matrix
Suppose that \( A \) is a square matrix and \( \lambda \) is an eigenvalue of \( A \). Then the eigenvalue \( \lambda \) of \( A \), denoted by \( E_A(\lambda) \), is the set of all the eigenvectors of \( A \) for \( \lambda \), with the addition of the zero vector.

Example SEE [373] hinted that the set of eigenvectors for a single eigenvalue might have some closure properties, and with the addition of the non-eigenvector, \( 0 \), we indeed get a whole subspace.

Theorem EMS
Eigenspace for a Matrix is a Subspace
Suppose \( A \) is a square matrix of size \( n \) and \( \lambda \) is an eigenvalue of \( A \). Then the eigenspace \( E_A(\lambda) \) is a subspace of the vector space \( \mathbb{C}^n \).

Proof We will check the three conditions of Theorem TSS [293]. First, Definition EM [382] explicitly includes the zero vector in \( E_A(\lambda) \), so the set is non-empty.

Suppose that \( x, y \in E_A(\lambda) \), that is, \( x \) and \( y \) are two eigenvectors of \( A \) for \( \lambda \). Then

\[
A(x + y) = Ax + Ay = \lambda x + \lambda y = \lambda (x + y) \]

Theorem MMDAA [195] \( x, y \) eigenvectors of \( A \)
Property DVAC [92] So either \( x + y = 0 \), or \( x + y \) is an eigenvector of \( A \) for \( \lambda \) (Definition EEM [373]). So, in either event, \( x + y \in E_A(\lambda) \), and we have additive closure.

Suppose that \( \alpha \in \mathbb{C} \), and that \( x \in E_A(\lambda) \), that is, \( x \) is an eigenvector of \( A \) for \( \lambda \). Then

\[
A(\alpha x) = \alpha (Ax) = \alpha \lambda x \]

Theorem MMSMM [196] \( x \) an eigenvector of \( A \)
Property SMAC [92] So either \( \alpha x = 0 \), or \( \alpha x \) is an eigenvector of \( A \) for \( \lambda \) (Definition EEM [373]). So, in either event, \( \alpha x \in E_A(\lambda) \), and we have scalar closure.

With the three conditions of Theorem TSS [293] met, we know \( E_A(\lambda) \) is a subspace.

Theorem EMS [382] tells us that an eigenspace is a subspace (and hence a vector space in its own right). Our next theorem tells us how to quickly construct this subspace.
Theorem EMNS
Eigenspace of a Matrix is a Null Space
Suppose $A$ is a square matrix of size $n$ and $\lambda$ is an eigenvalue of $A$. Then

$$E_A(\lambda) = N(A - \lambda I_n)$$

Proof The conclusion of this theorem is an equality of sets, so normally we would follow
the advice of Technique SE [17]. However, in this case we can construct a sequence of
equivalences which will together provide the two subset inclusions we need. First, notice
that $0 \in E_A(\lambda)$ by Definition EM [382] and $0 \in N(A - \lambda I_n)$ by Theorem HSC [64]. Now
consider any nonzero vector $x \in \mathbb{C}^n$,

\[
x \in E_A(\lambda) \iff Ax = \lambda x \quad \text{Definition EM [382]}
\]
\[
\iff Ax - \lambda I_n x = 0 \quad \text{Theorem MMIM [195]}
\]
\[
\iff (A - \lambda I_n)x = 0 \quad \text{Theorem MMDAA [195]}
\]
\[
\iff x \in N(A - \lambda I_n) \quad \text{Definition NSM [68]}
\]

You might notice the close parallels (and differences) between the proofs of Theorem EM-
RCP [381] and Theorem EMNS [383]. Since Theorem EMNS [383] describes the set of all
eigenvectors of $A$ as a null space we can use techniques such as Theorem BNS [141]
to provide concise descriptions of eigenspaces.

Example ESMS3
Eigenspaces of a matrix, size 3
Example CPMS3 [381] and Example EMS3 [382] describe the characteristic polynomial
and eigenvalues of the $3 \times 3$ matrix

$$F = \begin{bmatrix} -13 & -8 & -4 \\ 12 & 7 & 4 \\ 24 & 16 & 7 \end{bmatrix}$$

We will now take the each eigenvalue in turn and compute its eigenspace. To do this,
we row-reduce the matrix $F - \lambda I_3$ in order to determine solutions to the homogeneous
system $\mathbf{LS}(F - \lambda I_3, 0)$ and then express the eigenspace as the null space of $F - \lambda I_3$
(Theorem EMNS [383]). Theorem BNS [141] then tells us how to write the null space as
the span of a basis.

$\lambda = 3$ \hspace{1cm} $F - 3I_3 = \begin{bmatrix} -16 & -8 & -4 \\ 12 & 4 & 4 \\ 24 & 16 & 4 \end{bmatrix}$ \quad \text{RREF} \quad \begin{bmatrix} 1 & 0 & 1/2 \\ 0 & 1 & -1/2 \\ 0 & 0 & 0 \end{bmatrix}$

$$E_F(3) = N(F - 3I_3) = \mathcal{S}p \left( \begin{bmatrix} -1/2 \\ 1/2 \\ 1 \end{bmatrix} \right) = \mathcal{S}p \left( \begin{bmatrix} -1 \\ 1 \\ 2 \end{bmatrix} \right)$$

$\lambda = -1$ \hspace{1cm} $F + 1I_3 = \begin{bmatrix} -12 & -8 & -4 \\ 12 & 8 & 4 \\ 24 & 16 & 8 \end{bmatrix}$ \quad \text{RREF} \quad \begin{bmatrix} 1 & 2/3 & 1/3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$$E_F(-1) = N(F + 1I_3) = \mathcal{S}p \left( \begin{bmatrix} -2/3 \\ 1/3 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right) = \mathcal{S}p \left( \begin{bmatrix} -2 \\ 3 \\ 0 \\ 1 \\ 3 \end{bmatrix} \right)$$
Eigenspaces in hand, we can easily compute eigenvectors by forming nontrivial linear combinations of the basis vectors describing each eigenspace. In particular, notice that we can “pretty up” our basis vectors by using scalar multiples to clear out fractions.

Subsection ECEE

Examples of Computing Eigenvalues and Eigenvectors

No theorems in this section, just a selection of examples meant to illustrate the range of possibilities for the eigenvalues and eigenvectors of a matrix. These examples can all be done by hand, though the computation of the characteristic polynomial would be very time-consuming and error-prone. It can also be difficult to factor an arbitrary polynomial, though if we were to suggest that most of our eigenvalues are going to be integers, then it can be easier to hunt for roots. These examples are meant to look similar to a concatenation of Example CPMS3, Example EMS3, and Example ESMS3. First, we will sneak in a pair of definitions so we can illustrate them throughout this sequence of examples.

Definition AME

Algebraic Multiplicity of an Eigenvalue

Suppose that $A$ is a square matrix and $\lambda$ is an eigenvalue of $A$. Then the algebraic multiplicity of $\lambda$, $\alpha_A(\lambda)$, is the highest power of $(x - \lambda)$ that divides the characteristic polynomial, $p_A(x)$.

Since an eigenvalue $\lambda$ is a root of the characteristic polynomial, there is always a factor of $(x - \lambda)$, and the algebraic multiplicity is just the power of this factor in a factorization of $p_A(x)$. So in particular, $\alpha_A(\lambda) \geq 1$. Compare the definition of algebraic multiplicity with the next definition.

Definition GME

Geometric Multiplicity of an Eigenvalue

Suppose that $A$ is a square matrix and $\lambda$ is an eigenvalue of $A$. Then the geometric multiplicity of $\lambda$, $\gamma_A(\lambda)$, is the dimension of the eigenspace $E_A(\lambda)$.

Since every eigenvalue must have at least one eigenvector, the associated eigenspace cannot be trivial, and so $\gamma_A(\lambda) \geq 1$.

Example EMMS4

Eigenvalue multiplicities, matrix of size 4

Consider the matrix

$$B = \begin{bmatrix}
-2 & 1 & -2 & -4 \\
12 & 1 & 4 & 9 \\
6 & 5 & -2 & -4 \\
3 & -4 & 5 & 10
\end{bmatrix}$$

then

$$p_B(x) = 8 - 20x + 18x^2 - 7x^3 + x^4 = (x - 1)(x - 2)^3$$

So the eigenvalues are $\lambda = 1, 2$ with algebraic multiplicities $\alpha_B(1) = 1$ and $\alpha_B(2) = 3$. 
Computing eigenvectors,

$$\lambda = 1 \quad B - I_4 = \begin{bmatrix} -3 & 1 & -2 & -4 \\ 12 & 0 & 4 & 9 \\ 6 & 5 & -3 & -4 \\ 3 & -4 & 5 & 9 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & \frac{1}{3} & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$E_B(1) = N(B - I_4) = S \begin{bmatrix} -\frac{1}{3} \\ 1 \\ 1 \\ 0 \end{bmatrix} = S\begin{bmatrix} -1 \\ 3 \\ 0 \end{bmatrix}$$

$$\lambda = 2 \quad B - 2I_4 = \begin{bmatrix} -4 & 1 & -2 & -4 \\ 12 & -1 & 4 & 9 \\ 6 & 5 & -4 & -4 \\ 3 & -4 & 5 & 8 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 0 & 1/2 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 1/2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$E_B(2) = N(B - 2I_4) = S \begin{bmatrix} -\frac{1}{2} \\ 1 \\ \frac{1}{2} \\ 1 \end{bmatrix} = S\begin{bmatrix} -1 \\ 2 \\ -1 \\ 2 \end{bmatrix}$$

So each eigenspace has dimension 1 and so $\gamma_B(1) = 1$ and $\gamma_B(2) = 1$. This example is of interest because of the discrepancy between the two multiplicities for $\lambda = 2$. In many of our examples the algebraic and geometric multiplicities will be equal for all of the eigenvalues (as it was for $\lambda = 1$ in this example), so keep this example in mind. We will have some explanations for this phenomenon later (see Example NDMS4 [420]). ⊗

Example ESMS4
Eigenvalues, symmetric matrix of size 4
Consider the matrix

$$C = \begin{bmatrix} 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}$$

then

$$p_C(x) = -3 + 4x + 2x^2 - 4x^3 + x^4 = (x - 3)(x - 1)^2(x + 1)$$

So the eigenvalues are $\lambda = 3, 1, -1$ with algebraic multiplicities $\alpha_C(3) = 1$, $\alpha_C(1) = 2$ and $\alpha_C(-1) = 1$. 
Computing eigenvectors,

\[
\lambda = 3 \quad C - 3I_4 = \begin{bmatrix}
-2 & 0 & 1 & 1 \\
0 & -2 & 1 & 1 \\
1 & 1 & -2 & 0 \\
1 & 1 & 0 & -2
\end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix}
1 & 0 & 0 & -1 \\
0 & 1 & 0 & -1 \\
0 & 0 & 1 & -1 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

\[E_C(3) = N(C - 3I_4) = \text{Sp} \left( \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \right)\]

\[\lambda = 1 \quad C - I_4 = \begin{bmatrix}
0 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 \\
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0
\end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix}
1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

\[E_C(1) = N(C - I_4) = \text{Sp} \left( \begin{bmatrix} -1 \\ 1 \\ 0 \\ -1 \end{bmatrix} \right)\]

\[\lambda = -1 \quad C + I_4 = \begin{bmatrix}
2 & 0 & 1 & 1 \\
0 & 2 & 1 & 1 \\
1 & 1 & 2 & 0 \\
1 & 1 & 0 & 2
\end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & -1 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

\[E_C(-1) = N(C + I_4) = \text{Sp} \left( \begin{bmatrix} -1 \\ -1 \\ 1 \\ 1 \end{bmatrix} \right)\]

So the eigenspace dimensions yield geometric multiplicities \(\gamma_C(3) = 1\), \(\gamma_C(1) = 2\) and \(\gamma_C(-1) = 1\), the same as for the algebraic multiplicities. This example is of interest because \(A\) is a symmetric matrix, and will be the subject of \(\text{Theorem HMRE} 408\). ⊗

**Example HMEM5**

**High multiplicity eigenvalues, matrix of size 5**

Consider the matrix

\[
E = \begin{bmatrix}
29 & 14 & 2 & 6 & -9 \\
-47 & -22 & -1 & -11 & 13 \\
19 & 10 & 5 & 4 & -8 \\
-19 & -10 & -3 & -2 & 8 \\
7 & 4 & 3 & 1 & -3
\end{bmatrix}
\]

then

\[p_E(x) = -16 + 16x + 8x^2 - 16x^3 + 7x^4 - x^5 = -(x - 2)^4(x + 1)\]

So the eigenvalues are \(\lambda = 2, -1\) with algebraic multiplicities \(\alpha_E(2) = 4\) and \(\alpha_E(-1) = 1\).
Subsection EE.ECEE  Examples of Computing Eigenvalues and Eigenvectors  387

Computing eigenvectors,

$$\lambda = 2 \quad E - 2I_5 = \begin{bmatrix} 27 & 14 & 2 & 6 & -9 \\ -47 & -24 & -1 & -11 & 13 \\ 19 & 10 & 3 & 4 & -8 \\ -19 & -10 & -3 & -4 & 8 \\ 7 & 4 & 3 & 1 & -5 \end{bmatrix} \quad \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & -\frac32 & -\frac12 \\ 0 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$E_E(2) = \mathcal{N}(E - 2I_5) = S_p \begin{bmatrix} \begin{bmatrix} -1 \\ \frac32 \\ 1 \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \end{bmatrix} = S_p \begin{bmatrix} \begin{bmatrix} -2 \\ 0 \\ 3 \\ 2 \end{bmatrix} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \\ 2 \end{bmatrix} \end{bmatrix}$$

$$\lambda = -1 \quad E + 1I_5 = \begin{bmatrix} 30 & 14 & 2 & 6 & -9 \\ -47 & -21 & -1 & -11 & 13 \\ 19 & 10 & 6 & 4 & -8 \\ -19 & -10 & -3 & -1 & 8 \\ 7 & 4 & 3 & 1 & -2 \end{bmatrix} \quad \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 0 & 2 & 0 \\ 0 & 1 & 0 & -4 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$E_E(-1) = \mathcal{N}(E + 1I_5) = S_p \begin{bmatrix} \begin{bmatrix} -2 \\ 4 \\ -1 \\ 1 \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \end{bmatrix}$$

So the eigenspace dimensions yield geometric multiplicities $\gamma_E(2) = 2$ and $\gamma_E(-1) = 1$. This example is of interest because $\lambda = 2$ has such a large algebraic multiplicity, which is also not equal to its geometric multiplicity.

Example CEMS6

Complex eigenvalues, matrix of size 6

Consider the matrix


then

$$p_F(x) = -50 + 55x + 13x^2 - 50x^3 + 32x^4 - 9x^5 + x^6$$

$$= (x - 2)(x + 1)(x^2 - 4x + 5)^2$$

$$= (x - 2)(x + 1)((x - (2 + i))(x - (2 - i)))^2$$

$$= (x - 2)(x + 1)(x - (2 + i))^2(x - (2 - i))^2$$

So the eigenvalues are $\lambda = 2, -1, 2 + i, 2 - i$ with algebraic multiplicities $\alpha_F(2) = 1$, $\alpha_F(-1) = 1$, $\alpha_F(2 + i) = 2$ and $\alpha_F(2 - i) = 2$. 
Computing eigenvectors,

\[ \lambda = 2 \]

\[ F - 2I_6 = \begin{bmatrix}
-61 & -34 & 41 & 12 & 25 & 30 \\
1 & 5 & -46 & -36 & -11 & -29 \\
-233 & -119 & 56 & -35 & 75 & 54 \\
157 & 81 & -43 & 19 & -51 & -39 \\
-91 & -48 & 32 & -5 & 30 & 26 \\
209 & 107 & -55 & 28 & -69 & -52
\end{bmatrix} \rightarrow \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & \frac{1}{10} \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & -\frac{3}{5} \\
0 & 0 & 0 & 1 & 0 & -\frac{4}{5} \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \]

\[ E_F(2) = N(F - 2I_6) = Sp \begin{bmatrix}
-\frac{1}{5} \\
0 \\
-\frac{3}{5} \\
-\frac{4}{5} \\
1
\end{bmatrix} = Sp \begin{bmatrix}
-1 \\
0 \\
-3 \\
1 \\
-4 \\
5
\end{bmatrix} \]

\[ \lambda = -1 \]

\[ F + I_6 = \begin{bmatrix}
-58 & -34 & 41 & 12 & 25 & 30 \\
1 & 8 & -46 & -36 & -11 & -29 \\
-233 & -119 & 59 & -35 & 75 & 54 \\
157 & 81 & -43 & 22 & -51 & -39 \\
-91 & -48 & 32 & -5 & 33 & 26 \\
209 & 107 & -55 & 28 & -69 & -49
\end{bmatrix} \rightarrow \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & \frac{1}{2} \\
0 & 1 & 0 & 0 & 0 & -\frac{1}{2} \\
0 & 0 & 1 & 0 & 0 & \frac{1}{2} \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} \]

\[ E_F(-1) = N(F + I_6) = Sp \begin{bmatrix}
-\frac{1}{2} \\
-\frac{1}{2} \\
0 \\
1
\end{bmatrix} = Sp \begin{bmatrix}
-1 \\
-1 \\
0 \\
1 \\
2
\end{bmatrix} \]
\[ \lambda = 2 + i \]

\[
F - (2 + i)I_6 = 
\begin{bmatrix}
-61 - i & -34 & 41 & 12 & 25 & 30 \\
1 & 5 - i & -46 & -36 & -11 & -29 \\
-233 & -119 & 56 - i & -35 & 75 & 54 \\
157 & 81 & -43 & 19 - i & -51 & -39 \\
-91 & -48 & 32 & -5 & 30 - i & 26 \\
209 & 107 & -55 & 28 & -69 & -52 - i
\end{bmatrix}
\]

\[
E_F(2 + i) = N(F - (2 + i)I_6) = Sp \begin{pmatrix}
\begin{bmatrix}
\frac{1}{5}(7 + i) \\
\frac{1}{5}(9 + 2i)
\end{bmatrix} \\
\begin{bmatrix}
-\frac{1}{5}(7 + i) \\
-\frac{1}{5}(9 + 2i)
\end{bmatrix}
\end{pmatrix}
\]

\[ \lambda = 2 - i \]

\[
F - (2 - i)I_6 = 
\begin{bmatrix}
-61 + i & -34 & 41 & 12 & 25 & 30 \\
1 & 5 + i & -46 & -36 & -11 & -29 \\
-233 & -119 & 56 + i & -35 & 75 & 54 \\
157 & 81 & -43 & 19 + i & -51 & -39 \\
-91 & -48 & 32 & -5 & 30 + i & 26 \\
209 & 107 & -55 & 28 & -69 & -52 + i
\end{bmatrix}
\]

\[
E_F(2 - i) = N(F - (2 - i)I_6) = Sp \begin{pmatrix}
\begin{bmatrix}
\frac{1}{5}(7 - i) \\
\frac{1}{5}(9 - 2i)
\end{bmatrix} \\
\begin{bmatrix}
-\frac{1}{5}(7 - i) \\
-\frac{1}{5}(9 - 2i)
\end{bmatrix}
\end{pmatrix}
\]

So the eigenspace dimensions yield geometric multiplicities \( \gamma_F(2) = 1 \), \( \gamma_F(-1) = 1 \), \( \gamma_F(2 + i) = 1 \) and \( \gamma_F(2 - i) = 1 \). This example demonstrates some of the possibilities for the appearance of complex eigenvalues, even when all the entries of the matrix are...
real. Notice how all the numbers in the analysis of \( \lambda = 2 - i \) are conjugates of the corresponding number in the analysis of \( \lambda = 2 + i \). This is the content of the upcoming Theorem ERMCP [404].

**Example DEMS5**

**Distinct eigenvalues, matrix of size 5**  
Consider the matrix

\[
H = \begin{bmatrix}
15 & 18 & -8 & 6 & -5 \\
5 & 3 & 1 & -1 & -3 \\
0 & -4 & 5 & -4 & -2 \\
-43 & -46 & 17 & -14 & 15 \\
26 & 30 & -12 & 8 & -10
\end{bmatrix}
\]

then

\[
p_H(x) = -6x + x^2 + 7x^3 - x^4 - x^5 = x(x - 2)(x - 1)(x + 1)(x + 3)
\]

So the eigenvalues are \( \lambda = 2, 1, 0, -1, -3 \) with algebraic multiplicities \( \alpha_{H}(2) = 1, \alpha_{H}(1) = 1, \alpha_{H}(0) = 1, \alpha_{H}(-1) = 1 \) and \( \alpha_{H}(-3) = 1 \).

Computing eigenvectors,

\[
\lambda = 2 \quad H - 2I_5 = \begin{bmatrix}
13 & 18 & -8 & 6 & -5 \\
5 & 1 & 1 & -1 & -3 \\
0 & -4 & 3 & -4 & -2 \\
-43 & -46 & 17 & -16 & 15 \\
26 & 30 & -12 & 8 & -12
\end{bmatrix} \xrightarrow{RREF} \begin{bmatrix}
1 & 0 & 0 & 0 & -1 \\
0 & 1 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

\[
E_{H}(2) = \mathcal{N}(H - 2I_5) = Sp \begin{bmatrix}
1 \\
-1 \\
-2 \\
-1 \\
1
\end{bmatrix}
\]

\[
\lambda = 1 \quad H - 1I_5 = \begin{bmatrix}
14 & 18 & -8 & 6 & -5 \\
5 & 2 & 1 & -1 & -3 \\
0 & -4 & 4 & -4 & -2 \\
-43 & -46 & 17 & -15 & 15 \\
26 & 30 & -12 & 8 & -11
\end{bmatrix} \xrightarrow{RREF} \begin{bmatrix}
1 & 0 & 0 & 0 & -\frac{1}{2} \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & \frac{1}{2} \\
0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

\[
E_{H}(1) = \mathcal{N}(H - 1I_5) = Sp \begin{bmatrix}
\frac{1}{2} \\
0 \\
-\frac{1}{2} \\
-1 \\
1
\end{bmatrix} = Sp \begin{bmatrix}
1 \\
0 \\
-1 \\
-2 \\
2
\end{bmatrix}
\]
Suppose $A$ is the $2 \times 2$ matrix

$$A = \begin{bmatrix} -5 & 8 \\ -4 & 7 \end{bmatrix}$$
1. Find the eigenvalues of $A$.
2. Find the eigenspaces of $A$.
3. For the polynomial $p(x) = 3x^2 - x + 2$, compute $p(A)$. 
Subsection EXC

Exercises

C20  Find the eigenvalues, eigenspaces, algebraic multiplicities and geometric multiplicities for the matrix below. It is possible to do all these computations by hand, and it would be instructive to do so.

\[ B = \begin{bmatrix} -12 & 30 \\ -5 & 13 \end{bmatrix} \]

Contributed by Robert Beezer  Solution 395

C21  The matrix \( A \) below has \( \lambda = 2 \) as an eigenvalue. Find the geometric multiplicity of \( \lambda = 2 \) using your calculator only for row-reducing matrices.

\[ A = \begin{bmatrix} 18 & -15 & 33 & -15 \\ -4 & 8 & -6 & 6 \\ -9 & 9 & -16 & 9 \\ 5 & -6 & 9 & -4 \end{bmatrix} \]

Contributed by Robert Beezer  Solution 395

M60  Repeat Example CAEHW 378 by choosing \( x = \begin{bmatrix} 0 \\ 8 \\ 2 \\ 1 \\ 2 \end{bmatrix} \) and then arrive at an eigenvalue and eigenvector of the matrix \( A \). The hard way.

Contributed by Robert Beezer  Solution 395

T10  A matrix \( A \) is idempotent if \( A^2 = A \). Show that the only possible eigenvalues of an idempotent matrix are \( \lambda = 0 \) and \( \lambda = 1 \). Then give an example of a matrix that is idempotent and has both of these two values as eigenvalues.

Contributed by Robert Beezer  Solution 396
The characteristic polynomial of $B$ is

$$p_B(x) = \det (B - xI_2)$$

$$= \begin{vmatrix} -12 - x & 30 \\ -5 & 13 - x \end{vmatrix}$$

$$= (-12 - x)(13 - x) - (30)(-5)$$

$$= x^2 - x - 6$$

$$= (x - 3)(x + 2)$$

From this we find eigenvalues $\lambda = 3, -2$ with algebraic multiplicities $\alpha_B(3) = 1$ and $\alpha_B(-2) = 1$.

For eigenvectors and geometric multiplicities, we study the null spaces of $B - \lambda I_2$ (Theorem EMNS [383]).

$$\lambda = 3 \quad B - 3I_2 = \begin{bmatrix} -15 & 30 \\ -5 & 10 \end{bmatrix} \xrightarrow{\text{rref}} \begin{bmatrix} 1 & \phantom{2} 2 \\ 0 & \phantom{1} 0 \end{bmatrix}$$

$$E_B(3) = N(B - 3I_2) = sp\left(\begin{bmatrix} 2 \\ 1 \end{bmatrix}\right)$$

$$\lambda = -2 \quad B + 2I_2 = \begin{bmatrix} -10 & 30 \\ -5 & 15 \end{bmatrix} \xrightarrow{\text{rref}} \begin{bmatrix} 1 & -3 \\ 0 & \phantom{1} 0 \end{bmatrix}$$

$$E_B(-2) = N(B + 2I_2) = sp\left(\begin{bmatrix} 3 \\ 1 \end{bmatrix}\right)$$

Each eigenspace has dimension one, so we have geometric multiplicities $\gamma_B(3) = 1$ and $\gamma_B(-2) = 1$.

If $\lambda = 2$ is an eigenvalue of $A$, the matrix $A - 2I_4$ will be singular, and its null space will be the eigenspace of $A$. So we form this matrix and row-reduce,

$$A - 2I_4 = \begin{bmatrix} 16 & -15 & 33 & -15 \\ -4 & 6 & -6 & 6 \\ -9 & 9 & -18 & 9 \\ 5 & -6 & 9 & -6 \end{bmatrix} \xrightarrow{\text{rref}} \begin{bmatrix} 1 & 0 & 3 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

With two free variables, we know a basis of the null space (Theorem SSNS [122] and Theorem BNS [141]) will contain two vectors. Thus the null space of $A - 2I_4$ has dimension two, and so the eigenspace of $\lambda = 2$ has dimension two also (Theorem EMNS [383]), $\gamma_A(2) = 2$. 

Form the matrix $C$ whose columns are $x, Ax, A^2x, A^3x, A^4x, A^5x$ and row-reduce the
matrix,
\[
\begin{bmatrix}
0 & 6 & 32 & 102 & 320 & 966 \\
8 & 10 & 24 & 168 & 490 \\
2 & 12 & 50 & 156 & 482 & 1452 \\
1 & -5 & -47 & -149 & -479 & -1445 \\
2 & 12 & 50 & 156 & 482 & 1452
\end{bmatrix}
\]

The simplest possible relation of linear dependence on the columns of $C$ comes from using scalars $\alpha_4 = 1$ and $\alpha_5 = \alpha_6 = 0$ for the free variables in a solution to $\mathbf{LS}(C, \mathbf{0})$. The remainder of this solution is $\alpha_1 = 3$, $\alpha_2 = -1$, $\alpha_3 = -3$. This solution gives rise to the polynomial
\[
p(x) = 3 - x - 3x^2 + x^3 = (x - 3)(x - 1)(x + 1)
\]
which then has the property that $p(A)x = \mathbf{0}$.

No matter how you choose to order the factors of $p(x)$, the value of $k$ (in the language of Theorem EMHE 377 and Example CAEHW 378) is $k = 2$. For each of the three possibilities, we list the resulting eigenvector and the associated eigenvalue:

\[
(C - 3I_5)(C - I_5)\mathbf{z} = \begin{bmatrix} 8 \\ 8 \\ -24 \\ 8 \end{bmatrix} \quad \lambda = -1
\]
\[
(C - 3I_5)(C + I_5)\mathbf{z} = \begin{bmatrix} 20 \\ -20 \\ -40 \\ 20 \end{bmatrix} \quad \lambda = 1
\]
\[
(C + I_5)(C - I_5)\mathbf{z} = \begin{bmatrix} 32 \\ 16 \\ 48 \\ -48 \\ 48 \end{bmatrix} \quad \lambda = 3
\]

Note that each of these eigenvectors can be simplified by an appropriate scalar multiple, but we have shown here the actual vector obtained by the product specified in the theorem.

\textbf{T10} Contributed by Robert Beezer Statement 393
Suppose that $\lambda$ is an eigenvalue of $A$. Then there is an eigenvector $\mathbf{x}$, such that $A\mathbf{x} = \lambda\mathbf{x}$. We have,
\[
\lambda\mathbf{x} = A\mathbf{x} \quad \mathbf{x} \text{ eigenvector of } A
\]
\[
= A^2\mathbf{x} \quad A \text{ is idempotent}
\]
\[
= A(A\mathbf{x})
\]
\[
= A(\lambda\mathbf{x}) \quad \mathbf{x} \text{ eigenvector of } A
\]
\[
= \lambda(A\mathbf{x})
\]
\[
= \lambda(\lambda\mathbf{x}) \quad \text{Theorem MMSMM 196}
\]
\[
= \lambda^2\mathbf{x} \quad \mathbf{x} \text{ eigenvector of } A
\]
From this we get
\[ 0 = \lambda^2 \mathbf{x} - \lambda \mathbf{x} = (\lambda^2 - \lambda) \mathbf{x} \text{ Property DSAC 93} \]

Since \( \mathbf{x} \) is an eigenvector, it is nonzero, and Theorem SMEZV 284 leaves us with the conclusion that \( \lambda^2 - \lambda = 0 \), and the solutions to this quadratic polynomial equation in \( \lambda \) are \( \lambda = 0 \) and \( \lambda = 1 \).

The matrix
\[
\begin{bmatrix}
1 & 0 \\
0 & 0
\end{bmatrix}
\]
is idempotent (check this!) and since it is a diagonal matrix, its eigenvalues are the diagonal entries, \( \lambda = 0 \) and \( \lambda = 1 \), so each of these possible values for an eigenvalue of an idempotent matrix actually occurs as an eigenvalue of some idempotent matrix.
Section PEE  
Properties of Eigenvalues and Eigenvectors

The previous section introduced eigenvalues and eigenvectors, and concentrated on their existence and determination. This section will be more about theorems, and the various properties eigenvalues and eigenvectors enjoy. Like a good 4 \times 100 meter relay, we will lead-off with one of our better theorems and save the very best for the anchor leg.

**Theorem EDELI**

**Eigenvectors with Distinct Eigenvalues are Linearly Independent**

Suppose that $A$ is a square matrix and $S = \{v_1, v_2, v_3, \ldots, v_p\}$ is a set of eigenvectors with eigenvalues $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_p$ such that $\lambda_i \neq \lambda_j$ whenever $i \neq j$. Then $S$ is a linearly independent set.

**Proof** If $p = 1$, then the set $S = \{v_1\}$ is linearly independent since eigenvectors are nonzero (Definition EEM [373]), so assume for the remainder that $p \geq 2$.

Suppose to the contrary that $S$ is a linearly dependent set. Define $k$ to be the smallest integer, such that $\{v_1, v_2, v_3, \ldots, v_{k-1}\}$ is linearly independent and $\{v_1, v_2, v_3, \ldots, v_k\}$ is linearly dependent. Since eigenvectors are nonzero, the set $\{v_1\}$ is linearly independent, so $k \geq 2$. Since we are assuming that $S$ is linearly dependent, there is such a $k$ and $k \leq p$. So $2 \leq k \leq p$.

Since $\{v_1, v_2, v_3, \ldots, v_k\}$ is linearly dependent there are scalars, $a_1, a_2, a_3, \ldots, a_k$, some non-zero, so that

$$0 = a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_k v_k$$

In particular, we know that $a_k \neq 0$, for if $a_k = 0$, the scalars $a_1, a_2, a_3, \ldots, a_{k-1}$ would include some nonzero values and would give a nontrivial relation of linear dependence on $\{v_1, v_2, v_3, \ldots, v_{k-1}\}$, contradicting the linear independence of $\{v_1, v_2, v_3, \ldots, v_{k-1}\}$. Now

$$0 = A v = A (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_k v_k)$$

Substitute (*)

$$= A(a_1 v_1) + A(a_2 v_2) + A(a_3 v_3) + \cdots + A(a_k v_k)$$

Theorem MMDAA [195]

$$= a_1 A v_1 + a_2 A v_2 + a_3 A v_3 + \cdots + a_k A v_k$$

Theorem MMSMM [196]

$$= a_1 \lambda_1 v_1 + a_2 \lambda_2 v_2 + a_3 \lambda_3 v_3 + \cdots + a_k \lambda_k v_k$$

$x_i$ is an eigenvector of $A$ for $\lambda_i$ (**) (Substitute (**) $v_k = \lambda_k v_k$)

Also,

$$0 = \lambda_k \lambda_k$$

Theorem ZVSM [283]

$$= \lambda_k (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_k v_k)$$

Substitute (*)

$$= \lambda_k a_1 v_1 + \lambda_k a_2 v_2 + \lambda_k a_3 v_3 + \cdots + \lambda_k a_k v_k$$

Property DVAC [92] (***)

Theorem MMZM [194]

Theorem MMDAA [195]

Theorem MMSMM [196]

Theorem ZVSM [283]

Property DVAC [92]
Put it all together,

\[ 0 = 0 - 0 \]

\[ = (a_1\lambda_1 x_1 + a_2\lambda_2 x_2 + a_3\lambda_3 x_3 + \cdots + a_k\lambda_k x_k) \]

\[ - (\lambda_k a_1 x_1 + \lambda_k a_2 x_2 + \lambda_k a_3 x_3 + \cdots + \lambda_k a_k x_k) \]

\[ = (a_1\lambda_1 x_1 - \lambda_k a_1 x_1) + (a_2\lambda_2 x_2 - \lambda_k a_2 x_2) + (a_3\lambda_3 x_3 - \lambda_k a_3 x_3) \]

\[ + \cdots + (a_{k-1}\lambda_{k-1} x_{k-1} - \lambda_k a_{k-1} x_{k-1}) + (a_k\lambda_k x_k - \lambda_k a_k x_k) \]

\[ = a_1 (\lambda_1 - \lambda_k) x_1 + a_2 (\lambda_2 - \lambda_k) x_2 + a_3 (\lambda_3 - \lambda_k) x_3 \]

\[ + \cdots + a_{k-1} (\lambda_{k-1} - \lambda_k) x_{k-1} \]

This is a relation of linear dependence on the linearly independent set \( \{x_1, x_2, x_3, \ldots, x_k\} \), so the scalars must all be zero. That is, \( a_i (\lambda_i - \lambda_k) = 0 \) for \( 1 \leq i \leq k - 1 \). However, the eigenvalues were assumed to be distinct, so \( \lambda_i \neq \lambda_k \) for \( 1 \leq i \leq k - 1 \). Thus \( a_i = 0 \) for \( 1 \leq i \leq k - 1 \). Earlier, we deduced that \( a_k = 0 \) also. Now all these scalars are zero, while they were introduced as having some nonzero values. This is our desired contradiction, and therefore \( S \) is linearly independent.

There is a simple connection between the eigenvalues of a matrix and whether or not it is nonsingular.

**Theorem SMZE**

**Singular Matrices have Zero Eigenvalues**

Suppose \( A \) is a square matrix. Then \( A \) is singular if and only if \( \lambda = 0 \) is an eigenvalue of \( A \). □

**Proof** We have the following equivalences:

\[ A \text{ is singular} \iff \text{there exists } x \neq 0, Ax = 0 \quad \text{Definition NSM} \]

\[ \iff \text{there exists } x \neq 0, Ax = 0x \quad \text{Theorem ZSSM} \]

\[ \iff \lambda = 0 \text{ is an eigenvalue of } A \quad \text{Definition EEM} \]

With an equivalence about singular matrices we can update our list of equivalences about nonsingular matrices.

**Theorem NSME8**

**NonSingular Matrix Equivalences, Round 8**

Suppose that \( A \) is a square matrix of size \( n \). The following are equivalent.

1. \( A \) is nonsingular.
2. \( A \) row-reduces to the identity matrix.
3. The null space of \( A \) contains only the zero vector, \( \mathcal{N}(A) = \{0\} \).
4. The linear system \( \mathcal{L}(A, b) \) has a unique solution for every possible choice of \( b \).
5. The columns of \( A \) are a linearly independent set.
6. \( A \) is invertible.
7. The column space of \( A \) is \( \mathbb{C}^n \), \( \mathcal{C}(A) = \mathbb{C}^n \).
8. The columns of $A$ are a basis for $\mathbb{C}^n$.

9. The rank of $A$ is $n$, $r(A) = n$.

10. The nullity of $A$ is zero, $n(A) = 0$.

11. The determinant of $A$ is nonzero, $\det(A) \neq 0$.

12. $\lambda = 0$ is not an eigenvalue of $A$. □

**Proof** The equivalence of the first and last statements is the contrapositive of Theorem SMZE 400.

Certain changes to a matrix change its eigenvalues in a predictable way.

**Theorem ESMM**

**Eigenvalues of a Scalar Multiple of a Matrix**

Suppose $A$ is a square matrix and $\lambda$ is an eigenvalue of $A$. Then $\alpha \lambda$ is an eigenvalue of $\alpha A$.

**Proof** Let $x \neq 0$ be one eigenvector of $A$ for $\lambda$. Then

\[
(\alpha A)x = \alpha (Ax) \quad \text{Theorem MMSMM 196}
\]

\[
= \alpha (\lambda x) \quad \text{x eigenvector of } A
\]

\[
= (\alpha \lambda) x \quad \text{Property SMAC 92}
\]

So $x \neq 0$ is an eigenvector of $\alpha A$ for the eigenvalue $\alpha \lambda$. □

Unfortunately, there are not parallel theorems about the sum or product of arbitrary matrices. But we can prove a similar result for powers of a matrix.

**Theorem EOMP**

**Eigenvalues Of Matrix Powers**

Suppose $A$ is a square matrix, $\lambda$ is an eigenvalue of $A$, and $s \geq 0$ is an integer. Then $\lambda^s$ is an eigenvalue of $A^s$.

**Proof** Let $x \neq 0$ be one eigenvector of $A$ for $\lambda$. Suppose $A$ has size $n$. Then we proceed by induction on $s$. First, for $s = 0$,

\[
A^s x = A^0 x
\]

\[
= I_n x
\]

\[
= x \quad \text{Theorem MMIM 195}
\]

\[
= 1x \quad \text{Property OC 93}
\]

\[
= \lambda^0 x
\]

\[
= \lambda^s x
\]
so $\lambda^s$ is an eigenvalue of $A^s$ in this special case. If we assume the theorem is true for $s$, then we find

$$A^{s+1}x = A^s Ax$$

$$= A^s (\lambda x)$$

$$= \lambda (A^s x)$$

$$= \lambda (\lambda x)$$

$$= (\lambda \lambda x)$$

$$= \lambda^{s+1} x$$

Induction hypothesis

Property SMAC [92]

So $x \neq 0$ is an eigenvector of $A^{s+1}$ for $\lambda^{s+1}$, and induction (Technique XX [??]) tells us the theorem is true for all $s \geq 0$.

While we cannot prove that the sum of two arbitrary matrices behaves in any reasonable way with regard to eigenvalues, we can work with the sum of dissimilar powers of the same matrix. We have already seen two connections between eigenvalues and polynomials, in the proof of Theorem EMHE [377] and the characteristic polynomial (Definition CP [381]). Our next theorem strengthens this connection.

**Theorem EPM**

**Eigenvalues of the Polynomial of a Matrix**

Suppose $A$ is a square matrix and $\lambda$ is an eigenvalue of $A$. Let $q(x)$ be a polynomial in the variable $x$. Then $q(\lambda)$ is an eigenvalue of the matrix $q(A)$.

**Proof** Let $x \neq 0$ be one eigenvector of $A$ for $\lambda$, and write $q(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_m x^m$. Then

$$q(A)x = (a_0 A^0 + a_1 A^1 + a_2 A^2 + \cdots + a_m A^m) x$$

$$= (a_0 A^0) x + (a_1 A^1) x + (a_2 A^2) x + \cdots + (a_m A^m) x$$

$$= a_0 (A^0 x) + a_1 (A^1 x) + a_2 (A^2 x) + \cdots + a_m (A^m x)$$

$$= a_0 (\lambda^0 x) + a_1 (\lambda^1 x) + a_2 (\lambda^2 x) + \cdots + a_m (\lambda^m x)$$

$$= (a_0 \lambda^0) x + (a_1 \lambda^1) x + (a_2 \lambda^2) x + \cdots + (a_m \lambda^m) x$$

$$= a_0 \lambda^0 x + a_1 \lambda^1 x + a_2 \lambda^2 x + \cdots + a_m \lambda^m x$$

$$= q(\lambda) x$$

Property DSAC [93]

So $x \neq 0$ is an eigenvector of $q(A)$ for the eigenvalue $q(\lambda)$.

**Example BDE**

**Building desired eigenvalues**

In Example ESMS4 [385] the $4 \times 4$ symmetric matrix

$$C = \begin{bmatrix}
1 & 0 & 1 & 1 \\
0 & 1 & 1 & 1 \\
1 & 1 & 1 & 0 \\
1 & 1 & 0 & 1
\end{bmatrix}$$

is shown to have the three eigenvalues $\lambda = 3, 1, -1$. Suppose we wanted a $4 \times 4$ matrix that has the three eigenvalues $\lambda = 4, 0, -2$. We can employ Theorem EPM [402] by
finding a polynomial that converts 3 to 4, 1 to 0, and \(-1\) to \(-2\). Such a polynomial is called an interpolating polynomial, and in this example we can use

\[ r(x) = \frac{1}{4}x^2 + x - \frac{5}{4} \]

We will not discuss how to concoct this polynomial, but a text on numerical analysis should provide the details. In our case, simply verify that \(r(3) = 4\), \(r(1) = 0\) and \(r(-1) = -2\).

Now compute

\[ r(C) = \frac{1}{4}C^2 + C - \frac{5}{4}I \]

\[ = \frac{1}{4} \begin{bmatrix} 1 & 1 & 3 & 3 \\ 1 & 1 & 3 & 3 \\ 3 & 3 & 1 & 1 \\ 3 & 3 & 1 & 1 \end{bmatrix} \]

Theorem EPM \[402\] tells us that if \(r(x)\) transforms the eigenvalues in the desired manner, then \(r(C)\) will have the desired eigenvalues. You can check this by computing the eigenvalues of \(r(C)\) directly. Furthermore, notice that the multiplicities are the same, and the eigenspaces of \(C\) and \(r(C)\) are identical.

Inverses and transposes also behave predictably with regard to their eigenvalues.

**Theorem EIM**

*Eigenvalues of the Inverse of a Matrix*

Suppose \(A\) is a square nonsingular matrix and \(\lambda\) is an eigenvalue of \(A\). Then \(\frac{1}{\lambda}\) is an eigenvalue of the matrix \(A^{-1}\).

**Proof** Notice that since \(A\) is assumed nonsingular, \(A^{-1}\) exists by Theorem NSI \[225\], but more importantly, \(\frac{1}{\lambda}\) does not involve division by zero since Theorem SMZE \[400\] prohibits this possibility.

Let \(\mathbf{x} \neq 0\) be one eigenvector of \(A\) for \(\lambda\). Suppose \(A\) has size \(n\). Then

\[ A^{-1} \mathbf{x} = A^{-1}(1 \mathbf{x}) \]

\[ = A^{-1}(\frac{1}{\lambda} \mathbf{x}) \]

\[ = \frac{1}{\lambda} A^{-1}(\mathbf{x}) \]

\[ = \frac{1}{\lambda} \mathbf{x} \]

\[ = \frac{1}{\lambda} I_n \mathbf{x} \]

\[ = \frac{1}{\lambda} \mathbf{x} \]

So \(\mathbf{x} \neq 0\) is an eigenvector of \(A^{-1}\) for the eigenvalue \(\frac{1}{\lambda}\).
The theorems above have a similar style to them, a style you should consider using when confronted with a need to prove a theorem about eigenvalues and eigenvectors. So far we have been able to reserve the characteristic polynomial for strictly computational purposes. However, the next theorem, whose statement resembles the preceding theorems, has an easier proof if we employ the characteristic polynomial and results about determinants.

**Theorem ETM**

**Eigenvalues of the Transpose of a Matrix**

Suppose $A$ is a square matrix and $\lambda$ is an eigenvalue of $A$. Then $\lambda$ is an eigenvalue of the matrix $A^t$. □

**Proof** Let $x \neq 0$ be one eigenvector of $A$ for $\lambda$. Suppose $A$ has size $n$. Then

$$p_A(x) = \det (A - xI_n)$$

= $\det ((A - xI_n)^t)$

= $\det (A^t - (xI_n)^t)$

= $\det (A^t - xI_n^t)$

= $\det (A^t - xI_n)$

= $p_{A^t}(x)$

Definition CP [381]

Theorem DT [365]

Theorem TMA [184]

Theorem TMSM [184]

Definition IM [76]

Definition CP [381]

So $A$ and $A^t$ have the same characteristic polynomial, and by Theorem EMRCP [381], their eigenvalues are identical and have equal algebraic multiplicities. Notice that what we have proved here is a bit stronger than the stated conclusion in the theorem. □

If a matrix has only real entries, then the computation of the characteristic polynomial (Definition CP [381]) will result in a polynomial with coefficients that are real numbers. Complex numbers could result as roots of this polynomial, but they are roots of quadratic factors with real coefficients, and as such, come in conjugate pairs. The next theorem proves this, and a bit more, without mentioning the characteristic polynomial.

**Theorem ERMCP**

**Eigenvalues of Real Matrices come in Conjugate Pairs**

Suppose $A$ is a square matrix with real entries and $x$ is an eigenvector of $A$ for the eigenvalue $\lambda$. Then $\bar{x}$ is an eigenvector of $A$ for the eigenvalue $\bar{\lambda}$. □

**Proof**

$$A\bar{x} = \bar{\lambda}\bar{x}$$

$A$ has real entries

= $\bar{\lambda}\bar{x}$

Theorem MMCC [197]

= $\bar{\lambda}x$

$x$ eigenvector of $A$

= $\bar{\lambda}\bar{x}$

Theorem CRVSMxx [??]

So $\bar{x}$ is an eigenvector of $A$ for the eigenvalue $\bar{\lambda}$. □

This phenomenon is amply illustrated in Example CEMS6 [387], where the four complex eigenvalues come in two pairs, and the two basis vectors of the eigenspaces are complex conjugates of each other. Theorem ERMCP [404] can be a time-saver for computing eigenvalues and eigenvectors of real matrices with complex eigenvalues, since the conjugate eigenvalue and eigenspace can be inferred from the theorem rather than computed.
Subsection ME
Multiplicities of Eigenvalues

A polynomial of degree \( n \) will have exactly \( n \) roots. From this fact about polynomial equations we can say more about the algebraic multiplicities of eigenvalues.

Theorem DCP
Degree of the Characteristic Polynomial
Suppose that \( A \) is a square matrix of size \( n \). Then the characteristic polynomial of \( A \), \( p_A(x) \), has degree \( n \).

Proof We will prove a more general result by induction. Then the theorem will be true as a special case. We will carefully state this result as a proposition indexed by \( m \).

\( P(m) \): Suppose that \( A \) is an \( m \times m \) matrix whose entries are complex numbers or linear polynomials in the variable \( x \) of the form \( c-x \), where \( c \) is a complex number. Suppose further that there are exactly \( k \) entries that contain \( x \) and that no row or column contains more than one such entry. Then, when \( k = m \), \( \text{det}(A) \) is a polynomial in \( x \) of degree \( m \), with leading coefficient \( \pm 1 \), and when \( k < m \), \( \text{det}(A) \) is a polynomial in \( x \) of degree \( k \) or less.

Base Case: Suppose \( A \) is a \( 1 \times 1 \) matrix. Then its determinant is equal to the lone entry (Definition DM [361]). When \( k = m = 1 \), the entry is of the form \( c-x \), a polynomial in \( x \) of degree \( m = 1 \) with leading coefficient \(-1 \). When \( k < m \), then \( k = 0 \) and the entry is simply a complex number, a polynomial of degree \( 0 \leq k \). So \( P(1) \) is true.

Induction Step: Assume \( P(m) \) is true, and that \( A \) is an \((m+1) \times (m+1)\) matrix with \( k \) entries of the form \( c-x \). There are two cases to consider.

Suppose \( k = m+1 \). Then every row and every column will contain an entry of the form \( c-x \). Suppose that for the first row, this entry is in column \( t \). Compute the determinant of \( A \) by an expansion about this first row (Theorem DERC [364]). The term associated with entry \( t \) of this row will be of the form

\[(c-x)C_{A,1,t} = (c-x)M_{A,1,t} = (c-x)(-1)^{1+t}A_{1,t}\]

The submatrix \( A_{1,t} \) is an \( m \times m \) matrix with \( k = m \) terms of the form \( c-x \), no more than one per row or column. By the induction hypothesis, \( \text{det}(A_{1,t}) \) will be a polynomial in \( x \) of degree \( m \) with coefficient \( \pm 1 \). So this entire term is then a polynomial of degree \( m+1 \) with leading coefficient \( \pm 1 \).

The remaining terms (which constitute the sum that is the determinant of \( A \)) are products of complex numbers from the first row with cofactors built from submatrices that lack the first row of \( A \) and lack some column of \( A \), other than column \( t \). As such, these submatrices are \( m \times m \) matrices with \( k = m-1 < m \) entries of the form \( c-x \), no more than one per row or column. Applying the induction hypothesis, we see that these terms are polynomials in \( x \) of degree \( m-1 \) or less. Adding the single term from the entry in column \( t \) with all these others, we see that \( \text{det}(A) \) is a polynomial in \( x \) of degree \( m+1 \) and leading coefficient \( \pm 1 \).

The second case occurs when \( k < m+1 \). Now there is a row of \( A \) that does not contain an entry of the form \( c-x \). We consider the determinant of \( A \) by expanding about this row (Theorem DERC [364]), whose entries are all complex numbers. The cofactors employed are built from submatrices that are \( m \times m \) matrices with either \( k \) or
$k - 1$ entries of the form $c - x$, no more than one per row or column. In either case, $k \leq m$, and we can apply the induction hypothesis to see that the determinants computed for the cofactors are all polynomials of degree $k$ or less. Summing these contributions to the determinant of $A$ yields a polynomial in $x$ of degree $k$ or less, as desired.

**Definition CP** [381] tells us that the characteristic polynomial of an $n \times n$ matrix is the determinant of a matrix having exactly $n$ entries of the form $c - x$, no more than one per row or column. As such we can apply $P(n)$ to see that the characteristic polynomial has degree $n$. ■

**Theorem NEM**

**Number of Eigenvalues of a Matrix**

Suppose that $A$ is a square matrix of size $n$ with distinct eigenvalues $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k$. Then

$$\sum_{i=1}^{k} \alpha_A(\lambda_i) = n \square$$

**Proof** By the definition of the algebraic multiplicity (Definition AME [384]), we can factor the characteristic polynomial as

$$p_A(x) = (x - \lambda_1)^{\alpha_A(\lambda_1)}(x - \lambda_2)^{\alpha_A(\lambda_2)}(x - \lambda_3)^{\alpha_A(\lambda_3)} \cdots (x - \lambda_k)^{\alpha_A(\lambda_k)}$$

The left-hand side is a polynomial of degree $n$ by Theorem DCP [405] and the right-hand side is a polynomial of degree $\sum_{i=1}^{k} \alpha_A(\lambda_i) = n$, so the equality of the polynomials’ degrees gives the result. ■

**Theorem ME**

**Multiplicities of an Eigenvalue**

Suppose that $A$ is a square matrix of size $n$ and $\lambda$ is an eigenvalue. Then

$$1 \leq \gamma_A(\lambda) \leq \alpha_A(\lambda) \leq n \square$$

**Proof** Since $\lambda$ is an eigenvalue of $A$, there is an eigenvector of $A$ for $\lambda$, $x$. Then $x \in E_A(\lambda)$, so $\gamma_A(\lambda) \geq 1$, since we can extend $\{x\}$ into a basis of $E_A(\lambda)$ (Theorem ELIS [347]).

To show that $\gamma_A(\lambda) \leq \alpha_A(\lambda)$ is the most involved portion of this proof. To this end, let $g = \gamma_A(\lambda)$ and let $x_1, x_2, x_3, \ldots, x_g$ be a basis for the eigenspace of $\lambda$, $E_A(\lambda)$. Construct another $n - g$ vectors, $y_1, y_2, y_3, \ldots, y_{n-g}$, so that

$$\{x_1, x_2, x_3, \ldots, x_g, y_1, y_2, y_3, \ldots, y_{n-g}\}$$

is a basis of $\mathbb{C}^n$. This can be done by repeated applications of Theorem ELIS [347]. Finally, define a matrix $S$ by

$$S = [x_1 | x_2 | x_3 | \ldots | x_g | y_1 | y_2 | y_3 | \ldots | y_{n-g}] = [x_1 | x_2 | x_3 | \ldots | x_g | R]$$
where $R$ is an $n \times (n - g)$ matrix whose columns are $y_1, y_2, y_3, \ldots, y_{n-g}$. The columns of $S$ are linearly independent by design, so $S$ is nonsingular (Theorem NSLIC [139]) and therefore invertible (Theorem NSI [225]). Then,

$$
[e_1 | e_2 | e_3 | \ldots | e_n] = I_n = S^{-1}S = S^{-1} [x_1 | x_2 | x_3 | \ldots | x_g] R = [S^{-1}x_1 | S^{-1}x_2 | S^{-1}x_3 | \ldots | S^{-1}x_g] S^{-1}R
$$

So

$$
S^{-1}x_i = e_i, \quad 1 \leq i \leq g
$$

Preparations in place, we compute the characteristic polynomial of $A$,

$$
p_A(x) = \det(A - xI_n) = \det(I_n) \det(A - xI_n) = \det(S^{-1}) \det(A - xI_n) = \det(S^{-1}) \det(S) \det(A - xI_n) = \det(S^{-1}) \det(A - xI_n) \det(S) = \det(S^{-1}(A - xI_n) S) = \det(S^{-1}AS - S^{-1}xI_n S) = \det(S^{-1}AS - xS^{-1}I_n S) = \det(S^{-1}AS - xI_n) = p_{S^{-1}AS}(x)
$$

What can we learn then about the matrix $S^{-1}AS$?

$$
S^{-1}AS = S^{-1}A[x_1 | x_2 | x_3 | \ldots | x_g] R = S^{-1}[Ax_1 | Ax_2 | Ax_3 | \ldots | Ax_g] AR = S^{-1}[\lambda x_1 | \lambda x_2 | \lambda x_3 | \ldots | \lambda x_g] AR = [S^{-1}\lambda x_1 | S^{-1}\lambda x_2 | S^{-1}\lambda x_3 | \ldots | S^{-1}\lambda x_g] AR
$$

Now imagine computing the characteristic polynomial of $A$ by computing the characteristic polynomial of $S^{-1}AS$ using the form just obtained. The first $g$ columns of $S^{-1}AS$ are all zero, save for a $\lambda$ on the diagonal. So if we compute the determinant by expanding about the first column, successively, we will get successive factors of $(x - \lambda)$. More precisely, let $T$ be the square matrix of size $n - g$ that is formed from the last $n - g$ rows of $S^{-1}AR$. Then

$$
p_A(x) = p_{S^{-1}AS}(x) = (x - \lambda)^g p_T(x).
$$
This says that \( (x - \lambda) \) is a factor of the characteristic polynomial at least \( g \) times, so the algebraic multiplicity of \( \lambda \) as an eigenvalue of \( A \) is greater than or equal to \( g \) (Definition AME [384]). In other words,

\[
\gamma_A (\lambda) = g \leq \alpha_A (\lambda)
\]
as desired.

Theorem NEM [406] says that the sum of the algebraic multiplicities for all the eigenvalues of \( A \) is equal to \( n \). Since the algebraic multiplicity is a positive quantity, no single algebraic multiplicity can exceed \( n \) without the sum of all of the algebraic multiplicities doing the same. ■

**Theorem MNEM**

**Maximum Number of Eigenvalues of a Matrix**

Suppose that \( A \) is a square matrix of size \( n \). Then \( A \) cannot have more than \( n \) distinct eigenvalues. □

**Proof** Suppose that \( A \) has \( k \) distinct eigenvalues, \( \lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k \). Then

\[
k = \sum_{i=1}^{k} 1 \\
\leq \sum_{i=1}^{k} \alpha_A (\lambda) \tag{Theorem ME [406]}
\]

\[
= n \tag{Theorem NEM [406]}
\]

**Subsection EHM**

**Eigenvalues of Hermitian Matrices**

Recall that a matrix is Hermitian (or self-adjoint) if \( A = (A)\,^t \) (Definition HM [229]). In the case where \( A \) is a matrix whose entries are all real numbers, being Hermitian is identical to being symmetric (Definition SYM [183]). Keep this in mind as you read the next two theorems. Their hypotheses could be changed to “suppose \( A \) is a real symmetric matrix.”

**Theorem HMRE**

**Hermitian Matrices have Real Eigenvalues**

Suppose that \( A \) is a Hermitian matrix and \( \lambda \) is an eigenvalue of \( A \). Then \( \lambda \in \mathbb{R} \). □
Proof Let $x \neq 0$ be one eigenvector of $A$ for $\lambda$. Then

$$\lambda \langle x, x \rangle = \langle \lambda x, x \rangle = \langle x, x \rangle$$

$\lambda$ eigenvector of $A$

$$= \langle Ax, x \rangle$$

$x$ eigenvector of $A$

$$= (Ax)^t x$$

Theorem MMIP [197]

$$= x^t A^t x$$

Theorem MMT [198]

$$= x^t (\overline{(A)^t})^t x$$

Definition HM [229]

$$= x^t \overline{A} x$$

Theorem TT [184]

$$= x^t \overline{A} x$$

Theorem MMCC [197]

$$= \langle x, Ax \rangle$$

Theorem MMIP [197]

$$= \langle x, \lambda x \rangle$$

$x$ eigenvector of $A$

$$= \overline{\lambda} \langle x, x \rangle$$

Theorem IPSM [168]

Since $x \neq 0$, Theorem PIP [170] says that $\langle x, x \rangle \neq 0$, so we can “cancel” $\langle x, x \rangle$ from both sides of this equality. This leaves $\lambda = \overline{\lambda}$, so $\lambda$ has a complex part equal to zero, and therefore is a real number.

Look back and compare Example ESMS4 [385] and Example CEMS6 [387]. In Example CEMS6 [387] the matrix has only real entries, yet the characteristic polynomial has roots that are complex numbers, and so the matrix has complex eigenvalues. However, in Example ESMS4 [385], the matrix has only real entries, but is also symmetric. So by Theorem HMRE [408], we were guaranteed eigenvalues that are real numbers.

In many physical problems, a matrix of interest will be real and symmetric, or Hermitian. Then if the eigenvalues are to represent physical quantities of interest, Theorem HMRE [408] guarantees that these values will not be complex numbers.

The eigenvectors of a Hermitian matrix also enjoy a pleasing property that we will exploit later.

Theorem HMOE
Hermitian Matrices have Orthogonal Eigenvectors

Suppose that $A$ is a Hermitian matrix and $x$ and $y$ are two eigenvectors of $A$ for different eigenvalues. Then $x$ and $y$ are orthogonal vectors.

Proof Let $x \neq 0$ be an eigenvector of $A$ for $\lambda$ and let $y \neq 0$ be an eigenvector of $A$ for
$\rho$. By Theorem HMRE\ [408], we know that $\rho$ must be a real number. Then

$$
\lambda \langle x, y \rangle = \langle \lambda x, y \rangle = \langle Ax, y \rangle = \langle (Ax)^t y \rangle = x^t A^t y = x^t \left( (A^t)^t \right) y = x^t A \overline{y} = x^t A y = \langle x, Ay \rangle = \langle x, \rho y \rangle = \rho \langle x, y \rangle
$$

Since $\lambda \neq \rho$, we conclude that $\langle x, y \rangle = 0$ and so $x$ and $y$ are orthogonal vectors (Definition OV\ [171]).

Subsection READ

Reading Questions

1. How can you identify a nonsingular matrix just by looking at its eigenvalues?
2. How many different eigenvalues may a square matrix of size $n$ have?
3. What is amazing about the eigenvalues of a Hermitian matrix and why is it amazing?
Section SD

Similarity and Diagonalization

This section’s topic will perhaps seem out of place at first, but we will make the connection soon with eigenvalues and eigenvectors. This is also our first look at one of the central ideas of Chapter R [505].

Subsection SM

Similar Matrices

The notion of matrices being “similar” is a lot like saying two matrices are row-equivalent. Two similar matrices are not equal, but they share many important properties. This section, and later sections in Chapter R [505] will be devoted in part to discovering just what these common properties are.

First, the main definition for this section.

Definition SIM

Similar Matrices

Suppose \( A \) and \( B \) are two square matrices of size \( n \). Then \( A \) and \( B \) are similar if there exists a nonsingular matrix of size \( n \), \( S \), such that

\[
A = S^{-1}BS.
\]

We will say “\( A \) is similar to \( B \) via \( S \)” when we want to emphasize the role of \( S \) in the relationship between \( A \) and \( B \). Also, it doesn’t matter if we say \( A \) is similar to \( B \), or \( B \) is similar to \( A \). If one statement is true then so is the other, as can be seen by using \( S^{-1} \) in place of \( S \) (see Theorem SER [413] for the careful proof). Finally, we will refer to \( S^{-1}BS \) as a similarity transformation when we want to emphasize the way \( S \) changes \( B \). OK, enough about language, let’s build a few examples.

Example SMS5

Similar matrices of size 5

If you wondered if there are examples of similar matrices, then it won’t be hard to convince you they exist. Define

\[
B = \begin{bmatrix}
-4 & 1 & -3 & -2 & 2 \\
1 & 2 & -1 & 3 & -2 \\
-4 & 1 & 3 & 2 & 2 \\
-3 & 4 & -2 & -1 & -3 \\
3 & 1 & -1 & 1 & -4
\end{bmatrix} \quad S = \begin{bmatrix}
1 & 2 & -1 & 1 & 1 \\
0 & 1 & -1 & -2 & -1 \\
1 & 3 & -1 & 1 & 1 \\
-2 & -3 & 3 & 1 & -2 \\
1 & 3 & -1 & 2 & 1
\end{bmatrix}
\]
Check that $S$ is nonsingular and then compute

$$A = S^{-1}BS$$

$$= \begin{bmatrix}
10 & 1 & 0 & 2 & -5 \\
-1 & 0 & 1 & 0 & 0 \\
3 & 0 & 2 & 1 & -3 \\
0 & 0 & -1 & 0 & 1 \\
-4 & -1 & 1 & -1 & 1
\end{bmatrix}
\begin{bmatrix}
-4 & 1 & -3 & -2 & 2 \\
1 & 2 & -1 & 3 & -2 \\
-4 & 1 & 3 & 2 & 2 \\
-3 & 4 & -2 & -1 & -3 \\
3 & 1 & -1 & 1 & -4
\end{bmatrix}
\begin{bmatrix}
1 & 2 & -1 & 1 & 1 \\
0 & 1 & -1 & -2 & -1 \\
1 & 3 & -1 & 1 & 1 \\
-2 & -3 & 3 & 1 & -2 \\
1 & 3 & -1 & 2 & 1
\end{bmatrix}$$

$$= \begin{bmatrix}
-10 & -27 & -29 & -80 & -25 \\
-2 & 6 & 6 & 10 & -2 \\
-3 & 11 & -9 & -14 & -9 \\
-1 & -13 & 0 & -10 & -1 \\
11 & 35 & 6 & 49 & 19
\end{bmatrix}$$

So by this construction, we know that $A$ and $B$ are similar. Let’s do that again.

**Example SMS4**

**Similar matrices of size 4**

Define

$$B = \begin{bmatrix}
-13 & -8 & -4 \\
12 & 7 & 4 \\
24 & 16 & 7
\end{bmatrix} \quad S = \begin{bmatrix}
1 & 1 & 2 \\
-2 & -1 & -3 \\
1 & -2 & 0
\end{bmatrix}$$

Check that $S$ is nonsingular and then compute

$$A = S^{-1}BS$$

$$= \begin{bmatrix}
-6 & -4 & -1 \\
-3 & -2 & -1 \\
5 & 3 & 1
\end{bmatrix}
\begin{bmatrix}
-13 & -8 & -4 \\
12 & 7 & 4 \\
24 & 16 & 7
\end{bmatrix}
\begin{bmatrix}
1 & 1 & 2 \\
-2 & -1 & -3 \\
1 & -2 & 0
\end{bmatrix}$$

$$= \begin{bmatrix}
-1 & 0 & 0 \\
0 & 3 & 0 \\
0 & 0 & -1
\end{bmatrix}$$

So by this construction, we know that $A$ and $B$ are similar. But before we move on, look at how pleasing the form of $A$ is. Not convinced? Then consider that several computations related to $A$ are especially easy. For example, in the spirit of [Example DUTM][365], $\det(A) = (-1)(3)(-1) = 3$. Similarly, the characteristic polynomial is straightforward to compute by hand, $p_A(x) = (-1 - x)(3 - x)(-1 - x) = -(x - 3)(x + 1)^2$ and since the result is already factored, the eigenvalues are transparently $\lambda = 3, -1$. Finally, the eigenvectors of $A$ are just the standard unit vectors (Definition SUV[210]).

**Subsection PSM**

**Properties of Similar Matrices**

Similar matrices share many properties and it is these theorems that justify the choice of the word “similar.” First we will show that similarity is an equivalence relation.
Equivalence relations are important in the study of various algebras and can always be regarded as a kind of weak version of equality. Sort of alike, but not quite equal. The notion of two matrices being row-equivalent is an example of an equivalence relation we have been working with since the beginning of the course (see Exercise RREF.T11 [44]). Row-equivalent matrices are not equal, but they are a lot alike. For example, row-equivalent matrices have the same rank. Formally, an equivalence relation requires three conditions hold: reflexive, symmetric and transitive. We will illustrate these as we prove that similarity is an equivalence relation.

**Theorem SER**

**Similarity is an Equivalence Relation**

Suppose $A$, $B$ and $C$ are square matrices of size $n$. Then

1. $A$ is similar to $A$. (Reflexive)
2. If $A$ is similar to $B$, then $B$ is similar to $A$. (Symmetric)
3. If $A$ is similar to $B$ and $B$ is similar to $C$, then $A$ is similar to $C$. (Transitive)

**Proof** To see that $A$ is similar to $A$, we need only demonstrate a nonsingular matrix that effects a similarity transformation of $A$ to $A$. $I_n$ is nonsingular (since it row-reduces to the identity matrix, Theorem NSRRI [77]), and

$$I_n^{-1}AI_n = I_nA = A$$

If we assume that $A$ is similar to $B$, then we know there is a nonsingular matrix $S$ so that $A = S^{-1}BS$ by Definition SIM [411]. By Theorem MIMI [216], $S^{-1}$ is invertible, and by Theorem NSI [225] is therefore nonsingular. So

$$(S^{-1})^{-1}A(S^{-1}) = SAS^{-1}$$

$$= SS^{-1}BSS^{-1}$$

$$= (SS^{-1})B(SS^{-1})$$

$$= I_nBI_n$$

$$= B$$

and we see that $B$ is similar to $A$.

Assume that $A$ is similar to $B$, and $B$ is similar to $C$. This gives us the existence of two nonsingular matrices, $S$ and $R$, such that $A = S^{-1}BS$ and $B = R^{-1}CR$, by Definition SIM [411]. (Notice how we have to assume $S \neq R$, as will usually be the case.) Since $S$ and $R$ are invertible, so too $RS$ is invertible by Theorem SS [215] and then nonsingular by Theorem NSI [225]. Now

$$(RS)^{-1}C(RS) = S^{-1}R^{-1}CRS$$

$$= S^{-1}(R^{-1}CR)S$$

$$= S^{-1}BS$$

$$= A$$

so $A$ is similar to $C$ via the nonsingular matrix $RS$. □
Here’s another theorem that tells us exactly what sorts of properties similar matrices share.

**Theorem SMEE**
Similar Matrices have Equal Eigenvalues

Suppose $A$ and $B$ are similar matrices. Then the characteristic polynomials of $A$ and $B$ are equal, that is $p_A(x) = p_B(x)$. □

**Proof** Suppose $A$ and $B$ have size $n$ and are similar via the nonsingular matrix $S$, so $A = S^{-1}BS$ by Definition SIM [411].

\[
p_A(x) = \det(A - xI_n) = \det(S^{-1}BS - xI_n) = \det(S^{-1}BS - xS^{-1}I_nS) = \det(S^{-1}BS - S^{-1}xI_nS) = \det(S^{-1}(B - xI_n)S) = \det(S^{-1})\det(B - xI_n)\det(S) = \det(S^{-1})\det(S)\det(B - xI_n) = 1\det(B - xI_n) = p_B(x)
\]

So similar matrices not only have the same set of eigenvalues, the algebraic multiplicities of these eigenvalues will also be the same. However, be careful with this theorem. It is tempting to think the converse is true, and argue that if two matrices have the same eigenvalues, then they are similar. Not so, as the following example illustrates.

**Example EENS**
Equal eigenvalues, not similar

Define

\[
A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}
\]

and check that

\[
p_A(x) = p_B(x) = 1 - 2x + x^2 = (x - 1)^2
\]

and so $A$ and $B$ have equal characteristic polynomials. If the converse of Theorem SMEE [414] was true, then $A$ and $B$ would be similar. Suppose this is the case. In other words, there is a nonsingular matrix $S$ so that $A = S^{-1}BS$. Then

\[
A = S^{-1}BS = S^{-1}I_2S = S^{-1}S = I_2 \neq A
\]

this contradiction tells us that the converse of Theorem SMEE [414] is false. ⊗
Subsection D  
Diagonalization

Good things happen when a matrix is similar to a diagonal matrix. For example, the eigenvalues of the matrix are the entries on the diagonal of the diagonal matrix. And it can be a much simpler matter to compute high powers of the matrix. Diagonalizable matrices are also of interest in more abstract settings. Here are the relevant definitions, then our main theorem for this section.

Definition DIM  
Diagonal Matrix  
Suppose that $A$ is a square matrix. Then $A$ is a diagonal matrix if $[A]_{ij} = 0$ whenever $i \neq j$.

Definition DZM  
Diagonalizable Matrix  
Suppose $A$ is a square matrix. Then $A$ is diagonalizable if $A$ is similar to a diagonal matrix.

Example DAB  
Diagonalization of Archetype B  
Archetype B [568] has a $3 \times 3$ coefficient matrix

$$B = \begin{bmatrix} -7 & -6 & -12 \\ 5 & 5 & 7 \\ 1 & 0 & 4 \end{bmatrix}$$

and is similar to a diagonal matrix, as can be seen by the following computation with the nonsingular matrix $S$,

$$S^{-1}BS = \begin{bmatrix} -5 & -3 & -2 \\ 3 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} -7 & -6 & -12 \\ 5 & 5 & 7 \\ 1 & 0 & 4 \end{bmatrix} \begin{bmatrix} -5 & -3 & -2 \\ 3 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} -1 & -1 & -1 \\ 2 & 3 & 1 \\ -1 & -2 & 1 \end{bmatrix} \begin{bmatrix} -7 & -6 & -12 \\ 5 & 5 & 7 \\ 1 & 0 & 4 \end{bmatrix} \begin{bmatrix} -5 & -3 & -2 \\ 3 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

Example SMS4 [412] provides yet another example of a matrix that is subjected to a similarity transformation and the result is a diagonal matrix. Alright, just how would we find the magic matrix $S$ that can be used in a similarity transformation to produce a diagonal matrix? Before you read the statement of the next theorem, you might study the eigenvalues and eigenvectors of Archetype B [568] and compute the eigenvalues and eigenvectors of the matrix in Example SMS4 [412].

Theorem DC  
Diagonalization Characterization  
Suppose $A$ is a square matrix of size $n$. Then $A$ is diagonalizable if and only if there exists a linearly independent set $S$ that contains $n$ eigenvectors of $A$.  

Version 0.52
Proof (⇒) Let \( S = \{x_1, x_2, x_3, \ldots, x_n\} \) be a linearly independent set of eigenvectors of \( A \) for the eigenvalues \( \lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n \). Recall Definition SUV \[210\] and define
\[
R = [x_1 | x_2 | x_3 | \ldots | x_n] = \begin{bmatrix}
\lambda_1 & 0 & 0 & \cdots & 0 \\
0 & \lambda_2 & 0 & \cdots & 0 \\
0 & 0 & \lambda_3 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & \lambda_n
\end{bmatrix} = [\lambda_1e_1 | \lambda_2e_2 | \lambda_3e_3 | \ldots | \lambda_ne_n]
\]
The columns of \( R \) are the vectors of the linearly independent set \( S \) and so by Theorem NSLC \[139\] the matrix \( R \) is nonsingular. By Theorem NSI \[225\] we know \( R^{-1} \) exists.

\[
R^{-1}AR = R^{-1}A[x_1|x_2|x_3|\ldots|x_n]
\]
\[
= R^{-1}[Ax_1|Ax_2|Ax_3|\ldots|Ax_n]
\]
\[
= R^{-1}[\lambda_1x_1|\lambda_2x_2|\lambda_3x_3|\ldots|\lambda_nx_n]
\]
\[
= R^{-1}[\lambda_1Re_1|\lambda_2Re_2|\lambda_3Re_3|\ldots|\lambda_nRe_n]
\]
\[
= R^{-1}[R(\lambda_1e_1)|R(\lambda_2e_2)|R(\lambda_3e_3)|\ldots|R(\lambda_ne_n)]
\]
\[
= R^{-1}R[\lambda_1e_1|\lambda_2e_2|\lambda_3e_3|\ldots|\lambda_ne_n]
\]
\[
= I_nD
\]
\[
= D
\]
This says that \( A \) is similar to the diagonal matrix \( D \) via the nonsingular matrix \( R \). Thus \( A \) is diagonalizable (Definition DZM \[415\]).

(⇐) Suppose that \( A \) is diagonalizable, so there is a nonsingular matrix of size \( n \)

\[
T = [y_1 | y_2 | y_3 | \ldots | y_n]
\]
and a diagonal matrix (recall Definition SUV \[210\])

\[
E = \begin{bmatrix}
d_1 & 0 & 0 & \cdots & 0 \\
0 & d_2 & 0 & \cdots & 0 \\
0 & 0 & d_3 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & d_n
\end{bmatrix} = [d_1e_1 | d_2e_2 | d_3e_3 | \ldots | d_ne_n]
\]
such that \( T^{-1}AT = E \).

\[
[Ay_1 | Ay_2 | Ay_3 | \ldots | Ay_n] = A[y_1 | y_2 | y_3 | \ldots | y_n]
\]
\[
= AT
\]
\[
= I_nAT
\]
\[
= TT^{-1}AT
\]
\[
= TE
\]
\[
= T[d_1e_1 | d_2e_2 | d_3e_3 | \ldots | d_ne_n]
\]
\[
= [T(d_1e_1)|T(d_2e_2)|T(d_3e_3)|\ldots|T(d_ne_n)]
\]
\[
= [d_1Te_1 | d_2Te_2 | d_3Te_3 | \ldots | d_ne_n]
\]
\[
= [d_1y_1 | d_2y_2 | d_3y_3 | \ldots | d_ny_n]
\]
This equality of matrices allows us to conclude that the columns are equal vectors. That is, \( Ay_i = d_i y_i \) for \( 1 \leq i \leq n \). In other words, \( y_i \) is an eigenvector of \( A \) for the eigenvalue \( d_i \). (Why can’t \( y_i = 0 \)?) Because \( T \) is nonsingular, the set containing \( T \)'s columns, \( S = \{ y_1, y_2, y_3, \ldots, y_n \} \), is a linearly independent set (Theorem NSLIC [139]). So the set \( S \) has all the required properties.

Notice that the proof of Theorem DC [415] is constructive. To diagonalize a matrix, we need only locate \( n \) linearly independent eigenvectors. Then we can construct a nonsingular matrix using the eigenvectors as columns (\( R \)) so that \( R^{-1}AR \) is a diagonal matrix (\( D \)). The entries on the diagonal of \( D \) will be the eigenvalues of the eigenvectors used to create \( R \), in the same order as the eigenvectors appear in \( R \). We illustrate this by diagonalizing some matrices.

Example DMS3
Diagonalizing a matrix of size 3
Consider the matrix

\[
F = \begin{bmatrix}
-13 & -8 & -4 \\
12 & 7 & 4 \\
24 & 16 & 7
\end{bmatrix}
\]

of Example CPMS3 [381], Example EMS3 [382] and Example ESMS3 [383]. \( F \)'s eigenvalues and eigenspaces are

\[
\lambda = 3 \quad E_F(3) = Sp\left( \left\{ \begin{bmatrix} -\frac{1}{3} \\ 1 \\ 1 \end{bmatrix} \right\} \right)
\]

\[
\lambda = -1 \quad E_F(-1) = Sp\left( \left\{ \begin{bmatrix} -\frac{2}{3} \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{1}{3} \\ 0 \\ 1 \end{bmatrix} \right\} \right)
\]

Define the matrix \( S \) to be the \( 3 \times 3 \) matrix whose columns are the three basis vectors in the eigenspaces for \( F \),

\[
S = \begin{bmatrix}
-\frac{1}{2} & -\frac{2}{3} & -\frac{1}{3} \\
\frac{1}{2} & 1 & 0 \\
1 & 0 & 1
\end{bmatrix}
\]

Check that \( S \) is nonsingular (row-reduces to the identity matrix, Theorem NSRRI [77] or has a nonzero determinant, Theorem SMZD [366]). Then the three columns of \( S \) are a linearly independent set (Theorem NSLIC [139]). By Theorem DC [415] we now know that \( F \) is diagonalizable. Furthermore, the construction in the proof of Theorem DC [415] tells us that if we apply the matrix \( S \) to \( F \) in a similarity transformation, the result will be a diagonal matrix with the eigenvalues of \( F \) on the diagonal. The eigenvalues appear...
on the diagonal of the matrix in the same order as the eigenvectors appear in \( S \). So,

\[
S^{-1}FS = \begin{bmatrix}
-\frac{1}{2} & -\frac{2}{3} & -\frac{1}{3} \\
\frac{1}{2} & 1 & 0 \\
1 & 0 & 1
\end{bmatrix}^{-1} \begin{bmatrix}
-13 & -8 & -4 \\
12 & 7 & 4 \\
24 & 16 & 7
\end{bmatrix} \begin{bmatrix}
-\frac{1}{2} & -\frac{2}{3} & -\frac{1}{3} \\
\frac{1}{2} & 1 & 0 \\
1 & 0 & 1
\end{bmatrix}
\]

\[
= \begin{bmatrix}
6 & 4 & 2 \\
-3 & -1 & -1 \\
-6 & -4 & -1
\end{bmatrix} \begin{bmatrix}
-13 & -8 & -4 \\
12 & 7 & 4 \\
24 & 16 & 7
\end{bmatrix} \begin{bmatrix}
-\frac{1}{2} & -\frac{2}{3} & -\frac{1}{3} \\
\frac{1}{2} & 1 & 0 \\
1 & 0 & 1
\end{bmatrix}
\]

\[
= \begin{bmatrix}
3 & 0 & 0 \\
0 & -1 & 0 \\
0 & 0 & -1
\end{bmatrix}
\]

Note that the above computations can be viewed two ways. The proof of \textit{Theorem DC} \[415\] tells us that the four matrices \((F, S, F^{-1} \text{ and the diagonal matrix})\) \textit{will} interact the way we have written the equation. Or as an example, we can actually \textit{perform} the computations to verify what the theorem predicts. \(\Box\)

The dimension of an eigenspace can be no larger than the algebraic multiplicity of the eigenvalue by \textit{Theorem ME} \[406\]. When every eigenvalue’s eigenspace is this big, then we can diagonalize the matrix, and only then. Three examples we have seen so far in this section, \textit{Example SMS5} \[411\], \textit{Example DAB} \[415\] and \textit{Example DMS3} \[417\], illustrate the diagonalization of a matrix, with varying degrees of detail about just how the diagonalization is achieved. However, in each case, you can verify that the geometric and algebraic multiplicities are equal for every eigenvalue. This is the substance of the next theorem.

\textbf{Theorem DMLE}

\textbf{Diagonalizable Matrices have Large Eigenspaces}

Suppose \( A \) is a square matrix. Then \( A \) is diagonalizable if and only if \( \gamma_A(\lambda) = \alpha_A(\lambda) \) for every eigenvalue \( \lambda \) of \( A \).

\textbf{Proof} Suppose \( A \) has size \( n \) and \( k \) distinct eigenvalues, \( \lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k \).

\((\Leftarrow \Rightarrow)\) Let \( S_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{i\gamma_A(\lambda_i)}\} \), be a basis for the eigenspace of \( \lambda_i \), \( E_A(\lambda_i) \), \( 1 \leq i \leq k \). Then

\( S = S_1 \cup S_2 \cup S_3 \cup \cdots \cup S_k \)

is a set of eigenvectors for \( A \). A vector cannot be an eigenvector for two different eigenvalues (why not?) so the sets \( S_i \) have no vectors in common. Thus the size of \( S \) is

\[
\sum_{i=1}^{k} \gamma_A(\lambda_i) = \sum_{i=1}^{k} \alpha_A(\lambda_i) \quad \text{Hypothesis}
\]

\[
= n \quad \text{Theorem NEM} \[406\]
\]

We now want to show that \( S \) is a linearly independent set. So we will begin with a relation of linear dependence on \( S \), using doubly-subscripted eigenvectors,

\[
0 = (a_{11}x_{11} + a_{12}x_{12} + \cdots + a_{1\gamma_A(\lambda_1)}x_{1\gamma_A(\lambda_1)}) + (a_{21}x_{21} + a_{22}x_{22} + \cdots + a_{2\gamma_A(\lambda_2)}x_{2\gamma_A(\lambda_2)}) + \cdots + (a_{k1}x_{k1} + a_{k2}x_{k2} + \cdots + a_{k\gamma_A(\lambda_k)}x_{k\gamma_A(\lambda_k)})
\]
Define the vectors $y_i$, $1 \leq i \leq k$ by

$$y_1 = (a_{11}x_{11} + a_{12}x_{12} + a_{13}x_{13} + \cdots + a_{\gamma_A(1\lambda_i)}x_{1\gamma_A(1\lambda_i)})$$

$$y_2 = (a_{21}x_{21} + a_{22}x_{22} + a_{23}x_{23} + \cdots + a_{\gamma_A(2\lambda_i)}x_{2\gamma_A(2\lambda_i)})$$

$$y_3 = (a_{31}x_{31} + a_{32}x_{32} + a_{33}x_{33} + \cdots + a_{\gamma_A(3\lambda_i)}x_{3\gamma_A(3\lambda_i)})$$

$$\vdots$$

$$y_k = (a_{k1}x_{k1} + a_{k2}x_{k2} + a_{k3}x_{k3} + \cdots + a_{\gamma_A(k\lambda_i)}x_{k\gamma_A(k\lambda_i)})$$

Then the relation of linear dependence becomes

$$0 = y_1 + y_2 + y_3 + \cdots + y_k$$

Since the eigenspace $E_A(\lambda_i)$ is closed under vector addition and scalar multiplication, $y_i \in E_A(\lambda_i)$, $1 \leq i \leq k$. Thus, for each $i$, the vector $y_i$ is an eigenvector of $A$ for $\lambda_i$, or is the zero vector. Recall that sets of eigenvectors whose eigenvalues are distinct form a linearly independent set by Theorem EDELI [399]. Should any (or some) $y_i$ be nonzero, the previous equation would provide a nontrivial relation of linear dependence on a set of eigenvectors with distinct eigenvalues, contradicting Theorem EDELI [399]. Thus $y_i = 0$, $1 \leq i \leq k$.

Each of the $k$ equations, $y_i = 0$ is a relation of linear dependence on the corresponding set $S_i$, a set of basis vectors for the eigenspace $E_A(\lambda_i)$, which is therefore linearly independent. From these relations of linear dependence on linearly independent sets we conclude that $a_{ij} = 0$, $1 \leq j \leq \gamma_A(\lambda_i)$ for $1 \leq i \leq k$. This establishes that our original relation of linear dependence on $S$ has only the trivial solution, and hence $S$ is a linearly independent set.

We have determined that $S$ is a set of $n$ linearly independent eigenvectors for $A$, and so by Theorem DC [415] is diagonalizable.

($\Rightarrow$) Now we assume that $A$ is diagonalizable. Aiming for a contradiction, suppose that there is at least one eigenvalue, say $\lambda_t$, such that $\gamma_A(\lambda_t) \neq \alpha_A(\lambda_t)$. By Theorem ME [406] we must have $\gamma_A(\lambda_t) < \alpha_A(\lambda_t)$, and $\gamma_A(\lambda_i) \leq \alpha_A(\lambda_i)$ for $1 \leq i \leq k$, $i \neq t$.

Since $A$ is diagonalizable, Theorem DC [415] guarantees a set of $n$ linearly independent vectors, all of which are eigenvectors of $A$. Let $n_i$ denote the number of eigenvectors in $S$ that are eigenvectors for $\lambda_i$, and recall that a vector cannot be an eigenvector for two different eigenvalues. $S$ is a linearly independent set, so the the subset $S_i$ containing the $n_i$ eigenvectors for $\lambda_i$ must also be linearly independent. Because the eigenspace $E_A(\lambda_i)$ has dimension $\gamma_A(\lambda_i)$ and $S_i$ is a linearly independent subset in $E_A(\lambda_i)$, $n_i \leq \gamma_A(\lambda_i)$, $1 \leq i \leq k$. Now,

$$n = n_1 + n_2 + n_3 + \cdots + n_t + \cdots + n_k$$

Size of $S$

$$\leq \gamma_A(\lambda_1) + \gamma_A(\lambda_2) + \gamma_A(\lambda_3) + \cdots + \gamma_A(\lambda_t) + \cdots + \gamma_A(\lambda_k)$$

$S_i$ linearly independent

$$< \alpha_A(\lambda_1) + \alpha_A(\lambda_2) + \alpha_A(\lambda_3) + \cdots + \alpha_A(\lambda_t) + \cdots + \alpha_A(\lambda_k)$$

Assumption about $\lambda_i$

$$= n$$

Theorem NEM [406]

This is a contradiction (we can’t have $n < n!$) and so our assumption that some eigenspace had less than full dimension was false. ■

Example SEE [373], Example CAEHW [378], Example ESMS3 [383], Example ESMS4 [385], Example DEMS5 [390], Archetype B [568], Archetype F [585], Archetype K [609] and
Archetype L are all examples of matrices that are diagonalizable and that illustrate Theorem DMLE. While we have provided many examples of matrices that are diagonalizable, especially among the archetypes, there are many matrices that are not diagonalizable. Here’s one now.

Example NDMS4
A non-diagonalizable matrix of size 4
In Example EMMS4 the matrix
\[
B = \begin{bmatrix}
-2 & 1 & -2 & -4 \\
12 & 1 & 4 & 9 \\
6 & 5 & -2 & -4 \\
3 & -4 & 5 & 10
\end{bmatrix}
\]
was determined to have characteristic polynomial
\[p_B(x) = (x - 1)(x - 2)^3\]
and an eigenspace for \(\lambda = 2\) of
\[E_B(2) = \mathcal{S}p \left( \left\{ \begin{bmatrix} -\frac{1}{2} \\ 1 \\ -\frac{1}{2} \\ 1 \end{bmatrix} \right\} \right) \]
So the geometric multiplicity of \(\lambda = 2\) is \(\gamma_B(2) = 1\), while the algebraic multiplicity is \(\alpha_B(2) = 3\). By Theorem DMLE the matrix \(B\) is not diagonalizable.

Archetype A is the lone archetype with a square matrix that is not diagonalizable, as the algebraic and geometric multiplicities of the eigenvalue \(\lambda = 0\) differ. Example HMEM5 is another example of a matrix that cannot be diagonalized due to the difference between the geometric and algebraic multiplicities of \(\lambda = 2\), as is Example CEMS6 which has two complex eigenvalues, each with differing multiplicities. Likewise, Example EMMS4 has an eigenvalue with different algebraic and geometric multiplicities and so cannot be diagonalized.

Theorem DED
Distinct Eigenvalues implies Diagonalizable
Suppose \(A\) is a square matrix of size \(n\) with \(n\) distinct eigenvalues. Then \(A\) is diagonalizable.

Proof Let \(\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n\) denote the \(n\) distinct eigenvalues of \(A\). Then by Theorem NEM we have \(n = \sum_{i=1}^{n} \alpha_A(\lambda_i)\), which implies that \(\alpha_A(\lambda_i) = 1, 1 \leq i \leq n\). From Theorem ME it follows that \(\gamma_A(\lambda_i) = 1, 1 \leq i \leq n\). So \(\gamma_A(\lambda_i) = \alpha_A(\lambda_i), 1 \leq i \leq n\) and Theorem DMLE says \(A\) is diagonalizable.

Example DEHD
Distinct eigenvalues, hence diagonalizable
In Example DEMS5 the matrix
\[
H = \begin{bmatrix}
15 & 18 & -8 & 6 & -5 \\
5 & 3 & 1 & -1 & -3 \\
0 & -4 & 5 & -4 & -2 \\
-43 & -46 & 17 & -14 & 15 \\
26 & 30 & -12 & 8 & -10
\end{bmatrix}
\]
has characteristic polynomial
\[ p_H(x) = x(x - 2)(x - 1)(x + 1)(x + 3) \]
and so is a 5 \times 5 matrix with 5 distinct eigenvalues. By Theorem DED\(^{[420]}\) we know \(H\) must be diagonalizable. But just for practice, we exhibit the diagonalization itself. The matrix \(S\) contains eigenvectors of \(H\) as columns, one from each eigenspace, guaranteeing linear independent columns and thus the nonsingularity of \(S\). The diagonal matrix has the eigenvalues of \(H\) in the same order that their respective eigenvectors appear as the columns of \(S\). Notice that we are using the versions of the eigenvectors from Example DEMS5\(^{[390]}\) that have integer entries.

\[ S^{-1}HS \]

\[
\begin{bmatrix}
2 & 1 & -1 & 1 & 1 \\
-1 & 0 & 2 & 0 & -1 \\
-2 & 0 & 2 & -1 & -2 \\
-4 & -1 & 0 & -2 & -1 \\
2 & 2 & 1 & 2 & 1
\end{bmatrix}
\begin{bmatrix}
15 & 18 & -8 & 6 & -5 \\
5 & 3 & 1 & -1 & -3 \\
0 & -4 & 5 & -4 & -2 \\
-43 & -46 & 17 & -14 & 15 \\
26 & 30 & -12 & 8 & -10
\end{bmatrix}
\begin{bmatrix}
2 & 1 & -1 & 1 & 1 \\
-1 & 0 & 2 & 0 & -1 \\
-2 & 0 & 2 & -1 & -2 \\
-4 & -1 & 0 & -2 & -1 \\
2 & 2 & 1 & 2 & 1
\end{bmatrix}
\]

\[
\begin{bmatrix}
-3 & -3 & 1 & -1 & 1 \\
-1 & -2 & 1 & 0 & 1 \\
-5 & -4 & 1 & -1 & 2 \\
10 & 10 & -3 & 2 & -4 \\
-7 & -6 & 1 & -1 & 3
\end{bmatrix}
\begin{bmatrix}
15 & 18 & -8 & 6 & -5 \\
5 & 3 & 1 & -1 & -3 \\
0 & -4 & 5 & -4 & -2 \\
-43 & -46 & 17 & -14 & 15 \\
26 & 30 & -12 & 8 & -10
\end{bmatrix}
\begin{bmatrix}
2 & 1 & -1 & 1 & 1 \\
-1 & 0 & 2 & 0 & -1 \\
-2 & 0 & 2 & -1 & -2 \\
-4 & -1 & 0 & -2 & -1 \\
2 & 2 & 1 & 2 & 1
\end{bmatrix}
\]

\[
\begin{bmatrix}
-3 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 2
\end{bmatrix}
\]

Archetype B\(^{[568]}\) is another example of a matrix that has as many distinct eigenvalues as its size, and is hence diagonalizable by Theorem DED\(^{[420]}\).

Powers of a diagonal matrix are easy to compute, and when a matrix is diagonalizable, it is almost as easy. We could state a theorem here perhaps, but we will settle instead for an example that makes the point just as well.

**Example HPDM**

**High power of a diagonalizable matrix**

Suppose that
\[
A = \begin{bmatrix}
19 & 0 & 6 & 13 \\
-33 & -1 & -9 & -21 \\
21 & -4 & 12 & 21 \\
-36 & 2 & -14 & -28
\end{bmatrix}
\]

and we wish to compute \(A^{20}\). Normally this would require 19 matrix multiplications, but since \(A\) is diagonalizable, we can simplify the computations substantially. First, we diagonalize \(A\). With
\[
S = \begin{bmatrix}
1 & -1 & 2 & -1 \\
-2 & 3 & -3 & 3 \\
1 & 1 & 3 & 3 \\
-2 & 1 & -4 & 0
\end{bmatrix}
\]
we find

\[
D = S^{-1}AS = \begin{bmatrix} -6 & 1 & -3 & -6 \\ 0 & 2 & -2 & -3 \\ 3 & 0 & 1 & 2 \\ -1 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 19 & 0 & 6 & 13 \\ -33 & -1 & -9 & -21 \\ 21 & -4 & 12 & 21 \\ -36 & 2 & -14 & -28 \end{bmatrix} \begin{bmatrix} 1 & -1 & 2 & -1 \\ -2 & 3 & -3 & 3 \\ 1 & 1 & 3 & 3 \\ -2 & 1 & -4 & 0 \end{bmatrix}
\]

\[
= \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}
\]

Now we find an alternate expression for \(A^{20}\),

\[
A^{20} = AAA \ldots A = I_nAI_nAI_n \ldots I_nAI_n
\]

\[
= (SS^{-1})A(SS^{-1})A(SS^{-1}) \ldots (SS^{-1})A(SS^{-1})
\]

\[
= S(S^{-1}AS)(S^{-1}AS)(S^{-1}AS) \ldots (S^{-1}AS)S^{-1}
\]

\[
= SDDD \ldots DS
\]

and since \(D\) is a diagonal matrix, powers are much easier to compute,

\[
= S\begin{bmatrix} (-1)^{20} & 0 & 0 & 0 \\ 0 & (0)^{20} & 0 & 0 \\ 0 & 0 & (2)^{20} & 0 \\ 0 & 0 & 0 & (1)^{20} \end{bmatrix}S^{-1}
\]

\[
= S\begin{bmatrix} 1 & -1 & 2 & -1 \\ -2 & 3 & -3 & 3 \\ 1 & 1 & 3 & 3 \\ -2 & 1 & -4 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1048576 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -6 & 1 & -3 & -6 \\ -2 & 3 & -3 & 3 \\ 1 & 1 & 3 & 3 \\ -2 & 1 & -4 & 0 \end{bmatrix}
\]

\[
= \begin{bmatrix} 6291451 & 2 & 2097148 & 4194297 \\ -9437175 & -5 & -3145719 & -6291441 \\ 9437175 & -2 & 3145728 & 6291453 \\ -12582900 & -2 & -4194298 & -8388596 \end{bmatrix}
\]

Notice how we effectively replaced the twentieth power of \(A\) by the twentieth power of \(D\), and how a high power of a diagonal matrix is just a collection of powers of scalars on the diagonal. The price we pay for this simplification is the need to diagonalize the matrix (by computing eigenvalues and eigenvectors) and finding the inverse of the matrix of eigenvectors. And we still need to do two matrix products. But the higher the power, the greater the savings.
Every Hermitian matrix (Definition HM [229]) is diagonalizable (Definition DZM [415]), and the similarity transformation that accomplishes the diagonalization is an orthogonal matrix (Definition OM [226]). This means that for every Hermitian matrix of size $n$ there is a basis of $\mathbb{C}^n$ that is composed entirely of eigenvectors for the matrix and also forms an orthonormal set (Definition ONS [175]). Notice that for matrices with only real entries, we only need the hypothesis that the matrix is symmetric (Definition SYM [183]) to reach this conclusion (Example ESMS4 [385]). Can you imagine a prettier basis for use with a matrix? I can’t. Eventually we’ll include the precise statement of this result with a proof.

Subsection READ
Reading Questions

1. What is an equivalence relation?
2. State a condition that is equivalent to a matrix being diagonalizable, but is not the definition.
3. Find a diagonal matrix similar to

$$A = \begin{bmatrix} -5 & 8 \\ -4 & 7 \end{bmatrix}$$
Subsection EXC
Exercises

C20  Consider the matrix $A$ below. First, show that $A$ is diagonalizable by computing
the geometric multiplicities of the eigenvalues and quoting the relevant theorem. Sec-
ond, find a diagonal matrix $D$ and a nonsingular matrix $S$ so that $S^{-1}AS = D$. (See
Exercise EE.C20 \[393\] for some of the necessary computations.)

$$A = \begin{bmatrix}
18 & -15 & 33 & -15 \\
-4 & 8 & -6 & 6 \\
-9 & 9 & -16 & 9 \\
5 & -6 & 9 & -4
\end{bmatrix}$$

Contributed by Robert Beezer  Solution \[427\]

T15  Suppose that $A$ and $B$ are similar matrices. Prove that $A^3$ and $B^3$ are similar
matrices. Generalize.

Contributed by Robert Beezer  Solution \[427\]

T16  Suppose that $A$ and $B$ are similar matrices, with $A$ nonsingular. Prove that $B$ is
nonsingular, and that $A^{-1}$ is similar to $B^{-1}$.

Contributed by Robert Beezer
Using a calculator, we find that $A$ has three distinct eigenvalues, $\lambda = 3, 2, -1$, with $\lambda = 2$ having algebraic multiplicity two, $\alpha_A(2) = 2$. The eigenvalues $\lambda = 3, -1$ have algebraic multiplicity one, and so by Theorem ME 406 we can conclude that their geometric multiplicities are one as well. Together with the computation of the geometric multiplicity of $\lambda = 2$ from Exercise EE.C20 393, we know

$$\gamma_A(3) = \alpha_A(3) = 1 \quad \gamma_A(2) = \alpha_A(2) = 2 \quad \gamma_A(-1) = \alpha_A(-1) = 1$$

This satisfies the hypotheses of Theorem DMLE 418, and so we can conclude that $A$ is diagonalizable.

A calculator will give us four eigenvectors of $A$, the two for $\lambda = 2$ being linearly independent presumably. Or, by hand, we could find basis vectors for the three eigenspaces. For $\lambda = 3, -1$ the eigenspaces have dimension one, and so any eigenvector for these eigenvalues will be multiples of the ones we use below. For $\lambda = 2$ there are many different bases for the eigenspace, so your answer could vary. Our eigenvectors are the basis vectors we would have obtained if we had actually constructed a basis in Exercise EE.C20 393 rather than just computing the dimension.

By the construction in the proof of Theorem DC 415, the required matrix $S$ has columns that are four linearly independent eigenvectors of $A$ and the diagonal matrix has the eigenvalues on the diagonal (in the same order as the eigenvectors in $S$). Here are the pieces, “doing” the diagonalization,

$$\begin{bmatrix} -1 & 0 & -3 & 6 \\ -2 & -1 & -1 & 0 \\ 0 & 0 & 1 & -3 \\ 1 & 1 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 18 & -15 & 33 & -15 \\ -4 & 8 & -6 & 6 \\ -9 & 9 & -16 & 9 \\ 5 & -6 & 9 & -4 \end{bmatrix} \begin{bmatrix} -1 & 0 & -3 & 6 \\ -2 & -1 & -1 & 0 \\ 0 & 0 & 1 & -3 \\ 1 & 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

This equation says that $A^3$ is similar to $B^3$ (via the matrix $S$). More generally, if $A$ is similar to $B$, and $m$ is a non-negative integer, then $A^m$ is similar to $B^m$. This can be proved using induction (Technique XX [??]).
In the next linear algebra course you take, the first lecture might be a reminder about what a vector space is (Definition VS [275]), their ten properties, basic theorems and then some examples. The second lecture would likely be all about linear transformations. While it may seem we have waited a long time to present what must be a central topic, in truth we have already been working with linear transformations for some time.

Functions are important objects in the study of calculus, but have been absent from this course until now (well, not really, it just seems that way). In your study of more advanced mathematics it is nearly impossible to escape the use of functions — they are as fundamental as sets are.

Here’s a key definition.

**Definition LT**

**Linear Transformation**

A *linear transformation*, $T: U \mapsto V$, is a function that carries elements of the vector space $U$ (called the *domain*) to the vector space $V$ (called the *codomain*), and which has two additional properties

1. $T(u_1 + u_2) = T(u_1) + T(u_2)$ for all $u_1, u_2 \in U$
2. $T(\alpha u) = \alpha T(u)$ for all $u \in U$ and all $\alpha \in \mathbb{C}$

The two defining conditions of the definition of a linear transformations should “feel linear,” whatever that means. Conversely, these two conditions could be taken as a *exactly* what it means to be linear. As every vector space property derives from vector addition and scalar multiplication, so too, every property of a linear transformation derives from these two defining properties. While these conditions may be reminiscent of how we test subspaces, they really are quite different, so do not confuse the two.
Here are two diagrams that convey the essence of the two defining properties of a linear transformation. In each case, begin in the upper left-hand corner, and follow the arrows around the rectangle to the lower-right hand corner, taking two different routes and doing the indicated operations labeled on the arrows. There are two results there. For a linear transformation these two expressions are always equal.

\[
\begin{align*}
\begin{array}{c}
\mathbf{u}_1, \mathbf{u}_2 \\
\end{array}
\xrightarrow{T}
\begin{array}{c}
T(\mathbf{u}_1), T(\mathbf{u}_2) \\
+ \\
\mathbf{u}_1 + \mathbf{u}_2 \\
\xrightarrow{T}
\begin{array}{c}
T(\mathbf{u}_1) + T(\mathbf{u}_2), \\
T(\mathbf{u}_1 + \mathbf{u}_2) \\
\end{array}
\end{array}
\end{align*}
\]

A couple of words about notation. \( T \) is the name of the linear transformation, and should be used when we want to discuss the function as a whole. \( T(\mathbf{u}) \) is how we talk about the output of the function, it is a vector in the vector space \( V \). When we write \( T(\mathbf{x} + \mathbf{y}) = T(\mathbf{x}) + T(\mathbf{y}) \), the plus sign on the left is the operation of vector addition in the vector space \( U \), since \( \mathbf{x} \) and \( \mathbf{y} \) are elements of \( U \). The plus sign on the right is the operation of vector addition in the vector space \( V \), since \( T(\mathbf{x}) \) and \( T(\mathbf{y}) \) are elements of the vector space \( V \). These two instances of vector addition might be wildly different.

Let’s examine several examples and begin to form a catalog of known linear transformations to work with.

**Example ALT**

**A linear transformation**

Define \( T : \mathbb{C}^3 \rightarrow \mathbb{C}^2 \) by describing the output of the function for a generic input with the formula

\[
T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 + x_3 \\ -4x_2 \end{bmatrix}
\]
and check the two defining properties.

\[ T(\mathbf{x} + \mathbf{y}) = T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + T \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = T \begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \\ x_3 + y_3 \end{pmatrix} = \begin{bmatrix} 2(x_1 + y_1) + (x_3 + y_3) \\ -4(x_2 + y_2) \end{bmatrix} \]

\[ = \begin{bmatrix} 2(x_1 + x_3) + (2y_1 + y_3) \\ -4x_2 + (-4)y_2 \end{bmatrix} = \begin{bmatrix} 2x_1 + x_3 \\ -4x_2 \end{bmatrix} + \begin{bmatrix} 2y_1 + y_3 \\ -4y_2 \end{bmatrix} = T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + T \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = T(\mathbf{x}) + T(\mathbf{y}) \]

and

\[ T(\alpha \mathbf{x}) = T \begin{pmatrix} \alpha x_1 \\ \alpha x_2 \\ \alpha x_3 \end{pmatrix} = T \begin{bmatrix} \alpha x_1 \\ \alpha x_2 \\ \alpha x_3 \end{bmatrix} = \begin{bmatrix} 2(\alpha x_1) + (\alpha x_3) \\ -4(\alpha x_2) \end{bmatrix} = \begin{bmatrix} \alpha(2x_1 + x_3) \\ \alpha(-4x_2) \end{bmatrix} = \alpha \begin{bmatrix} 2x_1 + x_3 \\ -4x_2 \end{bmatrix} = \alpha T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \alpha T(\mathbf{x}) \]

So by Definition LT 429, \( T \) is a linear transformation.

It can be just as instructive to look at functions that are not linear transformations. Since the defining conditions must be true for all vectors and scalars, it is enough to find just one situation where the properties fail.

**Example NLT**

Not a linear transformation
Define $S: \mathbb{C}^3 \mapsto \mathbb{C}^3$ by

$$S \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 4x_1 + 2x_2 \\ 0 \\ x_1 + 3x_3 - 2 \end{bmatrix}$$

This function “looks” linear, but consider

$$3 S \left( \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \right) = 3 \begin{bmatrix} 8 \\ 0 \\ 8 \end{bmatrix} = \begin{bmatrix} 24 \\ 0 \\ 24 \end{bmatrix}$$

while

$$S \left( \begin{bmatrix} 3 \\ 2 \\ 3 \end{bmatrix} \right) = \begin{bmatrix} 24 \\ 0 \\ 28 \end{bmatrix}$$

So the second required property fails for the choice of $\alpha = 3$ and $x = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ and by **Definition LT [429]**, $S$ is not a linear transformation. It is just about as easy to find an example where the first defining property fails (try it!). Notice that it is the “-2” in the third component of the definition of $S$ that prevents the function from being a linear transformation.

**Example LTPM**

**Linear transformation, polynomials to matrices**

Define a linear transformation $T: P_3 \mapsto M_{22}$ by

$$T (a + bx + cx^2 + dx^3) = \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix}$$

$$T (x + y) = T \left( (a_1 + b_1 x + c_1 x^2 + d_1 x^3) + (a_2 + b_2 x + c_2 x^2 + d_2 x^3) \right)$$

$$= T \left( (a_1 + a_2) + (b_1 + b_2)x + (c_1 + c_2)x^2 + (d_1 + d_2)x^3 \right)$$

$$= \begin{bmatrix} (a_1 + a_2) + (b_1 + b_2) & (a_1 + a_2) - 2(c_1 + c_2) \\ d_1 + d_2 & (b_1 + b_2) - (d_1 + d_2) \end{bmatrix}$$

$$= \begin{bmatrix} (a_1 + b_1) + (a_2 + b_2) & (a_1 + a_2) - 2(c_1 + c_2) \\ d_1 + d_2 & (b_1 - d_1) + (b_2 - d_2) \end{bmatrix}$$

$$= \begin{bmatrix} a_1 + b_1 & a_1 - 2c_1 \\ d_1 & b_1 - d_1 \end{bmatrix} + \begin{bmatrix} a_2 + b_2 & a_2 - 2c_2 \\ d_2 & b_2 - d_2 \end{bmatrix}$$

$$= T \left( a_1 + b_1 x + c_1 x^2 + d_1 x^3 \right) + T \left( a_2 + b_2 x + c_2 x^2 + d_2 x^3 \right)$$

$$= T (x) + T (y)$$
Subsection LT.LT  Linear Transformations  433

and

\[ T(\alpha x) = T(\alpha(a + bx + cx^2 + dx^3)) = T((\alpha a) + (ab)x + (\alpha c)x^2 + (\alpha d)x^3) = \\
\begin{bmatrix}
(\alpha a) + (ab) & (\alpha a) - 2(\alpha c) \\
\alpha d & (ab) - (\alpha d)
\end{bmatrix} = \\
\begin{bmatrix}
\alpha(a + b) & \alpha(a - 2c) \\
\alpha d & \alpha(b - d)
\end{bmatrix} = \\
\alpha \begin{bmatrix}
a + b & a - 2c \\
d & b - d
\end{bmatrix} = \\
\alpha T(a + bx + cx^2 + dx^3) = \alpha T(x) \]

So by Definition LT [429], \( T \) is a linear transformation. ⊗

Example LTPP
Linear transformation, polynomials to polynomials
Define a function \( S: P_4 \rightarrow P_5 \) by

\[ S(p(x)) = (x - 2)p(x) \]

Then

\[ S(p(x) + q(x)) = (x - 2)(p(x) + q(x)) = (x - 2)p(x) + (x - 2)q(x) = S(p(x)) + S(q(x)) \]
\[ S(\alpha p(x)) = (x - 2)(\alpha p(x)) = (x - 2)\alpha p(x) = \alpha(x - 2)p(x) = \alpha S(p(x)) \]

So by Definition LT [429], \( S \) is a linear transformation. ⊗

Linear transformations have many amazing properties, which we will investigate through the next few sections. However, as a taste of things to come, here is a theorem we can prove now and put to use immediately.

Theorem LTTZZ
Linear Transformations Take Zero to Zero
Suppose \( T: U \rightarrow V \) is a linear transformation. Then \( T(0) = 0 \). ⊢

Proof The two zero vectors in the conclusion of the theorem are different. The first is from \( U \) while the second is from \( V \). We will subscript the zero vectors throughout this proof to highlight the distinction. Think about your objects.

\[ T(0_U) = T(0_U) + 0_V \]
\[ = T(0_U) + T(0_V) - T(0_U) \]
\[ = (T(0_U) + (T(0_U)) - T(0_U)) \]
\[ = T(0_U + 0_U) - T(0_U) \]
\[ = T(0_U) - T(0_U) \]
\[ = 0_V \]

Property Z [276] in \( V \)

Property AI [276] in \( V \)

Property AA [276] in \( V \)

Definition LT [429]

Property Z [276] in \( U \)

Property AI [276] in \( V \)
Return to Example NLT \[431\] and compute \( S \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -2 \end{bmatrix} \) to quickly see again that \( S \) is not a linear transformation, while in Example LTPM \[432\] and compute \( S (0 + 0x + 0x^2 + 0x^3) = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \) as an example of Theorem LTTZZ \[433\] at work.

**Subsection MLT**

**Matrices and Linear Transformations**

If you give me a matrix, then I can quickly build you a linear transformation. Always. First a motivating example and then the theorem.

**Example LTM**

**Linear transformation from a matrix**

Let

\[
A = \begin{bmatrix}
3 & -1 & 8 & 1 \\
2 & 0 & 5 & -2 \\
1 & 1 & 3 & -7
\end{bmatrix}
\]

and define a function \( P: \mathbb{C}^4 \mapsto \mathbb{C}^3 \) by

\[
P(x) = Ax
\]

So we are using an old friend, the matrix-vector product \( \text{Definition MVP} \[187\] \) as a way to convert a vector with 4 components into a vector with 3 components. Applying \( \text{Definition MVP} \[187\] \) allows us to write the defining formula for \( P \) in a slightly different form,

\[
P(x) = Ax = \begin{bmatrix} 3 & -1 & 8 & 1 \\ 2 & 0 & 5 & -2 \\ 1 & 1 & 3 & -7 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = x_1 \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + x_3 \begin{bmatrix} 8 \\ 5 \\ 3 \end{bmatrix} + x_4 \begin{bmatrix} 1 \\ -2 \\ -7 \end{bmatrix}
\]

So we recognize the action of the function \( P \) as using the components of the vector \( (x_1, x_2, x_3, x_4) \) as scalars to form the output of \( P \) as a linear combination of the four columns of the matrix \( A \), which are all members of \( \mathbb{C}^3 \), so the result is a vector in \( \mathbb{C}^3 \). We can rearrange this expression further, using our definitions of operations in \( \mathbb{C}^3 \).
P(x) = Ax = x_1 \begin{pmatrix} 3 \\ 2 \\ 1 \end{pmatrix} + x_2 \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix} + x_3 \begin{pmatrix} 8 \\ 5 \\ 3 \end{pmatrix} + x_4 \begin{pmatrix} 1 \\ -2 \\ -7 \end{pmatrix} \quad \text{Definition of } P

\begin{pmatrix} 3x_1 - x_2 + 8x_3 + x_4 \\ 2x_1 + 5x_3 - 2x_4 \\ x_1 + x_2 + 3x_3 - 7x_4 \end{pmatrix} \quad \text{Definition MVP } 187

You might recognize this final expression as being similar in style to some previous examples (Example ALT 430) and some linear transformations defined in the archetypes (Archetype M 617 through Archetype R 631). But the expression that says the output of this linear transformation is a linear combination of the columns of A is probably the most powerful way of thinking about examples of this type.

Almost forgot — we should verify that P is indeed a linear transformation. This is easy with two matrix properties from Section MM 187.

P(x + y) = A(x + y) = Ax + Ay = P(x) + P(y) \quad \text{Definition of } P

and

P(\alpha x) = A(\alpha x) = \alpha (Ax) = \alpha P(x) \quad \text{Definition of } P

So by Definition LT 429, P is a linear transformation.

So the multiplication of a vector by a matrix “transforms” the input vector into an output vector, possibly of a different size, by performing a linear combination. And this transformation happens in a “linear” fashion. This “functional” view of the matrix-vector product is the most important shift you can make right now in how you think about linear algebra. Here’s the theorem, whose proof is very nearly an exact copy of the verification in the last example.

Theorem MBLT
Matrices Build Linear Transformations
Suppose that A is an m \times n matrix. Define a function T: \mathbb{C}^n \mapsto \mathbb{C}^m by T(x) = Ax. Then T is a linear transformation.

Proof

T(x + y) = A(x + y) = Ax + Ay = T(x) + T(y) \quad \text{Definition of } T
and

\[ T(\alpha x) = A(\alpha x) \]  
Definition of \( T \)

\[ = \alpha (Ax) \]  
Theorem MMSMM \[196\]

\[ = \alpha T(x) \]  
Definition of \( T \)

So by Definition LT \[429\], \( T \) is a linear transformation. ■

So Theorem MBLT \[435\] gives us a rapid way to construct linear transformations. Grab an \( m \times n \) matrix \( A \), define \( T(x) = Ax \) and Theorem MBLT \[435\] tells us that \( T \) is a linear transformation from \( \mathbb{C}^n \) to \( \mathbb{C}^m \), without any further checking.

We can turn Theorem MBLT \[435\] around. You give me a linear transformation and I will give you a matrix.

**Example MFLT**

*Matrix from a linear transformation*

Define the function \( R: \mathbb{C}^3 \rightarrow \mathbb{C}^4 \) by

\[
R \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 - 3x_2 + 4x_3 \\ x_1 + x_2 + x_3 \\ -x_1 + 5x_2 - 3x_3 \\ x_2 - 4x_3 \end{bmatrix}
\]

You could verify that \( R \) is a linear transformation by applying the definition, but we will instead massage the expression defining a typical output until we recognize the form of a known class of linear transformations.

\[
R \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 \\ x_1 \\ -x_1 \\ 0 \end{bmatrix} + \begin{bmatrix} -3x_2 \\ x_2 \\ 5x_2 \\ x_2 \end{bmatrix} + \begin{bmatrix} 4x_3 \\ x_3 \\ -3x_3 \\ -4x_3 \end{bmatrix}
\]

\[
= x_1 \begin{bmatrix} 2 \\ 1 \\ -1 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} -3 \\ 1 \\ 5 \\ 1 \end{bmatrix} + x_3 \begin{bmatrix} 4 \\ 1 \\ -3 \\ -4 \end{bmatrix}
\]

Definition CVA \[89\]

Definition CVSM \[90\]

Definition MVP \[187\]

So if we define the matrix

\[
B = \begin{bmatrix} 2 & -3 & 4 \\ 1 & 1 & 1 \\ -1 & 5 & -3 \\ 0 & 1 & -4 \end{bmatrix}
\]

then \( R(x) = Bx \). By Theorem MBLT \[435\], we can easily recognize \( R \) as a linear transformation since it has the form described in the hypothesis of the theorem. ©
Example MFLT was not accident. Consider any one of the archetypes where both the domain and codomain are sets of column vectors (Archetype M through Archetype R) and you should be able to mimic the previous example. Here’s the theorem, which is notable since it is our first occasion to use the full power of the defining properties of a linear transformation when our hypothesis includes a linear transformation.

**Theorem MLTCV**

**Matrix of a Linear Transformation, Column Vectors**

Suppose that $T: \mathbb{C}^n \mapsto \mathbb{C}^m$ is a linear transformation. Then there is an $m \times n$ matrix $A$ such that $T(x) = Ax$.

**Proof** The conclusion says a certain matrix exists. What better way to prove something exists than to actually build it? So our proof will be constructive, and the procedure that we will use abstractly in the proof can be used concretely in specific examples.

Let $e_1, e_2, e_3, \ldots, e_n$ be the columns of the identity matrix of size $n$, $I_n$ (Definition SUV). Evaluate the linear transformation $T$ with each of these standard unit vectors as an input, and record the result. In other words, define $n$ vectors in $\mathbb{C}^m$, $A_i$, $1 \leq i \leq n$ by

$$A_i = T(e_i)$$

Then package up these vectors as the columns of a matrix

$$A = [A_1|A_2|A_3|\ldots|A_n]$$

Does $A$ have the desired properties? First, $A$ is clearly an $m \times n$ matrix. Then

$$T(x) = T(I_n x)$$

$$= T \left[ \begin{array}{c|c|c|c} x_1 & x_2 & x_3 & \ldots & x_n \end{array} \right]$$

$$= T \left( x_1 e_1 + x_2 e_2 + x_3 e_3 + \cdots + x_n e_n \right)$$

$$= x_1 T(e_1) + x_2 T(e_2) + x_3 T(e_3) + \cdots + x_n T(e_n)$$

$$= x_1 A_1 + x_2 A_2 + x_3 A_3 + \cdots + x_n A_n$$

Definition of $A_i$

$$= [A_1|A_2|A_3|\ldots|A_n]$$

Definition MVP

$$= Ax$$

as desired.

So if we were to restrict our study of linear transformations to those where the domain and codomain are both vector spaces of column vectors (Definition VSCV), every
matrix leads to a linear transformation of this type (Theorem MBLT \[435\]), while every such linear transformation leads to a matrix (Theorem MLTCV \[437\]). So matrices and linear transformations are fundamentally the same. We call the matrix $A$ of Theorem MLTCV \[437\] the matrix representation of $T$.

We have defined linear transformations for more general vector spaces than just $\mathbb{C}^m$, can we extend this correspondence between linear transformations and matrices to more general linear transformations (more general domains and codomains)? Yes, and this is the main theme of Chapter R \[505\]. Stay tuned. For now, let’s illustrate Theorem MLTCV \[437\] with an example.

**Example MOLT**

**Matrix of a linear transformation**

Suppose $S: \mathbb{C}^3 \rightarrow \mathbb{C}^4$ is defined by

$$S\left(\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}\right) = \begin{bmatrix} 3x_1 - 2x_2 + 5x_3 \\ x_1 + x_2 + x_3 \\ 9x_1 - 2x_2 + 5x_3 \\ 4x_2 \end{bmatrix}$$

Then

$$C_1 = S(e_1) = S\left(\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 3 \\ 1 \\ 9 \\ 0 \end{bmatrix}$$

$$C_2 = S(e_2) = S\left(\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} -2 \\ 1 \\ -2 \\ 4 \end{bmatrix}$$

$$C_3 = S(e_3) = S\left(\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 5 \\ 1 \\ 5 \\ 0 \end{bmatrix}$$

so define

$$C = [C_1|C_2|C_3] = \begin{bmatrix} 3 & -2 & 5 \\ 1 & 1 & 1 \\ 9 & -2 & 5 \\ 0 & 4 & 0 \end{bmatrix}$$

and Theorem MLTCV \[437\] guarantees that $S(x) = Cx$.

As an illuminating exercise, let $z = \begin{bmatrix} 2 \\ -3 \\ 3 \end{bmatrix}$ and compute $S(z)$ two different ways. First, return to the definition of $S$ and evaluate $S(z)$ directly. Then do the matrix-vector product $Cz$. In both cases you should obtain the vector $S(z) = \begin{bmatrix} 27 \\ 2 \\ 39 \\ -12 \end{bmatrix}$. ☑
It is the interaction between linear transformations and linear combinations that lies at the heart of many of the important theorems of linear algebra. The next theorem distills the essence of this. The proof is not deep, the result is hardly startling, but it will be referenced frequently. We have already passed by one occasion to employ it, in the proof of Theorem MLTCV \[437\]. Paraphrasing, this theorem says that we can “push” linear transformations “down into” linear combinations, or “pull” linear transformations “up out” of linear combinations. We’ll have opportunities to both push and pull.

Theorem LTLC

Linear Transformations and Linear Combinations

Suppose that $T : U \to V$ is a linear transformation, $u_1, u_2, u_3, \ldots, u_t$ are vectors from $U$ and $a_1, a_2, a_3, \ldots, a_t$ are scalars from $\mathbb{C}$. Then

$$T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t) = a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_tT(u_t) \quad \square$$

Proof

$$T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t)$$

$$= T(a_1u_1) + T(a_2u_2) + T(a_3u_3) + \cdots + T(a_tu_t) \quad \text{Definition LT} \ [429]$$

$$= a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_tT(u_t) \quad \text{Definition LT} \ [429] \quad \square$$

Our next theorem says, informally, that it is enough to know how a linear transformation behaves for inputs from a basis of the domain, and all other outputs are described by a linear combination of these values. Again, the theorem and its proof are not remarkable, but the insight that goes along with it is fundamental.

Theorem LTDB

Linear Transformation Defined on a Basis

Suppose that $T : U \to V$ is a linear transformation, $B = \{u_1, u_2, u_3, \ldots, u_n\}$ is a basis for $U$ and $w$ is a vector from $U$. Let $a_1, a_2, a_3, \ldots, a_n$ be the scalars from $\mathbb{C}$ such that

$$w = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_nu_n$$

Then

$$T(w) = a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_nT(u_n) \quad \square$$

Proof For any $w \in U$, Theorem VRRB \[324\] says there are (unique) scalars such that $w$ is a linear combination of the basis vectors in $B$. The result then follows from a straightforward application of Theorem LTLC \[439\] to the linear combination. \quad \square

Example LTDB1

Linear transformation defined on a basis

Suppose you are told that $T : \mathbb{C}^3 \to \mathbb{C}^2$ is a linear transformation and given the three values,

$$T\left(\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad T\left(\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} -1 \\ 4 \end{bmatrix} \quad T\left(\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 6 \\ 0 \end{bmatrix}$$
Because
\[ B = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} \right\} \]
is a basis for \( \mathbb{C}^3 \) (Theorem SUVB \[318\]). Theorem LTDB \[439\] says we can compute any output of \( T \) with just this information. For example, consider,
\[ w = \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix} = (2) \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + (-3) \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + (1) \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \]
so
\[ T(w) = (2) \begin{bmatrix} 5 \\ -1 \end{bmatrix} + (-3) \begin{bmatrix} -1 \\ 4 \end{bmatrix} + (1) \begin{bmatrix} 6 \\ 0 \end{bmatrix} = \begin{bmatrix} 13 \\ -10 \end{bmatrix} \]

Any other value of \( T \) could be computed in a similar manner. So rather than being given a formula for the outputs of \( T \), the requirement that \( T \) behave as a linear transformation, along with its values on a handful of vectors (the basis), are just as sufficient as a formula for computing any value of the function. You might notice some parallels between this example and Example MOLT \[438\] or Theorem MLTCV \[437\].

Example LTDB2
Linear transformation defined on a basis
Suppose you are told that \( R : \mathbb{C}^3 \rightarrow \mathbb{C}^2 \) is a linear transformation and given the three values,
\[ R \left( \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \right) = \begin{bmatrix} 5 \\ -1 \end{bmatrix} \quad R \left( \begin{bmatrix} -1 \\ 5 \\ 1 \end{bmatrix} \right) = \begin{bmatrix} 0 \\ 4 \end{bmatrix} \quad R \left( \begin{bmatrix} 3 \\ 1 \\ 4 \end{bmatrix} \right) = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \]
You can check that
\[ D = \left\{ \begin{bmatrix} 1 \\ 2 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 5 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ 4 \\ 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} \right\} \]
is a basis for \( \mathbb{C}^3 \) (make the vectors the columns of a square matrix and check that the matrix is nonsingular, Theorem CNSMB \[323\]). By Theorem LTDB \[439\] we can compute any output of \( R \) with just this information. However, we have to work just a bit harder to take an input vector and express it as a linear combination of the vectors in \( D \). For example, consider,
\[ y = \begin{bmatrix} 8 \\ -3 \\ 5 \end{bmatrix} \]

Then we must first write \( y \) as a linear combination of the vectors in \( D \) and solve for the unknown scalars, to arrive at
\[ y = \begin{bmatrix} 8 \\ -3 \\ 5 \end{bmatrix} = (3) \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + (-2) \begin{bmatrix} -1 \\ 5 \\ 1 \end{bmatrix} + (1) \begin{bmatrix} 3 \\ 1 \\ 4 \end{bmatrix} \]
Then Theorem LTDB \[439\] gives us
\[ R(y) = (3) \begin{bmatrix} 5 \\ -1 \end{bmatrix} + (-2) \begin{bmatrix} 0 \\ 4 \end{bmatrix} + (1) \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 17 \\ -8 \end{bmatrix} \]
Any other value of \( R \) could be computed in a similar manner.

Here is a third example of a linear transformation defined by its action on a basis, only with more abstract vector spaces involved.

**Example LTDB3**

**Linear transformation defined on a basis**

The set \( W = \{ p(x) \in P_3 \mid p(1) = 0, p(3) = 0 \} \subseteq P_3 \) is a subspace of the vector space of polynomials \( P_3 \). This subspace has \( C = \{3 - 4x + x^2, 12 - 13x + x^3\} \) as a basis (check this!). Suppose we define a linear transformation \( S: P_3 \rightarrow M_{2 \times 2} \) by the values

\[
S(3 - 4x + x^2) = \begin{bmatrix} 1 & -3 \\ 2 & 0 \end{bmatrix} \quad S(12 - 13x + x^3) = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}
\]

To illustrate a sample computation of \( S \), consider \( q(x) = 9 - 6x - 5x^2 + 2x^3 \). Verify that \( q(x) \) is an element of \( W \) (does it have roots at \( x = 1 \) and \( x = 3 \)?), then find the scalars needed to write it as a linear combination of the basis vectors in \( C \). Because

\[
q(x) = 9 - 6x - 5x^2 + 2x^3 = (-5)(3 - 4x + x^2) + (2)(12 - 13x + x^3)
\]

**Theorem LTDB** gives us

\[
S(q) = (-5) \begin{bmatrix} 1 & -3 \\ 2 & 0 \end{bmatrix} + (2) \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} -5 & 17 \\ -8 & 0 \end{bmatrix}
\]

And all the other outputs of \( S \) could be computed in the same manner. Every output of \( S \) will have a zero in the second row, second column. Can you see why this is so?

Subsection PI Pre-Images

The definition of a function requires that for each input in the domain there is *exactly* one output in the codomain. However, the correspondence does not have to behave the other way around. A member of the codomain might have many inputs from the domain that create it, or it may have none at all. To formalize our discussion of this aspect of linear transformations, we define the pre-image.

**Definition PI Pre-Image**

Suppose that \( T: U \rightarrow V \) is a linear transformation. For each \( v \), define the **pre-image** of \( v \) to be the subset of \( U \) given by

\[
T^{-1}(v) = \{ u \in U \mid T(u) = v \}
\]

In other words, \( T^{-1}(v) \) is the set of all those vectors in the domain \( U \) that get “sent” to the vector \( v \).

TODO: All preimages form a partition of \( U \), an equivalence relation is about. Maybe to exercises.
Example SPIAS
Sample pre-images, Archetype S

Archetype S 634 is the linear transformation defined by

$$T : \mathbb{C}^3 \mapsto M_{22}, \quad T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} a - b \\ 3a + b + c \\ 2a + 2b + c \\ -2a - 6b - 2c \end{bmatrix}$$

We could compute a pre-image for every element of the codomain $M_{22}$. However, even in a free textbook, we do not have the room to do that, so we will compute just two.

Choose

$$v = \begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \end{bmatrix} \in M_{22}$$

for no particular reason. What is $T^{-1}(v)$? Suppose $u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \in T^{-1}(v)$. That $T(u) = v$ becomes

$$\begin{bmatrix} 2 \\ 1 \\ 3 \\ 2 \end{bmatrix} = v = T(u) = T \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} u_1 - u_2 \\ 2u_1 + u_2 + u_3 \\ 3u_1 + u_2 + u_3 \\ -2u_1 - 6u_2 - 2u_3 \end{bmatrix}$$

Using matrix equality [Definition ME 179], we arrive at a system of four equations in the three unknowns $u_1$, $u_2$, $u_3$ with an augmented matrix that we can row-reduce in the hunt for solutions,

$$\begin{bmatrix} 1 & -1 & 0 & 2 \\ 2 & 2 & 1 & 1 \\ 3 & 1 & 1 & 3 \\ -2 & -6 & -2 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & -3 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

We recognize this system as having infinitely many solutions described by the single free variable $u_3$. Eventually obtaining the vector form of the solutions (Theorem VF-SLS 106), we can describe the preimage precisely as,

$$T^{-1}(v) = \{ u \in \mathbb{C}^3 \mid T(u) = v \}$$

$$= \left\{ \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \mid u_1 = 5/4 - 1/4u_3, \ u_2 = -3/4 - 1/4u_3 \right\}$$

$$= \left\{ \begin{bmatrix} 5/4 - 1/4u_3 \\ -3/4 - 1/4u_3 \\ u_3 \end{bmatrix} \mid u_3 \in \mathbb{C}^3 \right\}$$

$$= \left\{ \begin{bmatrix} 5/4 \\ -3/4 \\ 0 \end{bmatrix} + u_3 \begin{bmatrix} -1/4 \\ 1/4 \\ 1 \end{bmatrix} \mid u_3 \in \mathbb{C}^3 \right\}$$

$$= \begin{bmatrix} 5/4 \\ -3/4 \\ 0 \end{bmatrix} + \mathbb{S}p \left( \left\{ \begin{bmatrix} -1/4 \\ 1/4 \\ 1 \end{bmatrix} \right\} \right)$$

This last line is merely a suggestive way of describing the set on the previous line. You might create three or four vectors in the preimage, and evaluate $T$ with each. Was the
result what you expected? For a hint of things to come, you might try evaluating $T$ with just the lone vector in the spanning set above. What was the result? Now take a look back at \textbf{Theorem PSPHS} \ref{thm:pshps}. Hmmm.

OK, let’s compute another preimage, but with a different outcome this time. Choose

$$v = \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix} \in \mathbb{M}_{22}$$

What is $T^{-1}(v)$? Suppose $u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \in T^{-1}(v)$. That $T(u) = v$ becomes

$$\begin{bmatrix} 1 & 1 \\ 2 & 4 \end{bmatrix} = v = T(u) = T \left( \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \right) = \begin{bmatrix} u_1 - u_2 & 2u_1 + 2u_2 + u_3 \\ 3u_1 + u_2 + u_3 & -2u_1 - 6u_2 - 2u_3 \end{bmatrix}$$

Using matrix equality (Definition ME \ref{def:me}), we arrive at a system of four equations in the three unknowns $u_1, u_2, u_3$ with an augmented matrix that we can row-reduce in the hunt for solutions,

$$\begin{bmatrix} 1 & -1 & 0 & 1 \\ 2 & 2 & 1 & 1 \\ 3 & 1 & 1 & 2 \\ -2 & -6 & -2 & 4 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & \frac{1}{3} & 0 \\ 0 & 1 & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

By \textbf{Theorem RCLS} \ref{thm:rcls}, we recognize this system as inconsistent. So no vector $u$ is a member of $T^{-1}(v)$ and so

$$T^{-1}(v) = \emptyset$$

The preimage is just a set, it is rarely a subspace of $U$ (you might think about just when it is a subspace). We will describe its properties going forward, but in some ways it will be a notational convenience as much as anything else.

\textbf{Subsection NLTFO}

\textbf{New Linear Transformations From Old}

We can combine linear transformations in natural ways to create new linear transformations. So we will define these combinations and then prove that the results really are still linear transformations. First the sum of two linear transformations.

\textbf{Definition LTA}

\textbf{Linear Transformation Addition}

Suppose that $T: U \rightarrow V$ and $S: U \rightarrow V$ are two linear transformations with the same domain and codomain. Then their \textbf{sum} is the function $T + S: U \rightarrow V$ whose outputs are defined by

$$(T + S)(u) = T(u) + S(u)$$

Notice that the first plus sign in the definition is the operation being defined, while the second one is the vector addition in $V$. (Vector addition in $U$ will appear just now in the proof that $T + S$ is a linear transformation.) \textbf{Definition LTA} \ref{def:lta} only provides a function.
It would be nice to know that when the constituents \((T, S)\) are linear transformations, then so too is \(T + S\).

**Theorem SLTLT**

**Sum of Linear Transformations is a Linear Transformation**

Suppose that \(T: U \mapsto V\) and \(S: U \mapsto V\) are two linear transformations with the same domain and codomain. Then \(T + S: U \mapsto V\) is a linear transformation. □

**Proof** We simply check the defining properties of a linear transformation (Definition LT [429]). This is a good place to consistently ask yourself which objects are being combined with which operations.

\[(T + S)(x + y) = T(x + y) + S(x + y) = T(x) + T(y) + S(x) + S(y) = T(x) + S(x) + T(y) + S(y) = (T + S)(x) + (T + S)(y)\]

and

\[(T + S)(\alpha x) = T(\alpha x) + S(\alpha x) = \alpha T(x) + \alpha S(x) = \alpha (T(x) + S(x)) = \alpha (T + S)(x)\]

**Example STLTLT**

**Sum of two linear transformations**

Suppose that \(T: \mathbb{C}^2 \mapsto \mathbb{C}^3\) and \(S: \mathbb{C}^2 \mapsto \mathbb{C}^3\) are defined by

\[
T\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} x_1 + 2x_2 \\ 3x_1 - 4x_2 \\ 5x_1 + 2x_2 \end{bmatrix} \quad S\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} 4x_1 - x_2 \\ x_1 + 3x_2 \\ -7x_1 + 5x_2 \end{bmatrix}
\]

Then by Definition LTA [444], we have

\[
(T + S)\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = T\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) + S\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} x_1 + 2x_2 \\ 3x_1 - 4x_2 \\ 5x_1 + 2x_2 \end{bmatrix} + \begin{bmatrix} 4x_1 - x_2 \\ x_1 + 3x_2 \\ -7x_1 + 5x_2 \end{bmatrix} = \begin{bmatrix} 5x_1 + x_2 \\ 4x_1 - x_2 \\ -2x_1 + 7x_2 \end{bmatrix}
\]

and by Theorem SLTLT [444] we know \(T + S\) is also a linear transformation from \(\mathbb{C}^2\) to \(\mathbb{C}^3\). ☑

**Definition LTSM**

**Linear Transformation Scalar Multiplication**

Suppose that \(T: U \mapsto V\) is a linear transformation and \(\alpha \in \mathbb{C}\). Then the **scalar multiple** is the function \(\alpha T: U \mapsto V\) whose outputs are defined by

\[(\alpha T)(u) = \alpha T(u)\]

△
Given that $T$ is a linear transformation, it would be nice to know that $\alpha T$ is also a linear transformation.

**Theorem MLTLT**

**Multiple of a Linear Transformation is a Linear Transformation**

Suppose that $T: U \mapsto V$ is a linear transformation and $\alpha \in \mathbb{C}$. Then $(\alpha T): U \mapsto V$ is a linear transformation. □

**Proof** We simply check the defining properties of a linear transformation (Definition LT [429]). This is another good place to consistently ask yourself which objects are being combined with which operations.

\[
(\alpha T)(x + y) = \alpha (T(x + y)) \quad \text{Definition LTSM [445]}
\]

\[
= \alpha (T(x) + T(y)) \quad \text{Definition LT [429]}
\]

\[
= \alpha T(x) + \alpha T(y) \quad \text{Property DVA [276] in } V
\]

\[
= (\alpha T)(x) + (\alpha T)(y) \quad \text{Definition LTSM [445]}
\]

and

\[
(\alpha T)(\beta x) = \alpha T(\beta x) \quad \text{Definition LTSM [445]}
\]

\[
= \alpha (\beta T(x)) \quad \text{Definition LT [429]}
\]

\[
= (\alpha \beta) T(x) \quad \text{Property SMA [276] in } V
\]

\[
= \beta (\alpha T(x)) \quad \text{Commutativity in } \mathbb{C}
\]

\[
= \beta ((\alpha T)(x)) \quad \text{Definition LTSM [445]}
\]

**Example SMLT**

**Scalar multiple of a linear transformation**

Suppose that $T: \mathbb{C}^4 \mapsto \mathbb{C}^3$ is defined by

\[
T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \right) = \begin{bmatrix} x_1 + 2x_2 - x_3 + 2x_4 \\ x_1 + 5x_2 - 3x_3 + x_4 \\ -2x_1 + 3x_2 - 4x_3 + 2x_4 \end{bmatrix}
\]

For the sake of an example, choose $\alpha = 2$, so by Definition LTSM [445], we have

\[
\alpha T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \right) = 2T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \right) = 2 \begin{bmatrix} x_1 + 2x_2 - x_3 + 2x_4 \\ x_1 + 5x_2 - 3x_3 + x_4 \\ -2x_1 + 3x_2 - 4x_3 + 2x_4 \end{bmatrix} = \begin{bmatrix} 2x_1 + 4x_2 - 2x_3 + 4x_4 \\ 2x_1 + 10x_2 - 6x_3 + 2x_4 \\ -4x_1 + 6x_2 - 8x_3 + 4x_4 \end{bmatrix}
\]

and by Theorem MLTLT [445] we know $2T$ is also a linear transformation from $\mathbb{C}^4$ to $\mathbb{C}^3$. □

Now, let’s imagine we have two vector spaces, $U$ and $V$, and we collect every possible linear transformation from $U$ to $V$ into one big set, and call it $\text{LT}(U, V)$. Definition LTA [444] and Definition LTSM [445] tell us how we can “add” and “scalar multiply”...
two elements of $LT(U, V)$. Theorem SLTLT and Theorem MLTLT tell us that if we do these operations, then the resulting functions are linear transformations that are also in $LT(U, V)$. Hmmmm, sounds like a vector space to me! A set of objects, an addition and a scalar multiplication. Why not?

**Theorem VSLT**

Vector Space of Linear Transformations

Suppose that $U$ and $V$ are vector spaces. Then the set of all linear transformations from $U$ to $V$, $LT(U, V)$ is a vector space when the operations are those given in Definition LTA and Definition LTSM.

**Proof** Theorem SLTLT and Theorem MLTLT provide two of the ten axioms in Definition VS. However, we still need to verify the remaining eight axioms. By and large, the proofs are straightforward and rely on concocting the obvious object, or by reducing the question to the same vector space axiom in the vector space $V$.

The zero vector is of some interest, though. What linear transformation would we add to any other linear transformation, so as to keep the second one unchanged? The answer is $Z: U \mapsto V$ defined by $Z(u) = 0_V$ for every $u \in U$. Notice how we do not need to know any specifics about $U$ and $V$ to make this definition.

**Definition LTC**

Linear Transformation Composition

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are linear transformations. Then the composition of $S$ and $T$ is the function $(S \circ T): U \mapsto W$ whose outputs are defined by

$$(S \circ T)(u) = S(T(u))$$

Given that $T$ and $S$ are linear transformations, it would be nice to know that $S \circ T$ is also a linear transformation.

**Theorem CLTLT**

Composition of Linear Transformations is a Linear Transformation

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are linear transformations. Then $(S \circ T): U \mapsto W$ is a linear transformation.

**Proof** We simply check the defining properties of a linear transformation (Definition LT).
Example CTLT

Composition of two linear transformations

Suppose that \( T: \mathbb{C}^2 \to \mathbb{C}^4 \) and \( S: \mathbb{C}^4 \to \mathbb{C}^3 \) are defined by

\[
T \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) = \begin{bmatrix} x_1 + 2x_2 \\ 3x_1 - 4x_2 \\ 5x_1 + 2x_2 \\ 6x_1 - 3x_2 \end{bmatrix}, \quad S \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 - x_2 + x_3 - x_4 \\ 5x_1 - 3x_2 + 8x_3 - 2x_4 \\ -4x_1 + 3x_2 - 4x_3 + 5x_4 \end{bmatrix}
\]

Then by Definition LTC 446

\[
(S \circ T) \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) = S \left( T \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) \right)
= S \left( \begin{bmatrix} x_1 + 2x_2 \\ 3x_1 - 4x_2 \\ 5x_1 + 2x_2 \\ 6x_1 - 3x_2 \end{bmatrix} \right)
= \begin{bmatrix} 2(x_1 + 2x_2) - (3x_1 - 4x_2) + (5x_1 + 2x_2) - (6x_1 - 3x_2) \\ 5(x_1 + 2x_2) - 3(3x_1 - 4x_2) + 8(5x_1 + 2x_2) - 2(6x_1 - 3x_2) \\ -4(x_1 + 2x_2) + 3(3x_1 - 4x_2) - 4(5x_1 + 2x_2) + 5(6x_1 - 3x_2) \end{bmatrix}
= \begin{bmatrix} -2x_1 + 13x_2 \\ 24x_1 + 44x_2 \\ 15x_1 - 43x_2 \end{bmatrix}
\]

and by Theorem CLT 447 \( S \circ T \) is a linear transformation from \( \mathbb{C}^2 \) to \( \mathbb{C}^3 \).

Here is an interesting exercise that will presage an important result later. In Example STLT 444 compute (via Theorem MLTCV 437) the matrix of \( T \), \( S \) and \( T + S \). Do you see a relationship between these three matrices?

In Example SMLT 446 compute (via Theorem MLTCV 437) the matrix of \( T \) and \( 2T \). Do you see a relationship between these two matrices?

Here’s the tough one. In Example CTLT 447 compute (via Theorem MLTCV 437) the matrix of \( T \), \( S \) and \( S \circ T \). Do you see a relationship between these three matrices???

Subsection READ

Reading Questions

1. Is the function below a linear transformation? Why or why not?

\[
T: \mathbb{C}^3 \to \mathbb{C}^2, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 3x_1 - x_2 + x_3 \\ 8x_2 - 6 \end{bmatrix}
\]

2. Determine the matrix representation of the linear transformation \( S \) below.

\[
S: \mathbb{C}^2 \to \mathbb{C}^3, \quad S \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) = \begin{bmatrix} 3x_1 + 5x_2 \\ 8x_1 - 3x_2 \\ -4x_1 \end{bmatrix}
\]
3. **Theorem LTLC** [439] has a fairly simple proof. Yet the result itself is very powerful. Comment on why we might say this.
Subsection EXC
Exercises

C15 The archetypes below are all linear transformations whose domains and codomains
are vector spaces of column vectors (Definition VSCV [87]). For each one, compute the
matrix representation described in the proof of Theorem MLTCV [437].

Archetype M 617
Archetype N 620
Archetype O 622
Archetype P 625
Archetype Q 627
Archetype R 631
Contributed by Robert Beezer

C20 Let \( w = \begin{bmatrix} -3 \\ 1 \\ 4 \end{bmatrix} \). Referring to Example MOLT [438], compute \( S(w) \) two different
ways. First use the definition of \( S \), then compute the matrix-vector product \( Cw \) (Defi-
nition MVP [187]).
Contributed by Robert Beezer Solution 451

C25 Define the linear transformation
\[
T: \mathbb{C}^3 \rightarrow \mathbb{C}^2, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{pmatrix}
\]
Verify that \( T \) is a linear transformation.
Contributed by Robert Beezer Solution 451

C30 Define the linear transformation
\[
T: \mathbb{C}^3 \rightarrow \mathbb{C}^2, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{pmatrix}
\]
Compute the preimages, \( T^{-1} \left( \begin{bmatrix} 2 \\ 3 \end{bmatrix} \right) \) and \( T^{-1} \left( \begin{bmatrix} 4 \\ -8 \end{bmatrix} \right) \).
Contributed by Robert Beezer Solution 451

M10 Define two linear transformations, \( T: \mathbb{C}^4 \rightarrow \mathbb{C}^3 \) and \( S: \mathbb{C}^3 \rightarrow \mathbb{C}^2 \) by
\[
S \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} x_1 - 2x_2 + 3x_3 \\ 5x_1 + 4x_2 + 2x_3 \end{pmatrix}, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} -x_1 + 3x_2 + x_3 + 9x_4 \\ 2x_1 + x_3 + 7x_4 \\ 4x_1 + 2x_2 + x_3 + 2x_4 \end{pmatrix}
\]
Using the proof of Theorem MLTCV [437] compute the matrix representations of the
three linear transformations \( T, S \) and \( S \circ T \). Discover and comment on the relationship
between these three matrices.
Contributed by Robert Beezer Solution 451

Version 0.52
In both cases the result will be $S(w) = \begin{bmatrix} 9 \\ 2 \\ -9 \\ 4 \end{bmatrix}$.

We can rewrite $T$ as follows:

$$T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} \begin{bmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{bmatrix} \right) = x_1 \begin{bmatrix} 2 \\ -4 \end{bmatrix} + x_2 \begin{bmatrix} -1 \\ 2 \end{bmatrix} + x_3 \begin{bmatrix} 5 \\ -10 \end{bmatrix} = \begin{bmatrix} 2 & -1 & 5 \\ -4 & 2 & -10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

and Theorem MBLT [435] tell us that any function of this form is a linear transformation.

For the first pre-image, we want $x \in \mathbb{C}^3$ such that $T(x) = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$. This becomes,

$$\begin{bmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$$

Vector equality gives a system of two linear equations in three variables, represented by the augmented matrix

$$\begin{bmatrix} 2 & -1 & 5 & 2 \\ -4 & 2 & -10 & 3 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & -\frac{1}{2} & \frac{5}{2} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

so the system is inconsistent and the pre-image is the empty set. For the second pre-image the same procedure leads to an augmented matrix with a different vector of constants

$$\begin{bmatrix} 2 & -1 & 5 & 4 \\ -4 & 2 & -10 & -8 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & -\frac{1}{2} & \frac{5}{2} & 2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

We begin with just one solution to this system, $x = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}$, obtained by setting the two free variables ($x_2$ and $x_3$) both to zero. Then we apply Theorem KPI [459] to the non-empty pre-image to get

$$T^{-1} \left( \begin{bmatrix} 4 \\ -8 \end{bmatrix} \right) = x + \mathcal{K}(T) = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix} + S\rho \left( \left\{ \begin{bmatrix} -\frac{5}{2} \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} \frac{1}{2} \\ 1 \\ 0 \end{bmatrix} \right\} \right)$$

We have

$$\begin{bmatrix} 1 & -2 & 3 \\ 5 & 4 & 2 \end{bmatrix} \begin{bmatrix} -1 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 7 \\ 9 \\ 2 \\ 1 \end{bmatrix}$$
Section ILT
Injective Linear Transformations

Linear transformations have two key properties, which go by the names injective and surjective. We will see that they are closely related to ideas like linear independence and spanning, and subspaces like the null space and the column space. In this section we will define an injective linear transformation and analyze the resulting consequences. The next section will do the same for the surjective property. In the final section of this chapter we will see what happens when we have the two properties simultaneously.

As usual, we lead with a definition.

Definition ILT
Injective Linear Transformation
Suppose $T: U \mapsto V$ is a linear transformation. Then $T$ is injective if whenever $T(x) = T(y)$, then $x = y$.

Given an arbitrary function, it is possible for two different inputs to yield the same output (think about the function $f(x) = x^2$ and the inputs $x = 3$ and $x = -3$). For an injective function, this never happens. If we have equal outputs ($T(x) = T(y)$) then we must have achieved those equal outputs by employing equal inputs ($x = y$). Some authors prefer the term one-to-one where we use injective, and we will sometimes refer to an injective linear transformation as an injection.

Subsection EILT
Examples of Injective Linear Transformations

It is perhaps most instructive to examine a linear transformation that is not injective first.

Example NIAQ
Not injective, Archetype Q

Archetype Q [627] is the linear transformation $T: \mathbb{C}^5 \mapsto \mathbb{C}^5, T\left(\begin{array}{c} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{array}\right) = \left(\begin{array}{c} -2x_1 + 3x_2 + 3x_3 - 6x_4 + 3x_5 \\ -16x_1 + 9x_2 + 12x_3 - 28x_4 + 28x_5 \\ -19x_1 + 7x_2 + 14x_3 - 32x_4 + 37x_5 \\ -21x_1 + 9x_2 + 15x_3 - 35x_4 + 39x_5 \\ -9x_1 + 5x_2 + 7x_3 - 16x_4 + 16x_5 \end{array}\right)$

Notice that for

$x = \left(\begin{array}{c} 1 \\ 3 \\ -1 \\ 2 \\ 4 \end{array}\right)$

$y = \left(\begin{array}{c} 4 \\ 7 \\ 0 \\ 5 \\ 7 \end{array}\right)$
we have

\[
T \begin{pmatrix} 1 \\ 3 \\ -1 \\ 2 \\ 4 \end{pmatrix} = \begin{pmatrix} 4 \\ 55 \\ 72 \\ 77 \\ 31 \end{pmatrix} \quad T \begin{pmatrix} 4 \\ 7 \\ 0 \\ 5 \\ 7 \end{pmatrix} = \begin{pmatrix} 4 \\ 55 \\ 72 \\ 77 \\ 31 \end{pmatrix}
\]

So we have two vectors from the domain, \(\mathbf{x} \neq \mathbf{y}\), yet \(T(\mathbf{x}) = T(\mathbf{y})\), in violation of Definition ILT [453]. This is another example where you should not concern yourself with how \(\mathbf{x}\) and \(\mathbf{y}\) were selected, as this will be explained shortly. However, do understand why these two vectors provide enough evidence to conclude that \(T\) is not injective.

To show that a linear transformation is not injective, it is enough to find a single pair of inputs that get sent to the identical output, as in Example NIAQ [453]. However, to show that a linear transformation is injective we must establish that this coincidence of outputs never occurs. Here is an example that shows how to establish this.

**Example IAR**

**Injective, Archetype R**

Archetype R [631] is the linear transformation

\[
T : \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} -65x_1 + 128x_2 + 10x_3 - 262x_4 + 40x_5 \\ 36x_1 - 73x_2 - x_3 + 151x_4 - 16x_5 \\ -44x_1 + 88x_2 + 5x_3 - 180x_4 + 24x_5 \\ 34x_1 - 68x_2 - 3x_3 + 140x_4 - 18x_5 \\ 12x_1 - 24x_2 - x_3 + 49x_4 - 5x_5 \end{pmatrix}
\]
To establish that $R$ is injective we must begin with the assumption that $T(x) = T(y)$ and somehow arrive from this at the conclusion that $x = y$. Here we go,

$$T(x) = T(y) \quad \Rightarrow \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \right) = \left( \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix} \right) = \begin{bmatrix} -65x_1 + 128x_2 + 10x_3 - 262x_4 + 40x_5 \\ 36x_1 - 73x_2 - x_3 + 151x_4 - 16x_5 \\ -44x_1 + 88x_2 + 5x_3 - 180x_4 + 24x_5 \\ 34x_1 - 68x_2 - 3x_3 + 140x_4 - 18x_5 \\ 12x_1 - 24x_2 - x_3 + 49x_4 - 5x_5 \end{bmatrix} = \begin{bmatrix} -65y_1 + 128y_2 + 10y_3 - 262y_4 + 40y_5 \\ 36y_1 - 73y_2 - y_3 + 151y_4 - 16y_5 \\ -44y_1 + 88y_2 + 5y_3 - 180y_4 + 24y_5 \\ 34y_1 - 68y_2 - 3y_3 + 140y_4 - 18y_5 \\ 12y_1 - 24y_2 - y_3 + 49y_4 - 5y_5 \end{bmatrix}$$

Now we recognize that we have a homogeneous system of 5 equations in 5 variables (the terms $x_i - y_i$ are the variables), so we row-reduce the coefficient matrix to

$$\begin{bmatrix} -65 & 128 & -10 & -262 & 40 \\ 36 & -73 & -1 & 151 & -16 \\ -44 & 88 & 5 & -180 & 24 \\ 34 & -68 & -3 & 140 & -18 \\ 12 & -24 & -1 & 49 & -5 \end{bmatrix} \begin{bmatrix} x_1 - y_1 \\ x_2 - y_2 \\ x_3 - y_3 \\ x_4 - y_4 \\ x_5 - y_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

So the only solution is the trivial solution

$$x_1 - y_1 = 0 \quad x_2 - y_2 = 0 \quad x_3 - y_3 = 0 \quad x_4 - y_4 = 0 \quad x_5 - y_5 = 0$$

and we conclude that indeed $x = y$. By Definition [ILT 453], $T$ is injective. 

Let’s now examine an injective linear transformation between abstract vector spaces.

Example IAV
Injective, Archetype V
Archetype V is defined by
\[ T: P_3 \mapsto M_{22}, \quad T(a + bx + cx^2 + dx^3) = \begin{bmatrix} a+b & a-2c \\ d & b-d \end{bmatrix} \]

To establish that the linear transformation is injective, begin by supposing that two polynomial inputs yield the same output matrix,
\[ T(a_1 + b_1 x + c_1 x^2 + d_1 x^3) = T(a_2 + b_2 x + c_2 x^2 + d_2 x^3) \]

Then
\[ \mathcal{O} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = T(a_1 + b_1 x + c_1 x^2 + d_1 x^3) - T(a_2 + b_2 x + c_2 x^2 + d_2 x^3) \quad \text{Hypothesis} \\
= T((a_1 + b_1 x + c_1 x^2 + d_1 x^3) - (a_2 + b_2 x + c_2 x^2 + d_2 x^3)) \quad \text{Definition LT} \]
\[ = T((a_1 - a_2) + (b_1 - b_2)x + (c_1 - c_2)x^2 + (d_1 - d_2)x^3) \quad \text{Operations in } P_3 \\
= \begin{bmatrix} (a_1 - a_2) + (b_1 - b_2) & (a_1 - a_2) - 2(c_1 - c_2) \\ (d_1 - d_2) & (b_1 - b_2) - (d_1 - d_2) \end{bmatrix} \quad \text{Definition of } T \\
\]

This single matrix equality translates to the homogeneous system of equations in the variables \( a_i - b_i \),
\[
\begin{align*}
(a_1 - a_2) + (b_1 - b_2) &= 0 \\
(a_1 - a_2) - 2(c_1 - c_2) &= 0 \\
(d_1 - d_2) &= 0 \\
(b_1 - b_2) - (d_1 - d_2) &= 0
\end{align*}
\]

This system of equations can be rewritten as the matrix equation
\[
\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & -2 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} (a_1 - a_2) \\ (b_1 - b_2) \\ (c_1 - c_2) \\ (d_1 - d_2) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}
\]

Since the coefficient matrix is nonsingular (check this) the only solution is trivial, i.e.
\[
\begin{align*}
a_1 - a_2 &= 0 \\
b_1 - b_2 &= 0 \\
c_1 - c_2 &= 0 \\
d_1 - d_2 &= 0
\end{align*}
\]
so that
\[
\begin{align*}
a_1 &= a_2 \\
b_1 &= b_2 \\
c_1 &= c_2 \\
d_1 &= d_2
\end{align*}
\]
so the two inputs must be equal polynomials. By Definition ILT, \( T \) is injective. ⊓⊔

Subsection KLT
Kernel of a Linear Transformation

For a linear transformation \( T: U \mapsto V \), the kernel is a subset of the domain \( U \). Informally, it is the set of all inputs that the transformation sends to the zero vector of the codomain.
It will have some natural connections with the null space of a matrix, so we will keep the same notation, and if you think about your objects, then there should be little confusion. Here’s the careful definition.

**Definition KLT**

*Kernel of a Linear Transformation*

Suppose $T: U \mapsto V$ is a linear transformation. Then the kernel of $T$ is the set $\mathcal{K}(T) = \{ u \in U \mid T(u) = 0 \}$.

Notice that the kernel of $T$ is just the preimage of 0, $T^{-1}(0)$ (Definition PI [442]). Here’s an example.

**Example NKAO**

*Nontrivial kernel, Archetype O*

Archetype O [622] is the linear transformation

$T: \mathbb{C}^3 \mapsto \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} -x_1 + x_2 - 3x_3 \\ -x_1 + 2x_2 - 4x_3 \\ x_1 + x_2 + x_3 \\ 2x_1 + 3x_2 + x_3 \\ x_1 + 2x_3 \end{bmatrix}$

To determine the elements of $\mathbb{C}^3$ in $\mathcal{K}(T)$, find those vectors $u$ such that $T(u) = 0$, that is,

$T(u) = 0$

\[
\begin{bmatrix}
-u_1 + u_2 - 3u_3 \\
-u_1 + 2u_2 - 4u_3 \\
u_1 + u_2 + u_3 \\
2u_1 + 3u_2 + u_3 \\
u_1 + 2u_3
\end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}
\]

Vector equality (Definition CVE [88]) leads us to a homogeneous system of 5 equations in the variables $u_i$,

\[-u_1 + u_2 - 3u_3 = 0 \]
\[-u_1 + 2u_2 - 4u_3 = 0 \]
\[u_1 + u_2 + u_3 = 0 \]
\[2u_1 + 3u_2 + u_3 = 0 \]
\[u_1 + 2u_3 = 0 \]

Row-reducing the coefficient matrix gives

\[
\begin{bmatrix} 1 & 0 & 2 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

Version 0.52
The kernel of \( T \) is the set of solutions to this homogeneous system of equations, which by \textbf{Theorem BNS} 141 can be expressed as
\[
\mathcal{K}(T) = \mathcal{S}_p \left\{ \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix} \right\}
\]

We know that the span of a set of vectors is always a subspace (\textbf{Theorem SSS} 298), so the kernel computed in \textbf{Example NKAO} 457 is also a subspace. This is no accident, the kernel of a linear transformation is \textit{always} a subspace.

\textbf{Theorem KLTS}

\textbf{Kernel of a Linear Transformation is a Subspace}

Suppose that \( T : U \rightarrow V \) is a linear transformation. Then the kernel of \( T \), \( \mathcal{K}(T) \), is a subspace of \( U \).

\textbf{Proof} We can apply the three-part test of \textbf{Theorem TSS} 293. First \( T(0_U) = 0_V \) by \textbf{Theorem LTTZZ} 433, so \( 0_U \in \mathcal{K}(T) \) and we know that the kernel is non-empty.

Suppose we assume that \( x, y \in \mathcal{K}(T) \). Is \( x + y \in \mathcal{N}(T) \)?

\[
T(x + y) = T(x) + T(y) = 0 + 0 = 0
\]

This qualifies \( x + y \) for membership in \( \mathcal{K}(T) \). So we have additive closure.

Suppose we assume that \( \alpha \in \mathbb{C} \) and \( x \in \mathcal{K}(T) \). Is \( \alpha x \in \mathcal{K}(T) \)?

\[
T(\alpha x) = \alpha T(x) = \alpha 0 = 0
\]

This qualifies \( \alpha x \) for membership in \( \mathcal{K}(T) \). So we have scalar closure and \textbf{Theorem TSS} 293 tells us that \( \mathcal{N}(T) \) is a subspace of \( U \).

Let’s compute another kernel, now that we know in advance that it will be a subspace.

\textbf{Example TKAP}

\textbf{Trivial kernel, Archetype P}

\textbf{Archetype P} 625 is the linear transformation

\[
T : \mathbb{C}^3 \rightarrow \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} -x_1 + x_2 + x_3 \\ -x_1 + 2x_2 + 2x_3 \\ x_1 + x_2 + 3x_3 \\ 2x_1 + 3x_2 + x_3 \\ -2x_1 + x_2 + 3x_3 \end{bmatrix}
\]

To determine the elements of \( \mathbb{C}^3 \) in \( \mathcal{K}(T) \), find those vectors \( u \) such that \( T(u) = 0 \), that is,

\[
T(u) = 0
\]

\[
\begin{bmatrix} -u_1 + u_2 + u_3 \\ -u_1 + 2u_2 + 2u_3 \\ u_1 + u_2 + 3u_3 \\ 2u_1 + 3u_2 + u_3 \\ -2u_1 + u_2 + 3u_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}
\]
Vector equality (Definition CVE [88]) leads us to a homogeneous system of 5 equations in the variables $u_i$,

\begin{align*}
-u_1 + u_2 + u_3 &= 0 \\
-u_1 + 2u_2 + 2u_3 &= 0 \\
u_1 + u_2 + 3u_3 &= 0 \\
2u_1 + 3u_2 + u_3 &= 0 \\
-2u_1 + u_2 + 3u_3 &= 0
\end{align*}

Row-reducing the coefficient matrix gives

\[
\begin{pmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{pmatrix}
\]

The kernel of $T$ is the set of solutions to this homogeneous system of equations, which is simply the trivial solution $u = 0$, so

$\mathcal{K}(T) = \{0\} = \mathcal{S}p(\{\})$  \(\circ\)

Our next theorem says that if a preimage is a non-empty set then we can construct it by picking any one element and adding on elements of the kernel.

**Theorem KPI**

**Kernel and Pre-Image**

Suppose $T: U \rightarrow V$ is a linear transformation and $v \in V$. If the preimage $T^{-1}(v)$ is non-empty, and $u \in T^{-1}(v)$ then

$T^{-1}(v) = \{u + z | z \in \mathcal{K}(T)\} = u + \mathcal{K}(T)$  \(\square\)

**Proof** Let $M = \{u + z | z \in \mathcal{K}(T)\}$. First, we show that $M \subseteq T^{-1}(v)$. Suppose that $w \in M$, so $w$ has the form $w = u + z$, where $z \in \mathcal{K}(T)$. Then

\[
T(w) = T(u + z) \\
= T(u) + T(z) \quad \text{Definition LT [429]} \\
= v + 0 \quad \text{u} \in T^{-1}(v), \ z \in \mathcal{K}(T) \\
= v \quad \text{Property Z [276]}
\]

which qualifies $w$ for membership in the preimage of $v$, $w \in T^{-1}(v)$.

For the opposite inclusion, suppose $x \in T^{-1}(v)$. Then,

\[
T(x - u) = T(x) - T(u) \quad \text{Definition LT [429]} \\
= v - v \quad x, u \in T^{-1}(v) \\
= 0
\]

This qualifies $x - u$ for membership in the kernel of $T$, $\mathcal{K}(T)$. So there is a vector $z \in \mathcal{K}(T)$ such that $x - u = z$. Rearranging this equation gives $x = u + z$ and so $x \in M$. So $T^{-1}(v) \subseteq M$ and we see that $M = T^{-1}(v)$, as desired.  \(\blacksquare\)
This theorem, and its proof, should remind you very much of Theorem PSPHS \[199\]. Additionally, you might go back and review Example SPIAS \[442\]. Can you now tell which is the only preimage to be a subspace?

The next theorem is one we will cite frequently, as it characterizes injections by the size of the kernel.

**Theorem KILT**

**Kernel of an Injective Linear Transformation**

Suppose that $T: U \rightarrow V$ is a linear transformation. Then $T$ is injective if and only if the kernel of $T$ is trivial, $\mathcal{K}(T) = \{0\}$.

**Proof** ($\Rightarrow$) Suppose $x \in \mathcal{K}(T)$. Then by Definition KLT \[457\], $T(x) = 0$. By Theorem LTTZZ \[433\], $T(0) = 0$. Now, since $T(x) = T(0)$, we can apply Definition ILT \[453\] to conclude that $x = 0$. Therefore $\mathcal{K}(T) = \{0\}$.

($\Leftarrow$) To establish that $T$ is injective, appeal to Definition ILT \[453\] and begin with the assumption that $T(x) = T(y)$. Then

$$0 = T(x) - T(y) = T(x - y)$$

so by Definition KLT \[457\] and the hypothesis that the kernel is trivial,

$$x - y \in \mathcal{K}(T) = \{0\}$$

which means that

$$0 = x - y$$

$$x = y$$

thus establishing that $T$ is injective.

**Example NIAQR**

**Not injective, Archetype Q, revisited**

We are now in a position to revisit our first example in this section, Example NIAQ \[453\]. In that example, we showed that Archetype Q \[627\] is not injective by constructing two vectors, which when used to evaluate the linear transformation provided the same output, thus violating Definition ILT \[453\]. Just where did those two vectors come from?

The key is the vector

$$z = \begin{bmatrix} 3 \\ 4 \\ 1 \\ 3 \\ 3 \end{bmatrix}$$

which you can check is an element of $\mathcal{K}(T)$ for Archetype Q \[627\]. Choose a vector $x$ at random, and then compute $y = x + z$ (verify this computation back in Example NIAQ \[453\]). Then

$$T(y) = T(x + z) = T(x) + T(z) = T(x) + 0 = T(x)$$

Version 0.52
Whenever the kernel of a linear transformation is non-trivial, we can employ this device and conclude that the linear transformation is not injective. This is another way of viewing Theorem KILT [460]. For an injective linear transformation, the kernel is trivial and our only choice for $z$ is the zero vector, which will not help us create two different inputs for $T$ that yield identical outputs. For every one of the archetypes that is not injective, there is an example presented of exactly this form.

Example NIAO
Not injective, Archetype O

In Example NKAO [457] the kernel of Archetype O [622] was determined to be

$$S_p \left( \left\{ \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix} \right\} \right)$$

a subspace of $\mathbb{C}^3$ with dimension 1. Since the kernel is not trivial, Theorem KILT [460] tells us that $T$ is not injective.

Example IAP
Injective, Archetype P

In Example TKAP [458] it was shown that the linear transformation in Archetype P [625] has a trivial kernel. So by Theorem KILT [460], $T$ is injective.

Subsection ILTLI
Injective Linear Transformations and Linear Independence

There is a connection between injective linear transformations and linear independent sets that we will make precise in the next two theorems. However, more informally, we can get a feel for this connection when we think about how each property is defined. A set of vectors is linearly independent if the only relation of linear dependence is the trivial one. A linear transformation is injective if the only way two input vectors can produce the same output is if the trivial way, both input vectors are equal.

Theorem ILTLI
Injective Linear Transformations and Linear Independence

Suppose that $T: U \rightarrow V$ is an injective linear transformation and $S = \{u_1, u_2, u_3, \ldots, u_t\}$ is a linearly independent subset of $U$. Then $R = \{T(u_1), T(u_2), T(u_3), \ldots, T(u_t)\}$ is a linearly independent subset of $V$.

**Proof** Begin with a relation of linear dependence on $S$ (Definition RLD [309], Definition LI [309]),

$$a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \ldots + a_tT(u_t) = 0$$

$$T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t) = 0$$

$$a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t \in K(T)$$

$$a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t \in \{0\}$$

$$a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_tu_t = 0$$

*Version 0.52*
Since this is a relation of linear dependence on the linearly independent set $S$, we can conclude that

\[ a_1 = 0 \quad a_2 = 0 \quad a_3 = 0 \quad \ldots \quad a_t = 0 \]

and this establishes that $R$ is a linearly independent set.

**Theorem ILTB**

**Injective Linear Transformations and Bases**

Suppose that $T : U \rightarrow V$ is a linear transformation and $B = \{u_1, u_2, u_3, \ldots, u_m\}$ is a basis of $U$. Then $T$ is injective if and only if $C = \{T(u_1), T(u_2), T(u_3), \ldots, T(u_m)\}$ is a linearly independent subset of $V$.

**Proof** ($\Rightarrow$) Assume $T$ is injective. Since $B$ is a basis, we know $B$ is linearly independent (Definition B [317]). Then Theorem ILTLI [461] says that $C$ is a linearly independent subset of $V$.

($\Leftarrow$) Assume that $C$ is linearly independent. To establish that $T$ is injective, we will show that the kernel of $T$ is trivial (Theorem KILT [460]). Suppose that $u \in K(T)$. As an element of $U$, we can write $u$ as a linear combination of the basis vectors in $B$ (uniquely). So there are are scalars, $a_1, a_2, a_3, \ldots, a_m$, such that

\[ u = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_mu_m \]

Then,

\[ 0 = T(u) \quad u \in K(T) \]

\[ = T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_mu_m) \quad B \text{ spans } U \]

\[ = a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_mT(u_m) \quad \text{Theorem LTLC [439]} \]

This is a relation of linear dependence (Definition RLD [309]) on the linearly independent set $C$, so the scalars are all zero: $a_1 = a_2 = a_3 = \cdots = a_m = 0$. Then

\[ u = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_mu_m \]

\[ = 0u_1 + 0u_2 + 0u_3 + \cdots + 0u_m \quad \text{Theorem ZSSM [283]} \]

\[ = 0 + 0 + 0 + \cdots + 0 \quad \text{Theorem ZSSM [283]} \]

\[ = 0 \quad \text{Property Z [276]} \]

Since $u$ was chosen as an arbitrary vector from $K(T)$, we have $K(T) = \{0\}$ and Theorem KILT [460] tells us that $T$ is injective.

**Subsection ILTD**

**Injective Linear Transformations and Dimension**

**Theorem ILTD**

**Injective Linear Transformations and Dimension**

Suppose that $T : U \rightarrow V$ is an injective linear transformation. Then $\text{dim}(U) \leq \text{dim}(V)$.
Proof Suppose to the contrary that \( m = \dim(U) > \dim(V) = t \). Let \( B \) be a basis of \( U \), which will then contain \( m \) vectors. Apply \( T \) to each element of \( B \) to form a set \( C \) that is a subset of \( V \). By Theorem ILTB, \( C \) is linearly independent and therefore must contain \( m \) distinct vectors. So we have found a set of \( m \) linearly independent vectors in \( V \), a vector space of dimension \( t \), with \( m > t \). However, this contradicts Theorem G, so our assumption is false and \( \dim(U) \leq \dim(V) \). ■

Example NIDAU
Not injective by dimension, Archetype U
The linear transformation in Archetype U is
\[
T: M_{23} \rightarrow \mathbb{C}^4, \quad T \left( \begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix} \right) = \begin{bmatrix} a + 2b + 12c - 3d + e + 6f \\ 2a - b - c + d - 11f \\ a + b + 7c + 2d + e - 3f \\ a + 2b + 12c + 5e - 5f \end{bmatrix}
\]
Since \( \dim(M_{23}) = 6 > 4 = \dim(\mathbb{C}^4) \), \( T \) cannot be injective for then it would violate Theorem ILTD.

Notice that the previous example made no use of the actual formula defining the function. Merely a comparison of the dimensions of the domain and codomain are enough to conclude that the linear transformation is not injective. Archetype M and Archetype N are two more examples of linear transformations that have “big” domains and “small” codomains, resulting in “collisions” of outputs and thus are non-injective linear transformations.

Subsection CILT
Composition of Injective Linear Transformations

In Subsection LT.NLTFO, we saw how to combine linear transformations to build new linear transformations, specifically, how to build the composition of two linear transformations. It will be useful later to know that the composition of injective linear transformations is again injective, so we prove that here.

Theorem CILTI
Composition of Injective Linear Transformations is Injective
Suppose that \( T: U \rightarrow V \) and \( S: V \rightarrow W \) are injective linear transformations. Then \((S \circ T): U \rightarrow W\) is an injective linear transformation. ■

Proof That the composition is a linear transformation was established in Theorem CLTLT, so we need only establish that the composition is injective. Applying Definition ILT, choose \( x, y \) from \( U \). Then
\[
(S \circ T) (x) = (S \circ T) (y) \\
S (T(x)) = S (T(y)) \\
T (x) = T (y) \\
x = y
\]
Definition LTC 446
Definition ILT 453 for \( S \)
Definition ILT 453 for \( T \)
1. Suppose $T: \mathbb{C}^8 \rightarrow \mathbb{C}^5$ is a linear transformation. Why can’t $T$ be injective?

2. Describe the kernel of an injective linear transformation.

3. Theorem KPI [459] should remind you of Theorem PSPHS [199]. Why do we say this?
Subsection EXC
Exercises

C10 Each archetype below is a linear transformation. Compute the kernel for each.
Archetype M 617
Archetype N 620
Archetype O 622
Archetype P 625
Archetype Q 627
Archetype R 631
Archetype S 634
Archetype T 634
Archetype U 634
Archetype V 634
TODO: Check competeness of this list.
Contributed by Robert Beezer

C25 Define the linear transformation
\[ T: \mathbb{C}^3 \rightarrow \mathbb{C}^2, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{bmatrix} \]
Find a basis for the kernel of \( T \), \( \mathcal{K}(T) \). What is the nullity of \( T \), \( n(T) \)? Is \( T \) injective?
Contributed by Robert Beezer

T10 Suppose \( T: U \rightarrow V \) is a linear transformation. For which vectors \( v \in V \) is \( T^{-1}(v) \) a subspace of \( U \)?
Contributed by Robert Beezer

T15 Suppose that that \( T: U \rightarrow V \) and \( S: V \rightarrow W \) are linear transformations. Prove the following relationship between null spaces.
\[ \mathcal{K}(T) \subseteq \mathcal{K}(S \circ T) \]
Contributed by Robert Beezer

Version 0.52
Subsection SOL
Solutions

C25 Contributed by Robert Beezer Statement 465
To find the kernel, we require all \( x \in \mathbb{C}^3 \) such that \( T(x) = 0 \). This condition is
\[
\begin{bmatrix}
2x_1 - x_2 + 5x_3 \\
-4x_1 + 2x_2 - 10x_3
\end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}
\]
This leads to a homogeneous system of two linear equations in three variables, whose coefficient matrix row-reduces to
\[
\begin{bmatrix}
1 & -\frac{1}{2} & 5/2 \\
0 & 2 & 0
\end{bmatrix}
\]
With two free variables, Theorem SSNS 122 and Theorem BNS 141 yields the basis for the null space
\[
\left\{ \begin{bmatrix}
-5/2 \\
0 \\
1
\end{bmatrix}, \begin{bmatrix}
1/2 \\
1 \\
0
\end{bmatrix} \right\}
\]
The basis for the null space has size 2, so \( n(T) = 2 \).
With \( n(T) \neq 0 \), \( \mathcal{K}(T) \neq \{0\} \), so Theorem KILT 460 says \( T \) is not injective.

T15 Contributed by Robert Beezer Statement 465
We are asked to prove that \( \mathcal{K}(T) \) is a subset of \( \mathcal{K}(S \circ T) \). From comments in Technique SE 17, choose \( x \in \mathcal{K}(T) \). Then we know that \( T(x) = 0 \). So
\[
(S \circ T)(x) = S(T(x)) \quad \text{Definition LTC 446}
= S(0) \quad x \in \mathcal{K}(T) \quad \text{Theorem LTTZZ 433}
= 0
\]
This qualifies \( x \) for membership in \( \mathcal{K}(S \circ T) \).
Section SLT
Surjective Linear Transformations

The companion to an injection is a surjection. Surjective linear transformations are closely related to spanning sets and ranges. So as you read this section reflect back on Section ILT [453] and note the parallels and the contrasts. In the next section, Section IVLT [487], we will combine the two properties.

As usual, we lead with a definition.

Definition SLT
Surjective Linear Transformation
Suppose \( T: U \rightarrow V \) is a linear transformation. Then \( T \) is surjective if for every \( v \in V \) there exists a \( u \in U \) so that \( T(u) = v \).

Given an arbitrary function, it is possible for there to be an element of the codomain that is not an output of the function (think about the function \( y = f(x) = x^2 \) and the codomain element \( y = -3 \)). For a surjective function, this never happens. If we choose any element of the codomain \( (v \in V) \) then there must be an input from the domain \( (u \in U) \) which will create the output when used to evaluate the linear transformation \( (T(u) = v) \). Some authors prefer the term onto where we use surjective, and we will sometimes refer to a surjective linear transformation as a surjection.

Subsection ESLT
Examples of Surjective Linear Transformations

It is perhaps most instructive to examine a linear transformation that is not surjective first.

Example NSAQ
Not surjective, Archetype Q
Archetype Q [627] is the linear transformation

\[
T: \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \right) = \begin{bmatrix} -2x_1 + 3x_2 + 3x_3 - 6x_4 + 3x_5 \\ -16x_1 + 9x_2 + 12x_3 - 28x_4 + 28x_5 \\ -19x_1 + 7x_2 + 14x_3 - 32x_4 + 37x_5 \\ -21x_1 + 9x_2 + 15x_3 - 35x_4 + 39x_5 \\ -9x_1 + 5x_2 + 7x_3 - 16x_4 + 16x_5 \end{bmatrix}
\]

We will demonstrate that

\[
v = \begin{bmatrix} -1 \\ 2 \\ 3 \\ -1 \\ 4 \end{bmatrix}
\]
is an unobtainable element of the codomain. Suppose to the contrary that \( u \) is an element of the domain such that \( T(u) = v \). Then

\[
\begin{bmatrix}
-1 \\
2 \\
3 \\
-1 \\
4
\end{bmatrix} = v = T(u) = T
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5
\end{bmatrix}
\]

\[
\begin{bmatrix}
-2u_1 + 3u_2 + 3u_3 - 6u_4 + 3u_5 \\
-16u_1 + 9u_2 + 12u_3 - 28u_4 + 28u_5 \\
-19u_1 + 7u_2 + 14u_3 - 32u_4 + 37u_5 \\
-21u_1 + 9u_2 + 15u_3 - 35u_4 + 39u_5 \\
-9u_1 + 5u_2 + 7u_3 - 16u_4 + 16u_5
\end{bmatrix}
= \begin{bmatrix}
-2 & 3 & 3 & -6 & 3 \\
-16 & 12 & -28 & 28 & \\
-19 & 14 & -32 & 37 & \\
-21 & 15 & -35 & 39 & \\
-9 & 7 & -16 & 16 &
\end{bmatrix}
\begin{bmatrix}
\begin{bmatrix} u_1 \\
u_2 \\
u_3 \\
u_4 \\
u_5 \end{bmatrix}
\end{bmatrix}
\]

Now we recognize the appropriate input vector \( u \) as a solution to a linear system of equations. Form the augmented matrix of the system, and row-reduce to

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & -1 & 0 \\
0 & 1 & 0 & 0 & -\frac{4}{3} & 0 \\
0 & 0 & 1 & 0 & -\frac{1}{3} & 0 \\
0 & 0 & 0 & 1 & -1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

With a leading 1 in the last column, Theorem RCLS 53 tells us the system is inconsistent. From the absence of any solutions we conclude that no such vector \( u \) exists, and by Definition SLT 469, \( T \) is not surjective.

Again, do not concern yourself with how \( v \) was selected, as this will be explained shortly. However, do understand why this vector provides enough evidence to conclude that \( T \) is not surjective. 

To show that a linear transformation is not surjective, it is enough to find a single element of the codomain that is never created by any input, as in Example NSAQ 469. However, to show that a linear transformation is surjective we must establish that every element of the codomain occurs as an output of the linear transformation for some appropriate input.

Example SAR
Surjective, Archetype R
Archetype R 631 is the linear transformation

\[
T: \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \right) = \begin{bmatrix} -65x_1 + 128x_2 + 10x_3 - 262x_4 + 40x_5 \\
36x_1 - 73x_2 - x_3 + 151x_4 - 16x_5 \\
-44x_1 + 88x_2 + 5x_3 - 180x_4 + 24x_5 \\
34x_1 - 68x_2 - 3x_3 + 140x_4 - 18x_5 \\
12x_1 - 24x_2 - x_3 + 49x_4 - 5x_5 \end{bmatrix}
\]
To establish that $R$ is surjective we must begin with a totally arbitrary element of the codomain, $\mathbf{v}$ and somehow find an input vector $\mathbf{u}$ such that $T(\mathbf{u}) = \mathbf{v}$. We desire,

$$T(\mathbf{u}) = \mathbf{v}$$

$$\begin{bmatrix}
-65u_1 + 128u_2 + 10u_3 - 262u_4 + 40u_5 \\
36u_1 - 73u_2 - u_3 + 151u_4 - 16u_5 \\
-44u_1 + 88u_2 + 5u_3 - 180u_4 + 24u_5 \\
34u_1 - 68u_2 - 3u_3 + 140u_4 - 18u_5 \\
12u_1 - 24u_2 - u_3 + 49u_4 - 5u_5
\end{bmatrix}
= \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{bmatrix}$$

We recognize this equation as a system of equations in the variables $u_i$, but our vector of constants contains symbols. In general, we would have to row-reduce the augmented matrix by hand, due to the symbolic final column. However, in this particular example, the $5 \times 5$ coefficient matrix is nonsingular and so has an inverse (Theorem NSI [225], Definition MI [208]).

$$\begin{bmatrix}
-65 & 128 & 10 & -262 & 40 \\
36 & -73 & -1 & 151 & -16 \\
-44 & 88 & 5 & -180 & 24 \\
34 & -68 & -3 & 140 & -18 \\
12 & -24 & -1 & 49 & -5
\end{bmatrix}
^{-1}
= \begin{bmatrix}
-47 & 92 & 1 & -181 & -14 \\
27 & -55 & \frac{7}{2} & \frac{221}{4} & 11 \\
-32 & 64 & -1 & -126 & -12 \\
25 & -50 & \frac{3}{2} & \frac{199}{2} & 9 \\
9 & -18 & \frac{1}{2} & \frac{71}{2} & 4
\end{bmatrix}$$

so we find that

$$\begin{bmatrix}
u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5\end{bmatrix}
= \begin{bmatrix}
-47v_1 + 92v_2 + v_3 - 181v_4 - 14v_5 \\
27v_1 - 55v_2 + \frac{7}{2}v_3 + \frac{221}{4}v_4 + 11v_5 \\
-32v_1 + 64v_2 - v_3 - 126v_4 - 12v_5 \\
25v_1 - 50v_2 + \frac{3}{2}v_3 + \frac{199}{2}v_4 + 9v_5 \\
9v_1 - 18v_2 + \frac{1}{2}v_3 + \frac{71}{2}v_4 + 4v_5
\end{bmatrix}$$

This establishes that if we are given any output vector $\mathbf{v}$, we can use its components in this final expression to formulate a vector $\mathbf{u}$ such that $T(\mathbf{u}) = \mathbf{v}$. So by Definition SLT [469] we now know that $T$ is surjective. You might try to verify this condition in its full generality (i.e. evaluate $T$ with this final expression and see if you get $\mathbf{v}$ as the result), or test it more specifically for some numerical vector $\mathbf{v}$.

Let's now examine a surjective linear transformation between abstract vector spaces.

Example SAV

Surjective, Archetype V
Archetype V \[634\] is defined by

\[T : P_3 \mapsto M_{22}, \quad T (a + bx + cx^2 + dx^3) = \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix} \]

To establish that the linear transformation is surjective, begin by choosing an arbitrary output. In this example, we need to choose an arbitrary \(2 \times 2\) matrix, say

\[\mathbf{v} = \begin{bmatrix} x & y \\ z & w \end{bmatrix}\]

and we would like to find an input polynomial

\[\mathbf{u} = a + bx + cx^2 + dx^3\]

so that \(T (\mathbf{u}) = \mathbf{v}\). So we have,

\[
\begin{bmatrix} x & y \\ z & w \end{bmatrix} = T (\mathbf{u}) = T (a + bx + cx^2 + dx^3) = \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix}
\]

Matrix equality leads us to the system of four equations in the four unknowns, \(x, y, z, w\),

\[
\begin{align*}
  a + b &= x \\
  a - 2c &= y \\
  d &= z \\
  b - d &= w
\end{align*}
\]

which can be rewritten as a matrix equation,

\[
\begin{bmatrix}
  1 & 1 & 0 & 0 \\
  1 & 0 & -2 & 0 \\
  0 & 0 & 0 & 1 \\
  0 & 1 & 0 & -1
\end{bmatrix}
\begin{bmatrix}
  a \\
  b \\
  c \\
  d
\end{bmatrix}
= \begin{bmatrix}
  x \\
  y \\
  z \\
  w
\end{bmatrix}
\]

The coefficient matrix is nonsingular, hence it has an inverse,

\[
\begin{bmatrix}
  1 & 1 & 0 & 0 \\
  1 & 0 & -2 & 0 \\
  0 & 0 & 0 & 1 \\
  0 & 1 & 0 & -1
\end{bmatrix}^{-1}
= \begin{bmatrix}
  1 & 0 & -1 & -1 \\
  0 & 0 & 1 & 1 \\
  \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\
  0 & 0 & 1 & 0
\end{bmatrix}
\]

so we have

\[
\begin{bmatrix}
  a \\
  b \\
  c \\
  d
\end{bmatrix}
= \begin{bmatrix}
  1 & 0 & -1 & -1 \\
  0 & 0 & 1 & 1 \\
  \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\
  0 & 0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
  x \\
  y \\
  z \\
  w
\end{bmatrix}
= \begin{bmatrix}
  x - z - w \\
  z + w \\
  \frac{1}{2}(x - y - z - w) \\
  z
\end{bmatrix}
\]
So the input polynomial \( u = (x - z - w) + (z + w)x + \frac{1}{2}(x - y - z - w)x^2 + zx^3 \) will yield the output matrix \( v \), no matter what form \( v \) takes. This means by Definition SLT that \( T \) is surjective. All the same, let’s do a concrete demonstration and evaluate \( T \) with \( u \).

\[
T (u) = T \left( (x - z - w) + (z + w)x + \frac{1}{2}(x - y - z - w)x^2 + zx^3 \right) \\
= \left[ \begin{array}{c} (x - z - w) + (z + w)(x - z - w) - 2 \left( \frac{1}{2}(x - y - z - w) \right) \\ z \\ (z + w) - z \\
\end{array} \right] \\
= \left[ \begin{array}{c} x \\ y \\ z \\ w \\
\end{array} \right] \\
= v
\]

Subsection RLT
Range of a Linear Transformation

For a linear transformation \( T: U \mapsto V \), the range is a subset of the codomain \( V \). Informally, it is the set of all outputs that the transformation creates when fed every possible input from the domain. It will have some natural connections with the range of a matrix, so we will keep the same notation, and if you think about your objects, then there should be little confusion. Here’s the careful definition.

Definition RLT
Range of a Linear Transformation

Suppose \( T: U \mapsto V \) is a linear transformation. Then the range of \( T \) is the set

\[
\mathcal{R}(T) = \{ T(u) \mid u \in U \}
\]

Example RAO
Range, Archetype O

Archetype O 622 is the linear transformation

\[
T: \mathbb{C}^3 \mapsto \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} -x_1 + x_2 - 3x_3 \\ -x_1 + 2x_2 - 4x_3 \\ x_1 + x_2 + x_3 \\ 2x_1 + 3x_2 + x_3 \\ x_1 + 2x_3 \end{bmatrix}
\]
To determine the elements of \( \mathbb{C}^5 \) in \( \mathcal{R}(T) \), find those vectors \( \mathbf{v} \) such that \( T(\mathbf{u}) = \mathbf{v} \) for some \( \mathbf{u} \in \mathbb{C}^3 \),

\[
\mathbf{v} = T(\mathbf{u}) = \begin{bmatrix}
-u_1 + u_2 - 3u_3 \\
-u_1 + 2u_2 - 4u_3 \\
u_1 + u_2 + u_3 \\
2u_1 + 3u_2 + u_3 \\
-u_1 \\
u_1 \\
2u_1 \\
u_1 \\
-1 \\
-1 \\
1 \\
2 \\
1
\end{bmatrix}
\begin{bmatrix}
u_2 \\
2u_2 \\
3u_2 \\
0
\end{bmatrix}
\begin{bmatrix}
-3u_3 \\
-4u_3 \\
u_3 \\
u_3 \\
-3 \\
-4 \\
1 \\
1 \\
1 \\
2
\end{bmatrix}
\]

This says that every output of \( T(\mathbf{v}) \) can be written as a linear combination of the three vectors

\[
\begin{bmatrix}
-1 \\
-1 \\
1 \\
2 \\
1
\end{bmatrix},
\begin{bmatrix}
1 \\
2 \\
1 \\
3 \\
0
\end{bmatrix},
\begin{bmatrix}
-3 \\
-4 \\
1 \\
1 \\
2
\end{bmatrix}
\]

using the scalars \( u_1, u_2, u_3 \). Furthermore, since \( \mathbf{u} \) can be any element of \( \mathbb{C}^3 \), every such linear combination is an output. This means that

\[
\mathcal{R}(T) = S_p \left( \left\{ \begin{bmatrix}
-1 \\
1 \\
2 \\
1
\end{bmatrix}, \begin{bmatrix}
1 \\
2 \\
1 \\
3 \\
0
\end{bmatrix}, \begin{bmatrix}
-3 \\
-4 \\
1 \\
1 \\
2
\end{bmatrix} \right\} \right)
\]

The three vectors in this spanning set for \( \mathcal{R}(T) \) form a linearly dependent set (check this!). So we can find a more economical presentation by any of the various methods from Section CRS [235] and Section FS [255]. We will place the vectors into a matrix as rows, row-reduce, toss out zero rows and appeal to Theorem BRS [245], so we can describe the range of \( T \) with a basis,

\[
\mathcal{R}(T) = S_p \left( \left\{ \begin{bmatrix}
1 \\
0 \\
-3 \\
-7 \\
-2
\end{bmatrix}, \begin{bmatrix}
0 \\
1 \\
2 \\
5 \\
1
\end{bmatrix} \right\} \right)
\]
We know that the span of a set of vectors is always a subspace (Theorem SSS 298), so the range computed in Example RAO 473 is also a subspace. This is no accident, the range of a linear transformation is always a subspace.

**Theorem RLTS**

**Range of a Linear Transformation is a Subspace**

Suppose that $T : U \rightarrow V$ is a linear transformation. Then the range of $T$, $\mathcal{R}(T)$, is a subspace of $V$.

**Proof** We can apply the three-part test of Theorem TSS 293. First, $0_U \in U$ and $T(0_U) = 0_V$ by Theorem LTTZZ 433, so $0_V \in \mathcal{R}(T)$ and we know that the range is non-empty.

Suppose we assume that $x, y \in \mathcal{R}(T)$. Is $x + y \in \mathcal{R}(T)$? If $x, y \in \mathcal{R}(T)$ then we know there are vectors $w, z \in U$ such that $T(w) = x$ and $T(z) = y$. Because $U$ is a vector space, additive closure implies that $w + z \in U$. Then

$$T(w + z) = T(w) + T(z)$$

Definition LT 429

Definition of $w$ and $z$

So we have found an input $(w + z)$ which when fed into $T$ creates $x + y$ as an output. This qualifies $x + y$ for membership in $\mathcal{R}(T)$. So we have additive closure.

Suppose we assume that $\alpha \in \mathbb{C}$ and $x \in \mathcal{R}(T)$. Is $\alpha x \in \mathcal{R}(T)$? If $x \in \mathcal{R}(T)$, then there is a vector $w \in U$ such that $T(w) = x$. Because $U$ is a vector space, scalar closure implies that $\alpha w \in U$. Then

$$T(\alpha w) = \alpha T(w)$$

Definition LT 429

Definition of $w$

So we have found an input $(\alpha w)$ which when fed into $T$ creates $\alpha x$ as an output. This qualifies $\alpha x$ for membership in $\mathcal{R}(T)$. So we have scalar closure and Theorem TSS 293 tells us that $\mathcal{R}(T)$ is a subspace of $V$.

Let’s compute another range, now that we know in advance that it will be a subspace.

**Example FRAN**

**Full range, Archetype N**

Archetype N 620 is the linear transformation

$$T : \mathbb{C}^5 \rightarrow \mathbb{C}^3, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 + x_2 + 3x_3 - 4x_4 + 5x_5 \\ x_1 - 2x_2 + 3x_3 - 9x_4 + 3x_5 \\ 3x_1 + 4x_3 - 6x_4 + 5x_5 \end{bmatrix}$$
To determine the elements of $\mathbb{C}^3$ in $\mathcal{R}(T)$, find those vectors $v$ such that $T(u) = v$ for some $u \in \mathbb{C}^5$,

$$v = T(u) = \begin{bmatrix} 2u_1 + u_2 + 3u_3 - 4u_4 + 5u_5 \\ u_1 - 2u_2 + 3u_3 - 9u_4 + 3u_5 \\ 3u_1 + 4u_3 - 6u_4 + 5u_5 \end{bmatrix} = \begin{bmatrix} u_1 \\ -2u_2 \\ 0 \end{bmatrix} + \begin{bmatrix} 2u_1 \\ u_3 \\ 3u_1 \end{bmatrix} + \begin{bmatrix} -2u_2 \\ 3 \\ 4 \end{bmatrix} + \begin{bmatrix} 3u_1 \\ -9u_4 \\ -6u_4 \end{bmatrix} + \begin{bmatrix} -4u_4 \\ -9 \\ -6 \end{bmatrix} + u_5 \begin{bmatrix} 5 \\ 3 \\ 5 \end{bmatrix}$$

This says that every output of $T(v)$ can be written as a linear combination of the five vectors

$$\begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ -2 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 3 \\ 4 \end{bmatrix}, \begin{bmatrix} -4 \\ -9 \\ -6 \end{bmatrix}, \begin{bmatrix} 5 \\ 3 \\ 5 \end{bmatrix}$$

using the scalars $u_1, u_2, u_3, u_4, u_5$. Furthermore, since $u$ can be any element of $\mathbb{C}^5$, every such linear combination is an output. This means that

$$\mathcal{R}(T) = \mathcal{S}p \left( \left\{ \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ -2 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 3 \\ 4 \end{bmatrix}, \begin{bmatrix} -4 \\ -9 \\ -6 \end{bmatrix}, \begin{bmatrix} 5 \\ 3 \\ 5 \end{bmatrix} \right\} \right)$$

The five vectors in this spanning set for $\mathcal{R}(T)$ form a linearly dependent set (Theorem MVSLD 139). So we can find a more economical presentation by any of the various methods from Section CRS 235 and Section FS 255. We will place the vectors into a matrix as rows, row-reduce, toss out zero rows and appeal to Theorem BRS 245, so we can describe the range of $T$ with a (nice) basis,

$$\mathcal{R}(T) = \mathcal{S}p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \right) = \mathbb{C}^3$$

In contrast to injective linear transformations having small (trivial) kernels (Theorem KILT 460), surjective linear transformations have large ranges, as indicated in the next theorem.

**Theorem RSLT**

**Range of a Surjective Linear Transformation**

Suppose that $T: U \rightarrow V$ is a linear transformation. Then $T$ is surjective if and only if the range of $T$ equals the codomain, $\mathcal{R}(T) = V$.

**Proof** ($\Rightarrow$) By Definition RLT 473, we know that $\mathcal{R}(T) \subseteq V$. To establish the reverse inclusion, assume $v \in V$. Then since $T$ is surjective (Definition SLT 469), there exists a vector $u \in U$ so that $T(u) = v$. However, the existence of $u$ gains $v$ membership in $\mathcal{R}(T)$, so $V \subseteq \mathcal{R}(T)$. Thus, $\mathcal{R}(T) = V$.  

Version 0.52
(⇐) To establish that \( T \) is surjective, choose \( \mathbf{v} \in V \). Since we are assuming that \( R(T) = V \), \( \mathbf{v} \in R(T) \). This says there is a vector \( \mathbf{u} \in U \) so that \( T(\mathbf{u}) = \mathbf{v} \), i.e. \( T \) is surjective.

Example NSAQR

Not surjective, Archetype Q, revisited

We are now in a position to revisit our first example in this section, Example NSAQ \[469\]. In that example, we showed that Archetype Q \[627\] is not surjective by constructing a vector in the codomain where no element of the domain could be used to evaluate the linear transformation to create the output, thus violating Definition SLT \[469\]. Just where did this vector come from?

The short answer is that the vector

\[
\mathbf{v} = \begin{pmatrix} -1 \\ 2 \\ 3 \\ -1 \\ -4 \end{pmatrix}
\]

was constructed to lie outside of the range of \( T \). How was this accomplished? First, the range of \( T \) is given by

\[
R(T) = \text{sp} \left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 2 \end{pmatrix} \right\}
\]

Suppose an element of the range \( \mathbf{v}^* \) has its first 4 components equal to \(-1, 2, 3, -1\), in that order. Then to be an element of \( R(T) \), we would have

\[
\mathbf{v}^* = (-1) \begin{pmatrix} 1 \\ 0 \\ 0 \\ 1 \end{pmatrix} + (2) \begin{pmatrix} 0 \\ 1 \\ 0 \\ -1 \end{pmatrix} + (3) \begin{pmatrix} 0 \\ 0 \\ 1 \\ 2 \end{pmatrix} + (-1) \begin{pmatrix} 0 \\ 0 \\ 0 \\ -1 \end{pmatrix} = \begin{pmatrix} -1 \\ 2 \\ 3 \\ -8 \end{pmatrix}
\]

So the only vector in the range with these first four components specified, must have \(-8\) in the fifth component. To set the fifth component to any other value (say, 4) will result in a vector (\( \mathbf{v} \) in Example NSAQ \[469\]) outside of the range. Any attempt to find an input for \( T \) that will produce \( \mathbf{v} \) as an output will be doomed to failure.

Whenever the range of a linear transformation is not the whole codomain, we can employ this device and conclude that the linear transformation is not surjective. This is another way of viewing Theorem RSLT \[476\]. For a surjective linear transformation, the range is all of the codomain and there is no choice for a vector \( \mathbf{v} \) that lies in \( V \), yet not in the range. For every one of the archetypes that is not surjective, there is an example presented of exactly this form.

Example NSAO

Not surjective, Archetype O
In Example RAO 473 the range of Archetype O 622 was determined to be

\[ \mathcal{R}(T) = \mathcal{S}_{p}\left( \begin{bmatrix} 1 & 0 \\ -3 & 2 \\ -7 & 5 \\ -2 & 1 \end{bmatrix} \right) \]

a subspace of dimension 2 in \( \mathbb{C}^5 \). Since \( \mathcal{R}(T) \neq \mathbb{C}^5 \), Theorem RSLT 476 says \( T \) is not surjective.

Example SAN
Surjective, Archetype N

The range of Archetype N 620 was computed in Example FRAN 475 to be

\[ \mathcal{R}(T) = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \]

Since the basis for this subspace is the set of standard unit vectors for \( \mathbb{C}^3 \) (Theorem SUVB 318), we have \( \mathcal{R}(T) = \mathbb{C}^3 \) and by Theorem RSLT 476, \( T \) is surjective.

Subsection SSSLT
Spanning Sets and Surjective Linear Transformations

Just as injective linear transformations are allied with linear independence (Theorem ILTLI 461, Theorem ILTB 462), surjective linear transformations are allied with spanning sets.

Theorem SSRLT
Spanning Set for Range of a Linear Transformation

Suppose that \( T: U \rightarrow V \) is a linear transformation and \( S = \{u_1, u_2, u_3, \ldots, u_t\} \) spans \( U \). Then \( R = \{T(u_1), T(u_2), T(u_3), \ldots, T(u_t)\} \) spans \( \mathcal{R}(T) \).

Proof We need to establish that every element of \( \mathcal{R}(T) \) can be written as a linear combination of the vectors in \( R \). To this end, choose \( v \in \mathcal{R}(T) \). Then there exists a vector \( u \in U \), such that \( T(u) = v \) (Definition RLT 473).

Because \( S \) spans \( U \) there are scalars, \( a_1, a_2, a_3, \ldots, a_t \), such that

\[ u = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_t u_t \]

Then

\[ v = T(u) \]
\[ = T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_t u_t) \]
\[ = a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_t T(u_t) \]

which establishes that \( R \) spans the range of \( T, \mathcal{R}(T) \).
Theorem SSRLT \[478\] provides an easy way to begin the construction of a basis for the range of a linear transformation, since the construction of a spanning set requires simply evaluating the linear transformation on a spanning set of the domain. In practice the best choice for a spanning set of the domain would be as small as possible, in other words, a basis. The resulting spanning set for the codomain may not be linearly independent, so to find a basis for the range might require tossing out redundant vectors from the spanning set. Here’s an example.

Example BRLT

A basis for the range of a linear transformation

Define the linear transformation

\[ T : M_{22} \rightarrow P_2 \] by

\[ T \begin{bmatrix} a & b \\ c & d \end{bmatrix} = (a + 2b + 8c + d) + (-3a + 2b + 5d)x + (a + b + c)x^2 \]

A convenient spanning set for \( M_{22} \) is the basis

\[ S = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} \]

So by Theorem SSRLT \[478\], a spanning set for \( R(T) \) is

\[ R = \left\{ T \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, T \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, T \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, T \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} = \{ 1 - 3x + x^2, 2 + 2x + x^2, 8 + 5x^2, 1 + 5x \} \]

The set \( R \) is not linearly independent, so if we desire a basis for \( R(T) \), we need to eliminate some redundant vectors. Two particular relations of linear dependence on \( R \) are

\[ (-2)(1 - 3x + x^2) + (-3)(2 + 2x + x^2) + (8 + 5x^2) = 0 + 0x + 0x^2 = 0 \]
\[ (1 - 3x + x^2) + (-1)(2 + 2x + x^2) + (1 + 5x) = 0 + 0x + 0x^2 = 0 \]

These, individually, allow us to remove \( 8 + 5x^2 \) and \( 1 + 5x \) from \( R \) with out destroying the property that \( R \) spans \( R(T) \). The two remaining vectors are linearly independent (check this!), so we can write

\[ R(T) = Sp\left\{ 1 - 3x + x^2, 2 + 2x + x^2 \right\} \]

and see that \( \dim (R(T)) = 2 \). ⊓⊔

Elements of the range are precisely those elements of the codomain with non-empty preimages.

Theorem RPI

Range and Pre-Image

Suppose that \( T : U \rightarrow V \) is a linear transformation. Then

\[ v \in R(T) \text{ if and only if } T^{-1}(v) \neq \emptyset \]
Proof \((\Rightarrow)\) If \(v \in \mathcal{R}(T)\), then there is a vector \(u \in U\) such that \(T(u) = v\). This qualifies \(u\) for membership in \(T^{-1}(v)\), and thus the preimage of \(v\) is not empty.

\((\Leftarrow)\) Suppose the preimage of \(v\) is not empty, so we can choose a vector \(u \in U\) such that \(T(u) = v\). Then \(v \in \mathcal{R}(T)\).

\(-1\)

**Theorem SLTB**

**Surjective Linear Transformations and Bases**

Suppose that \(T : U \rightarrow V\) is a linear transformation and \(B = \{u_1, u_2, u_3, \ldots, u_m\}\) is a basis of \(U\). Then \(T\) is surjective if and only if \(C = \{T(u_1), T(u_2), T(u_3), \ldots, T(u_m)\}\) is a spanning set for \(V\).

Proof \((\Rightarrow)\) Assume \(T\) is surjective. Since \(B\) is a basis, we know \(B\) is a spanning set of \(U\) \(\text{[Definition B [317]]}\). Then Theorem SSRLT \(\text{[478]}\) says that \(C\) spans \(\mathcal{R}(T)\). But the hypothesis that \(T\) is surjective means \(V = \mathcal{R}(T)\) \(\text{[Theorem RSLT [476]]}\), so \(C\) spans \(V\).

\((\Leftarrow)\) Assume that \(C\) spans \(V\). To establish that \(T\) is surjective, we will show that every element of \(V\) is an output of \(T\) for some input \(\text{[Definition SLT [469]]}\). Suppose that \(v \in V\). As an element of \(V\), we can write \(v\) as a linear combination of the spanning set \(C\). So there are are scalars, \(b_1, b_2, b_3, \ldots, b_m\), such that
\[
v = b_1 T(u_1) + b_2 T(u_2) + b_3 T(u_3) + \cdots + b_m T(u_m)
\]
Now define the vector \(u \in U\) by
\[
u = b_1 u_1 + b_2 u_2 + b_3 u_3 + \cdots + b_m u_m
\]
Then
\[
T(u) = T(b_1 u_1 + b_2 u_2 + b_3 u_3 + \cdots + b_m u_m)
\]
\[
= b_1 T(u_1) + b_2 T(u_2) + b_3 T(u_3) + \cdots + b_m T(u_m) \quad \text{Theorem LTLC [439]}
\]
\[
= v
\]
So, given any choice of a vector \(v \in V\), we can design an input \(u \in U\) to produce \(v\) as an output of \(T\). Thus, by \(\text{Definition SLT [469]}\), \(T\) is surjective.

\(-1\)

**Subsection SLTD**

**Surjective Linear Transformations and Dimension**

**Theorem SLTD**

**Surjective Linear Transformations and Dimension**

Suppose that \(T : U \rightarrow V\) is a surjective linear transformation. Then \(\dim(U) \geq \dim(V)\).□

Proof Suppose to the contrary that \(m = \dim(U) < \dim(V) = t\). Let \(B\) be a basis of \(U\), which will then contain \(m\) vectors. Apply \(T\) to each element of \(B\) to form a set \(C\) that is a subset of \(V\). By \(\text{Theorem SLTB [480]}\), \(C\) is spanning set of \(V\) with \(m\) or fewer vectors. So we have a set of \(m\) or fewer vectors that span \(V\), a vector space of dimension \(t\), with \(m < t\). However, this contradicts \(\text{Theorem G [348]}\), so our assumption is false and \(\dim(U) \geq \dim(V)\).
Example NSDAT

Not surjective by dimension, Archetype T

The linear transformation in Archetype T is

\[ T: P_4 \mapsto P_5, \quad T(p(x)) = (x - 2)p(x) \]

Since \( \dim(P_4) = 5 < 6 = \dim(P_5) \), \( T \) cannot be surjective for then it would violate Theorem SLTD.

Notice that the previous example made no use of the actual formula defining the function. Merely a comparison of the dimensions of the domain and codomain are enough to conclude that the linear transformation is not surjective. Archetype O and Archetype P are two more examples of linear transformations that have “small” domains and “big” codomains, resulting in an inability to create all possible outputs and thus they are non-surjective linear transformations.

Subsection CSLT

Composition of Surjective Linear Transformations

In Subsection LT.NLTLT we saw how to combine linear transformations to build new linear transformations, specifically, how to build the composition of two linear transformations (Definition LTC). It will be useful later to know that the composition of surjective linear transformations is again surjective, so we prove that here.

Theorem CSLTS

Composition of Surjective Linear Transformations is Surjective

Suppose that \( T: U \mapsto V \) and \( S: V \mapsto W \) are surjective linear transformations. Then \( (S \circ T): U \mapsto W \) is a surjective linear transformation.

Proof

That the composition is a linear transformation was established in Theorem CLTLT, so we need only establish that the composition is surjective. Applying Definition SLT, choose \( w \in W \).

Because \( S \) is surjective, there must be a vector \( v \in V \), such that \( S(v) = w \). With the existence of \( v \) established, that \( T \) is injective guarantees a vector \( u \in U \) such that \( T(u) = v \). Now,

\[
(S \circ T)(u) = S(T(u)) = S(v) = w
\]

This establishes that any element of the codomain \( w \) can be created by evaluating \( S \circ T \) with the right input \( u \). Thus, by Definition SLT, \( S \circ T \) is surjective.

Subsection READ

Reading Questions

1. Suppose \( T: \mathbb{C}^5 \mapsto \mathbb{C}^8 \) is a linear transformation. Why can’t \( T \) be surjective?
2. What is the relationship between a surjective linear transformation and its range?

3. Compare and contrast injective and surjective linear transformations.
Subsection EXC
Exercises

C10  Each archetype below is a linear transformation. Compute the range for each.

Archetype M 617
Archetype N 620
Archetype O 622
Archetype P 625
Archetype Q 627
Archetype R 631
Archetype S 634
Archetype T 634
Archetype U 634
Archetype V 634

TODO: Check competeness of this list.
Contributed by Robert Beezer

C20  Example SAR 470 concludes with an expression for a vector $u \in \mathbb{C}^5$ that we believe will create the vector $v \in \mathbb{C}^5$ when used to evaluate $T$. That is, $T(u) = v$. Verify this assertion by actually evaluating $T$ with $u$. If you don’t have the patience to push around all these symbols, try choosing a numerical instance of $v$, compute $u$, and then compute $T(u)$, which should result in $v$.

Contributed by Robert Beezer

C25  Define the linear transformation

$$T: \mathbb{C}^3 \rightarrow \mathbb{C}^2, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 - x_2 + 5x_3 \\ -4x_1 + 2x_2 - 10x_3 \end{bmatrix}$$

Find a basis for the range of $T$, $\mathcal{R}(T)$. What is the rank of $T$, $\text{r}(T)$? Is $T$ surjective?

Contributed by Robert Beezer  
Solution 485
To find the range of $T$, apply $T$ to the elements of a spanning set for $\mathbb{C}^3$ as suggested in Theorem SSRLT. We will use the standard basis vectors (Theorem SUVB).

$$R(T) = \mathcal{S}p\left(\{T(e_1), T(e_2), T(e_3)\}\right) = \mathcal{S}p\left(\left\{\begin{bmatrix} 2 \\ -4 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ 5 \end{bmatrix}, \begin{bmatrix} -10 \end{bmatrix}\right\}\right)$$

Each of these vectors is a scalar multiple of the others, so we can toss two of them in reducing the spanning set to a linearly independent set (or be more careful and apply Theorem BCSOC on a matrix with these three vectors as columns). The result is the basis of the range,

$$\left\{\begin{bmatrix} 1 \\ -2 \end{bmatrix}\right\}$$

The basis for the range has size 1, so $r(T) = 1$.

With $r(T) \neq 2$, $R(T) \neq \mathbb{C}^2$, so Theorem RSLT says $T$ is not surjective.
In this section we will conclude our introduction to linear transformations by bringing together the twin properties of injectivity and surjectivity and consider linear transformations with both of these properties.

One preliminary definition, and then we will have our main definition for this section.

Definition IDLT
Identity Linear Transformation
The identity linear transformation on the vector space \( W \) is defined as
\[
I_W : W \mapsto W, \quad I_W(w) = w
\]
Informally, \( I_W \) is the “do-nothing” function. You should check that \( I_W \) is really a linear transformation, as claimed, and then compute its kernel and range to see that it is both injective and surjective. All of these facts should be straightforward to verify. With this in hand we can make our main definition.

Definition IVLT
Invertible Linear Transformations
Suppose that \( T : U \mapsto V \) is a linear transformation. If there is a function \( S : V \mapsto U \) such that
\[
S \circ T = I_U \quad \text{and} \quad T \circ S = I_V
\]
then \( T \) is invertible. In this case, we call \( S \) the inverse of \( T \) and write \( S = T^{-1} \).

Informally, a linear transformation \( T \) is invertible if there is a companion linear transformation, \( S \), which "undoes" the action of \( T \). When the two linear transformations are applied consecutively (composition), in either order, the result is to have no real effect. It is entirely analogous to squaring a positive number and then taking its (positive) square root.

Here is an example of a linear transformation that is invertible. As usual at the beginning of a section, do not be concerned with where \( S \) came from, just understand how it illustrates Definition IVLT.

Example AIVLT
An invertible linear transformation
Archetype V is the linear transformation
\[
T : P_3 \mapsto M_{22}, \quad T(a + bx + cx^2 + dx^3) = \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix}
\]
Define the function $S: M_{22} \mapsto P_3$ defined by

$$S \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) = (a - c - d) + (c + d)x + \frac{1}{2}(a - b - c - d)x^2 + cx^3$$

Then

$$(T \circ S) \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) = T \left( S \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) \right)$$

$$= T \left( (a - c - d) + (c + d)x + \frac{1}{2}(a - b - c - d)x^2 + cx^3 \right)$$

$$= \begin{bmatrix} (a - c - d) + (c + d) & (a - c - d) - 2\left(\frac{1}{2}(a - b - c - d)\right) \\ c & (c + d) - c \end{bmatrix}$$

$$= \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

$$= I_{M_{22}} \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right)$$

And

$$(S \circ T) (a + bx + cx^2 + dx^3) = S \left( T \left( a + bx + cx^2 + dx^3 \right) \right)$$

$$= S \left( \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix} \right)$$

$$= ((a + b) - d - (b - d)) + (d + (b - d))x$$

$$+ \frac{1}{2}((a + b) - (a - 2c) - d - (b - d)) x^2 + (d)x^3$$

$$= a + bx + cx^2 + dx^3$$

$$= I_{P_3} \left( a + bx + cx^2 + dx^3 \right)$$

For now, understand why these computations show that $T$ is invertible, and that $S = T^{-1}$. Maybe even be amazed by how $S$ works so perfectly in concert with $T$! We will see later just how to arrive at the correct form of $S$ (when it is possible).

It can be as instructive to study a linear transformation that is not invertible.

**Example ANILT**

**A non-invertible linear transformation**

Consider the linear transformation $T: \mathbb{C}^3 \mapsto M_{22}$ defined by

$$T \left( \begin{bmatrix} a \\ b \\ c \end{bmatrix} \right) = \begin{bmatrix} a - b & 2a + 2b + c \\ 3a + b + c & -2a - 6b - 2c \end{bmatrix}$$

Suppose we were to search for an inverse function $S: M_{22} \mapsto \mathbb{C}^3$.

First verify that the $2 \times 2$ matrix $A = \begin{bmatrix} 5 & 3 \\ 8 & 2 \end{bmatrix}$ is not in the range of $T$. This will
amount to finding an input to $T$, \[
\begin{bmatrix}
  a \\
  b \\
  c
\end{bmatrix},
\]
such that
\[
\begin{align*}
  a - b &= 5 \\
  2a + 2b + c &= 3 \\
  3a + b + c &= 8 \\
  -2a - 6b - 2c &= 2
\end{align*}
\]
As this system of equations is inconsistent, there is no input column vector, and $A \notin \mathcal{R}(T)$. How should we define $S(A)$? Note that
\[
T(S(A)) = (T \circ S)(A) = I_{M_{22}}(A) = A
\]
So any definition we would provide for $S(A)$ must then be a column vector that $T$ sends to $A$ and we would have $A \in \mathcal{R}(T)$, contrary to the definition of $T$. This is enough to see that there is no function $S$ that will allow us to conclude that $T$ is invertible, since we cannot provide a consistent definition for $S(A)$ if we assume $T$ is invertible.

Even though we now know that $T$ is not invertible, let's not leave this example just yet. Check that
\[
T \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix} = B
\]
How would we define $S(B)$?
\[
S(B) = S \left( T \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix} \right) = (S \circ T) \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix} = I_{C^3} \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix} = \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix}
\]
or
\[
S(B) = S \left( T \begin{bmatrix}
  0 \\
  -3 \\
  8
\end{bmatrix} \right) = (S \circ T) \begin{bmatrix}
  0 \\
  -3 \\
  8
\end{bmatrix} = I_{C^3} \begin{bmatrix}
  0 \\
  -3 \\
  8
\end{bmatrix} = \begin{bmatrix}
  0 \\
  -3 \\
  8
\end{bmatrix}
\]
Which definition should we provide for $S(B)$? Both are necessary. But then $S$ is not a function. So we have a second reason to know that there is no function $S$ that will allow us to conclude that $T$ is invertible. It happens that there are infinitely many column vectors that $S$ would have to take to $B$. Construct the kernel of $T$,
\[
\mathcal{K}(T) = \mathcal{S}_p \left( \left\{ \begin{bmatrix}
  -1 \\
  -1 \\
  4
\end{bmatrix} \right\} \right)
\]
Now choose either of the two inputs used above for $T$ and add to it a scalar multiple of the basis vector for the kernel of $T$. For example,
\[
x = \begin{bmatrix}
  1 \\
  -2 \\
  4
\end{bmatrix} + (-2) \begin{bmatrix}
  -1 \\
  -1 \\
  4
\end{bmatrix} = \begin{bmatrix}
  3 \\
  0 \\
  -4
\end{bmatrix}
\]
then verify that $T(x) = B$. Practice creating a few more inputs for $T$ that would be sent to $B$, and see why it is hopeless to think that we could ever provide a reasonable definition for $S(B)$! There is a “whole subspace’s worth” of values that $S(B)$ would have to take on.

In Example ANILT 488 you may have noticed that $T$ is not surjective, since the matrix $A$ was not in the range of $T$. And $T$ is not injective since there are two different input column vectors that $T$ sends to the matrix $B$. Linear transformations $T$ that are not surjective lead to putative inverse functions $S$ that are undefined on inputs outside of the range of $T$. Linear transformations $T$ that are not injective lead to putative inverse functions $S$ that are multiply-defined on each of their inputs. We will formalize these ideas in Theorem ILTIS 491.

But first notice in Definition IVLT 487 that we only require the inverse (when it exists) to be a function. When it does exist, it too is a linear transformation.

**Theorem ILTLT**

**Inverse of a Linear Transformation is a Linear Transformation**

Suppose that $T : U \mapsto V$ is an invertible linear transformation. Then the function $T^{-1} : V \mapsto U$ is a linear transformation.

**Proof** We work through verifying Definition LT 429 for $T^{-1}$, employing as we go properties of $T$ given by Definition LT 429. To this end, suppose $x, y \in V$ and $\alpha \in \mathbb{C}$.

\[
T^{-1}(x + y) = T^{-1}(T(T^{-1}(x)) + T(T^{-1}(y)))
\]

$T$, $T^{-1}$ inverse functions

\[
= T^{-1}(T(T^{-1}(x) + T^{-1}(y)))
\]

$T$ a linear transformation

\[
= T^{-1}(x) + T^{-1}(y)
\]

$T^{-1}$, $T$ inverse functions

Now check the second defining property of a linear transformation for $T^{-1}$,

\[
T^{-1}(\alpha x) = T^{-1}(\alpha T(T^{-1}(x)))
\]

$T$, $T^{-1}$ inverse functions

\[
= T^{-1}(T(\alpha T^{-1}(x)))
\]

$T$ a linear transformation

\[
= \alpha T^{-1}(x)
\]

$T^{-1}$, $T$ inverse functions

So $T^{-1}$ fulfills the requirements of Definition LT 429 and is therefore a linear transformation. So when $T$ has an inverse, $T^{-1}$ is also a linear transformation. Additionally, $T^{-1}$ is invertible and its inverse is what you might expect.

**Theorem IILT**

**Inverse of an Invertible Linear Transformation**

Suppose that $T : U \mapsto V$ is an invertible linear transformation. Then $T^{-1}$ is an invertible linear transformation and $(T^{-1})^{-1} = T$.

**Proof** Because $T$ is invertible, Definition IVLT 487 tells us there is a function $T^{-1} : V \mapsto U$ such that

\[
T^{-1} \circ T = I_U
\]

$T \circ T^{-1} = I_V$

Additionally, Theorem ILTLT 490 tells us that $T^{-1}$ is more than just a function, it is a linear transformation. Now view these two statements as properties of the linear transformation $T^{-1}$. In light of Definition IVLT 487, they together say that $T^{-1}$ is invertible (let $T$ play the role of $S$ in the statement of the definition). Furthermore, the inverse of $T^{-1}$ is then $T$, i.e. $(T^{-1})^{-1} = T$. ■
Subsection IV
Invertibility

We now know what an inverse linear transformation is, but just which linear transformations have inverses? Here is a theorem we have been preparing for all chapter.

Theorem ILTIS
Invertible Linear Transformations are Injective and Surjective
Suppose \( T: U \rightarrow V \) is a linear transformation. Then \( T \) is invertible if and only if \( T \) is injective and surjective.

Proof (\( \Rightarrow \)) Since \( T \) is presumed invertible, we can employ its inverse, \( T^{-1} \) (Definition IVLT 487). To see that \( T \) is injective, suppose \( x, y \in U \) and assume that \( T(x) = T(y) \),

\[
\begin{align*}
x &= I_U(x) \\
&= (T^{-1} \circ T)(x) & \text{Definition IVLT 487} \\
&= T^{-1}(T(x)) & \text{Definition LTC 446} \\
&= T^{-1}(T(y)) & \text{Definition ILT 453} \\
&= (T^{-1} \circ T)(y) & \text{Definition LTC 446} \\
&= I_U(y) & \text{Definition IVLT 487} \\
&= y & \text{Definition IDLT 487}
\end{align*}
\]

So by Definition ILT 453, \( T \) is injective. To check that \( T \) is surjective, suppose \( v \in V \). Employ \( T^{-1} \) again by defining \( u = T^{-1}(v) \). Then

\[
\begin{align*}
T(u) &= T(T^{-1}(v)) & \text{Substitution for } u \\
&= (T \circ T^{-1})(v) & \text{Definition LTC 446} \\
&= I_V(v) & \text{\( T, T^{-1} \) inverse functions} \\
&= v & \text{Definition IDLT 487}
\end{align*}
\]

So there is an input to \( T, u \), that produces the chosen output, \( v \), and hence \( T \) is surjective by Definition SLT 469.

(\( \Leftarrow \)) Now assume that \( T \) is both injective and surjective. We will build a function \( S: V \rightarrow U \) that will establish that \( T \) is invertible. To this end, choose any \( v \in V \). Since \( T \) is surjective, Theorem RSLT 476 says \( \mathcal{R}(T) = V \), so we have \( v \in \mathcal{R}(T) \). Theorem RPI 479 says that the pre-image of \( v \), \( T^{-1}(v) \), is nonempty. So we can choose a vector from the pre-image of \( v \), say \( u \). In other words, there exists \( u \in T^{-1}(v) \).

Since \( T^{-1}(v) \) is non-empty, Theorem KPI 459 then says that

\[
T^{-1}(v) = \{ u + z \mid z \in \mathcal{K}(T) \}
\]

However, because \( T \) is injective, by Theorem KILT 460 the kernel is trivial, \( \mathcal{K}(T) = \{0\} \). So the pre-image is a set with just one element, \( T^{-1}(v) = \{u\} \). Now we can define \( S \) by \( S(v) = u \). This is the key to this half of this proof. Normally the preimage of a vector from the codomain might be an empty set, or an infinite set. But surjectivity requires
that the preimage not be empty, and then injectivity limits the preimage to a singleton. Since our choice of \( v \) was arbitrary, we know that every pre-image for \( T \) is a set with a single element. This allows us to construct \( S \) as a function. Now that it is defined, verifying that it is the inverse of \( T \) will be easy. Here we go.

Choose \( u \in U \). Define \( v = T(u) \). Then \( T^{-1}(v) = \{u\} \), so that \( S(v) = u \) and,

\[
(S \circ T)(u) = S(T(u)) = S(v) = u = I_U(u)
\]

and since our choice of \( u \) was arbitrary we have function equality, \( S \circ T = I_U \).

Now choose \( v \in V \). Define \( u \) to be the single vector in the set \( T^{-1}(v) \), in other words, \( u = S(v) \). Then \( T(u) = v \), so

\[
(T \circ S)(v) = T(S(v)) = T(u) = v = I_V(v)
\]

and since our choice of \( v \) was arbitrary we have function equality, \( T \circ S = I_V \).

We will make frequent use of this characterization of invertible linear transformations. The next theorem is a good example of this, and we will use it often, too.

**Theorem CIVLT**

**Composition of Invertible Linear Transformations**

Suppose that \( T: U \rightarrow V \) and \( S: V \rightarrow W \) are invertible linear transformations. Then the composition, \((S \circ T): U \rightarrow W\) is an invertible linear transformation.

**Proof** Since \( S \) and \( T \) are both linear transformations, \( S \circ T \) is also a linear transformation by Theorem CLTILT \[447\]. Since \( S \) and \( T \) are both invertible, Theorem ILTIS \[491\] says that \( S \) and \( T \) are both injective and surjective. Then Theorem CILTI \[463\] says \( S \circ T \) is injective, and Theorem CSLTS \[481\] says \( S \circ T \) is surjective. Now apply the “other half” of Theorem ILTIS \[491\] and conclude that \( S \circ T \) is invertible.

When a composition is invertible, the inverse is easy to construct.

**Theorem ICLT**

**Inverse of a Composition of Linear Transformations**

Suppose that \( T: U \rightarrow V \) and \( S: V \rightarrow W \) are invertible linear transformations. Then \( S \circ T \) is invertible and \((S \circ T)^{-1} = T^{-1} \circ S^{-1}\).

**Proof** Compute, for all \( w \in W \)

\[
((S \circ T) \circ (T^{-1} \circ S^{-1}))(w) = S \left( T \left( T^{-1} \left( S^{-1}(w) \right) \right) \right)
\]

\[
= S \left( I_V \left( S^{-1}(w) \right) \right)
\]

\[
= S \left( S^{-1}(w) \right)
\]

\[
= w
\]

\[
= I_W(w)
\]

so \((S \circ T) \circ (T^{-1} \circ S^{-1}) = I_W\) and also

\[
\left( (T^{-1} \circ S^{-1}) \circ (S \circ T) \right)(u) = T^{-1} \left( S^{-1} \left( S \left( T(u) \right) \right) \right)
\]

\[
= T^{-1} \left( I_V \left( T(u) \right) \right)
\]

\[
= T^{-1} \left( T(u) \right)
\]

\[
= u
\]

\[
= I_U(u)
\]

Version 0.52
so \((T^{-1} \circ S^{-1}) \circ (S \circ T) = I_U\). By Definition IVLT\(^{487}\), \(S \circ T\) is invertible and \((S \circ T)^{-1} = T^{-1} \circ S^{-1}\).

Notice that this theorem not only establishes what the inverse of \(S \circ T\) is, it also duplicates the conclusion of Theorem CIVLT\(^{492}\), and also establishes the invertibility of \(S \circ T\). But somehow, the proof of Theorem CIVLT\(^{492}\) is nicer way to get this property.

Does Theorem ICLT\(^{492}\) remind you of the flavor of any theorem we have seen about matrices? (Hint: Think about getting dressed.) Hmmm.

Subsection SI
Structure and Isomorphism

A vector space is defined (Definition VS\(^{275}\)) as a set of objects (“vectors”) endowed with a definition of vector addition (+) and a definition of scalar multiplication (juxtaposition). Many of our definitions about vector spaces involve linear combinations (Definition LC\(^{297}\)), such as the span of a set (Definition SS\(^{298}\)) and linear independence (Definition LI\(^{309}\)). Other definitions are built up from these ideas, such as bases (Definition B\(^{317}\)) and dimension (Definition D\(^{331}\)). The defining properties of a linear transformation require that a function “respect” the operations of the two vector spaces that are the domain and the codomain (Definition LT\(^{429}\)). Finally, an invertible linear transformation is one that can be “undone” — it has a companion that reverses its effect. In this subsection we are going to begin to roll all these ideas into one.

A vector space has “structure” derived from definitions of the two operations and the requirement that these operations interact in ways that satisfy the ten axioms of Definition VS\(^{275}\). When two different vector spaces have an invertible linear transformation defined between them, then we can translate questions about linear combinations (spans, linear independence, bases, dimension) from the first vector space to the second. The answers obtained in the second vector space can then be translated back, via the inverse linear transformation, and interpreted in the setting of the first vector space. We say that these invertible linear transformations “preserve structure.” And we say that the two vector spaces are “structurally the same.” The precise term is “isomorphic,” from Greek meaning “of the same form.” Let’s begin to try to understand this important concept.

Definition IVS
Isomorphic Vector Spaces

Two vector spaces \(U\) and \(V\) are isomorphic if there exists an invertible linear transformation \(T\) with domain \(U\) and codomain \(V\), \(T: U \mapsto V\). In this case, we write \(U \cong V\), and the linear transformation \(T\) is known as an isomorphism between \(U\) and \(V\). \(\triangle\)

A few comments on this definition. First, be careful with your language (Technique L\(^{22}\)). Two vector spaces are isomorphic, or not. It is a yes/no situation and the term only applies to a pair of vector spaces. Any invertible linear transformation can be called an isomorphism, it is a term that applies to functions. Second, a given pair of vector spaces there might be several different isomorphisms between the two vector spaces. But it only takes the existence of one to call the pair isomorphic. Third, \(U\) isomorphic to \(V\), or \(V\) isomorphic to \(U\)? Doesn’t matter, since the inverse linear transformation will provide
the needed isomorphism in the “opposite” direction. Being “isomorphic to” is an equivalence relation on the set of all vector spaces (see Theorem SER for a reminder about equivalence relations).

**Example IVSAV**

**Isomorphic vector spaces, Archetype V**

Archetype V is a linear transformation from $P^3$ to $M_{22}$, $T: P^3 \mapsto M_{22}$, $T(a + bx + cx^2 + dx^3) = \begin{bmatrix} a+b & a-2c \\ d & b-d \end{bmatrix}$

Since it is injective and surjective, Theorem ILTIS tells us that it is an invertible linear transformation. By Definition IVS we say $P^3$ and $M_{22}$ are isomorphic.

At a basic level, the term “isomorphic” is nothing more than a codeword for the presence of an invertible linear transformation. However, it is also a description of a powerful idea, and this power only becomes apparent in the course of studying examples and related theorems. In this example, we are led to believe that there is nothing “structurally” different about $P^3$ and $M_{22}$. In a certain sense they are the same. Not equal, but the same. One is as good as the other. One is just as interesting as the other.

Here is an extremely basic application of this idea. Suppose we want to compute the following linear combination of polynomials in $P^3$,

$$5(2 + 3x - 4x^2 + 5x^3) + (-3)(3 - 5x + 3x^2 + x^3)$$

Rather than doing it straight-away (which is very easy), we will apply the transformation $T$ to convert into a linear combination of matrices, and then compute in $M_{22}$ according to the definitions of the vector space axioms there (Example VSM),

$$T \left( 5(2 + 3x - 4x^2 + 5x^3) + (-3)(3 - 5x + 3x^2 + x^3) \right) = 5T \left( 2 + 3x - 4x^2 + 5x^3 \right) + (-3)T \left( 3 - 5x + 3x^2 + x^3 \right) \quad \text{Theorem LTLC}$$

$$= 5 \begin{bmatrix} 5 & 10 \\ 5 & -2 \end{bmatrix} + (-3) \begin{bmatrix} -2 & -3 \\ 1 & -6 \end{bmatrix} \quad \text{Definition of } T$$

$$= \begin{bmatrix} 31 & 59 \\ 22 & 8 \end{bmatrix} \quad \text{Operations in } M_{22}$$

Now we will translate our answer back to $P^3$ by applying $T^{-1}$, which we found in Example AIVLT, $T^{-1}: M_{22} \mapsto P^3$, $T^{-1} \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) = (a - c - d) + (c + d)x + \frac{1}{2}(a - b - c - d)x^2 + cx^3$

We compute,

$$T^{-1} \left( \begin{bmatrix} 31 & 59 \\ 22 & 8 \end{bmatrix} \right) = 1 + 30x - 29x^2 + 22x^3$$

which is, as expected, exactly what we would have computed for the original linear combination had we just used the definitions of the operations in $P^3$ (Example VSP). Checking the dimensions of two vector spaces can be a quick way to establish that they are not isomorphic. Here’s the theorem.
Subsection IVLT.RNLT  
Rank and Nullity of a Linear Transformation  495

Theorem IVSED  
Isomorphic Vector Spaces have Equal Dimension  
Suppose $U$ and $V$ are isomorphic vector spaces. Then $\dim(U) = \dim(V)$. □

Proof  
If $U$ and $V$ are isomorphic, there is an invertible linear transformation $T: U \leftrightarrow V$ (Definition IVS [493]). $T$ is injective by Theorem ILTIS [491] and so by Theorem ILTD [462], $\dim(U) \leq \dim(V)$. Similarly, $T$ is surjective by Theorem ILTIS [491] and so by Theorem SLTD [480], $\dim(U) \geq \dim(V)$. The net effect of these two inequalities is that $\dim(U) = \dim(V)$. ■

The contrapositive of Theorem IVSED [495] says that if $U$ and $V$ have different dimensions, then they are not isomorphic. Dimension is the simplest “structural” characteristic that will allow you to distinguish non-isomorphic vector spaces. For example $P_6$ is not isomorphic to $M_{34}$ since their dimensions (7 and 12, respectively) are not equal. With tools developed in Section VR [505] we will be able to establish that the converse of Theorem IVSED [495] is true. Think about that one for a moment.

Subsection RNLT  
Rank and Nullity of a Linear Transformation  

Just as a matrix has a rank and a nullity, so too do linear transformations. And just like the rank and nullity of a matrix are related (they sum to the number of columns, Theorem RPNC [339]) the rank and nullity of a linear transformation are related. Here are the definitions and theorems, see the Archetypes (Chapter A [559]) for loads of examples.

Definition ROLT  
Rank Of a Linear Transformation  
Suppose that $T: U \rightarrow V$ is a linear transformation. Then the **rank** of $T$, $r(T)$, is the dimension of the range of $T$, $r(T) = \dim(\mathcal{R}(T))$ △

Definition NOLT  
Nullity Of a Linear Transformation  
Suppose that $T: U \rightarrow V$ is a linear transformation. Then the **nullity** of $T$, $n(T)$, is the dimension of the kernel of $T$, $n(T) = \dim(\mathcal{K}(T))$ △

Here are two quick theorems.

Theorem ROSLT  
Rank Of a Surjective Linear Transformation  
Suppose that $T: U \rightarrow V$ is a linear transformation. Then the rank of $T$ is the dimension of $V$, $r(T) = \dim(V)$, if and only if $T$ is surjective. □

Proof  
By Theorem RSLT [476], $T$ is surjective if and only if $\mathcal{R}(T) = V$. Applying Definition ROLT [495], $\mathcal{R}(T) = V$ if and only if $r(T) = \dim(\mathcal{R}(T)) = \dim(V)$. ■
Suppose that \( T : U \rightarrow V \) is an injective linear transformation. Then the nullity of \( T \) is zero, \( n(T) = 0 \), if and only if \( T \) is injective.

**Proof** By Theorem KILT [460], \( T \) is injective if and only if \( \mathcal{K}(T) = \{0\} \). Applying Definition NOLT [495], \( \mathcal{K}(T) = \{0\} \) if and only if \( n(T) = 0 \).

Just as injectivity and surjectivity come together in invertible linear transformations, there is a clear relationship between rank and nullity of a linear transformation. If one is big, the other is small.

**Theorem RPNDD**

**Rank Plus Nullity is Domain Dimension**

Suppose that \( T : U \rightarrow V \) is a linear transformation. Then

\[
r(T) + n(T) = \dim(U)
\]

**Proof** Let \( r = r(T) \) and \( s = n(T) \). Suppose that \( R = \{v_1, v_2, v_3, \ldots, v_r\} \subseteq V \) is a basis of the range of \( T \), \( \mathcal{R}(T) \), and \( S = \{u_1, u_2, u_3, \ldots, u_s\} \subseteq U \) is a basis of the kernel of \( T \), \( \mathcal{K}(T) \). Note that \( R \) and \( S \) are possibly empty, which means that some of the sums in this proof are “empty” and are equal to the zero vector.

Because the elements of \( R \) are all in the range of \( T \), each must have a non-empty pre-image by Theorem RPI [479]. Choose vectors \( w_i \in U \), \( 1 \leq i \leq r \) such that \( w_i \in T^{-1}(v_i) \). So \( T(w_i) = v_i \), \( 1 \leq i \leq r \). Consider the set

\[
B = \{u_1, u_2, u_3, \ldots, u_s, w_1, w_2, w_3, \ldots, w_r\}
\]

We claim that \( B \) is a basis for \( U \).

To establish linear independence for \( B \), begin with a relation of linear dependence on \( B \). So suppose there are scalars \( a_1, a_2, a_3, \ldots, a_s \) and \( b_1, b_2, b_3, \ldots, b_r \)

\[
0 = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_su_s + b_1w_1 + b_2w_2 + b_3w_3 + \cdots + b_rw_r
\]

Then

\[
0 = T(0) = T(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_su_s + b_1w_1 + b_2w_2 + b_3w_3 + \cdots + b_rw_r)
\]

Substitution

\[
= a_1T(u_1) + a_2T(u_2) + a_3T(u_3) + \cdots + a_sT(u_s) + b_1T(w_1) + b_2T(w_2) + b_3T(w_3) + \cdots + b_rT(w_r)
\]

Theorem LTLC [439]

\[
= a_10 + a_20 + a_30 + \cdots + a_s0 + b_1T(w_1) + b_2T(w_2) + b_3T(w_3) + \cdots + b_rT(w_r) = 0 + 0 + 0 + \cdots + 0
\]

Property zero vector

\[
= b_1T(w_1) + b_2T(w_2) + b_3T(w_3) + \cdots + b_rT(w_r)
\]

Theorem ZVSM [283]

\[
= b_1v_1 + b_2v_2 + b_3v_3 + \cdots + b_rv_r, \quad w_i \in T^{-1}(v_i)
\]

Version 0.52
This is a relation of linear dependence on $R$ (Definition RLD [309]), and since $R$ is a linearly independent set (Definition LI [309]), we see that $b_1 = b_2 = b_3 = \ldots = b_r = 0$. Then the original relation of linear dependence on $B$ becomes

$$0 = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_su_s + 0w_1 + 0w_2 + \ldots + 0w_r$$
$$= a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_su_s + 0 + 0 + \ldots + 0$$

Theorem ZSSM 283

Property zero vector

But this is again a relation of linear independence (Definition RLD [309]), now on the set $S$. Since $S$ is linearly independent (Definition LI [309]), we have $a_1 = a_2 = a_3 = \ldots = a_r = 0$. Since we now know that all the scalars in the relation of linear dependence on $B$ must be zero, we have established the linear independence of $S$ through Definition LI [309].

To now establish that $B$ spans $U$, choose an arbitrary vector $u \in U$. Then $T(u) \in R(T)$, so there are scalars $c_1, c_2, c_3, \ldots, c_r$ such that

$$T(u) = c_1v_1 + c_2v_2 + c_3v_3 + \cdots + c_rv_r$$

Use the scalars $c_1, c_2, c_3, \ldots, c_r$ to define a vector $y \in U$,

$$y = c_1w_1 + c_2w_2 + c_3w_3 + \cdots + c_rw_r$$

Then

$$T(u - y) = T(u) - T(y)$$
$$= T(u) - T(c_1w_1 + c_2w_2 + c_3w_3 + \cdots + c_rw_r)$$
$$= T(u) - (c_1T(w_1) + c_2T(w_2) + \cdots + c_rT(w_r))$$
$$= T(u) - (c_1v_1 + c_2v_2 + c_3v_3 + \cdots + c_rv_r)$$
$$= T(u) - T(u)$$
$$= 0$$

Theorem LTLC 439

Substitution

Additive inverses

So the vector $u - y$ is sent to the zero vector by $T$ and hence is an element of the kernel of $T$. As such it can be written as a linear combination of the basis vectors for $K(T)$, the elements of the set $S$. So there are scalars $d_1, d_2, d_3, \ldots, d_s$ such that

$$u - y = d_1u_1 + d_2u_2 + d_3u_3 + \cdots + d_su_s$$

Then

$$u = (u - y) + y$$
$$= d_1u_1 + d_2u_2 + d_3u_3 + \cdots + d_su_s + c_1w_1 + c_2w_2 + c_3w_3 + \cdots + c_rw_r$$

This says that for any vector, $u$, from $U$, there exist scalars $(d_1, d_2, d_3, \ldots, d_s, c_1, c_2, c_3, \ldots, c_r)$ that form $u$ as a linear combination of the vectors in the set $B$. In other words, $B$ spans $U$ (Definition SS [298]).

So $B$ is a basis (Definition B [317]) of $U$ with $s + r$ vectors, and thus

$$\dim(U) = s + r = n(T) + r(T)$$

as desired. ■
Theorem RPNC \[339\] said that the rank and nullity of a matrix sum to the number of columns of the matrix. This result is now an easy consequence of Theorem RPNDD \[496\] when we consider the linear transformation \(T: \mathbb{C}^n \rightarrow \mathbb{C}^m\) defined with the \(m \times n\) matrix \(A\) by \(T(x) = Ax\). The range and kernel of \(T\) are identical to the column space and null space of the matrix \(A\) (can you prove this?), so the rank and nullity of the matrix \(A\) are identical to the rank and nullity of the linear transformation \(T\). The dimension of the domain of \(T\) is the dimension of \(\mathbb{C}^n\), exactly the number of columns for the matrix \(A\).

This theorem can be especially useful in determining basic properties of linear transformations. For example, suppose that \(T: \mathbb{C}^6 \rightarrow \mathbb{C}^6\) is a linear transformation and you are able to quickly establish that the kernel is trivial. Then \(n(T) = 0\). First this means that \(T\) is injective by Theorem NOILT \[496\]. Also, Theorem RPNDD \[496\] becomes

\[6 = \dim(\mathbb{C}^6) = r(T) + n(T) = r(T) + 0 = r(T)\]

So the rank of \(T\) is equal to the rank of the codomain, and by Theorem ROSLT \[495\] we know \(T\) is surjective. Finally, we know \(T\) is invertible by Theorem ILTIS \[491\]. So from the determination that the kernel is trivial, and consideration of various dimensions, the theorems of this section allow us to conclude the existence of an inverse linear transformation for \(T\).

Similarly, Theorem RPND \[496\] can be used to provide alternative proofs for Theorem ILTD \[462\], Theorem SLTD \[480\] and Theorem IVSED \[495\]. It would be an interesting exercise to construct these proofs.

It would be instructive to study the archetypes that are linear transformations and see how many of their properties can be deduced just from considering the dimensions of the domain and codomain, and possibly with just the nullity or rank. The table preceding all of the archetypes could be a good place to start this analysis.

**Subsection SLELT**

**Systems of Linear Equations and Linear Transformations**

This subsection does not really belong in this section, or any other section, for that matter. Its just the right time to have a discussion about the connections between the central topic of linear algebra, linear transformations, and our motivating topic from Chapter SLE \[3\], systems of linear equations. We will discuss several theorems we have seen already, but we will also make some forward-looking statements that will be justified in Chapter R \[505\].

Archetype D \[577\] and Archetype E \[581\] are ideal examples to illustrate connections with linear transformations. Both have the same coefficient matrix,

\[
D = \begin{bmatrix}
2 & 1 & 7 & -7 \\
-3 & 4 & -5 & -6 \\
1 & 1 & 4 & -5
\end{bmatrix}
\]

To apply the theory of linear transformations to these two archetypes, employ matrix

Version 0.52
Subsection IVLT.SLELT Systems of Linear Equations and Linear Transformations

multiplication (Definition MM \[191\]) and define the linear transformation,

\[
T: \mathbb{C}^4 \rightarrow \mathbb{C}^3, \quad T(x) = Dx = x_1 \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 1 \\ 4 \\ 1 \end{bmatrix} + x_3 \begin{bmatrix} 7 \\ -5 \\ 4 \end{bmatrix} + x_4 \begin{bmatrix} -7 \\ -6 \\ -5 \end{bmatrix}
\]

Theorem MBLT \[435\] tells us that \(T\) is indeed a linear transformation. Archetype D \[577\] asks for solutions to \(LS(D, b)\), where \(b = \begin{bmatrix} 8 \\ -12 \\ -4 \end{bmatrix}\). In the language of linear transformations this is equivalent to asking for \(T^{-1}(b)\). In the language of vectors and matrices it asks for a linear combination of the four columns of \(D\) that will equal \(b\). One solution listed is \(w = \begin{bmatrix} 7 \\ 8 \\ 1 \\ 3 \end{bmatrix}\). With a non-empty preimage, Theorem KPI \[459\] tells us that the complete solution set of the linear system is the preimage of \(b\),

\[w + \mathcal{N}(T) = \{w + z \mid z \in \mathcal{K}(T)\}\]

The kernel of the linear transformation \(T\) is exactly the null space of the matrix \(D\) (Theorem XX \[??\]), so this approach to the solution set should be reminiscent of Theorem PSPHS \[199\]. The kernel of the linear transformation is the preimage of the zero vector, exactly equal to the solution set of the homogeneous system \(LS(D, 0)\). Since \(D\) has a null space of dimension two, every preimage (and in particular the preimage of \(b\)) is as “big” as a subspace of dimension two (but is not a subspace).

Archetype E \[581\] is identical to Archetype D \[577\] but with a different vector of constants, \(d = \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}\). We can use the same linear transformation \(T\) to discuss this system of equations since the coefficient matrix is identical. Now the set of solutions to \(LS(D, d)\) is the pre-image of \(d\), \(T^{-1}(d)\). However, the vector \(d\) is not in the range of the linear transformation (nor is it in the column space of the matrix, since these two sets are equal by Theorem XX \[??\]). So the empty pre-image is equivalent to the inconsistency of the linear system.

These two archetypes each have three equations in four variables, so either the resulting linear systems are inconsistent, or they are consistent and application of Theorem CMVEI \[56\] tells us that the system has infinitely many solutions. Considering these same parameters for the linear transformation, the dimension of the domain, \(\mathbb{C}^4\), is four, while the codomain, \(\mathbb{C}^3\), has dimension three. Then

\[
n(T) = \dim(\mathbb{C}^4) - r(T) = 4 - \dim(\mathcal{R}(T)) \geq 4 - 3 = 1
\]

So the kernel of \(T\) is nontrivial simply by considering the dimensions of the domain (number of variables) and the codomain (number of equations). Pre-images of elements of the codomain that are not in the range of \(T\) are empty (inconsistent systems). For elements of the codomain that are in the range of \(T\) (consistent systems), Theorem KPI \[459\] tells
us that the pre-images are built from the kernel, and with a non-trivial kernel, these pre-images are infinite (infinitely many solutions).

When do systems of equations have unique solutions? Consider the system of linear equations \( LS(C, f) \) and the linear transformation \( S(x) = Cx \). If \( S \) has a trivial kernel, then pre-images will either be empty or be finite sets with single elements. Correspondingly, the coefficient matrix \( C \) will have a trivial null space and solution sets with either be empty (inconsistent) or contain a single solution (unique solution). Should the matrix be square and have a trivial null space then we recognize the matrix as being nonsingular. A square matrix means that the corresponding linear transformation, \( T \), has equal-sized domain and codomain. With a nullity of zero, \( T \) is injective, and also \[\text{Theorem RPNDD} \] tells us that rank of \( T \) is equal to the dimension of the domain, which in turn is equal to the dimension of the codomain. In other words, \( T \) is surjective. Injective and surjective, and \[\text{Theorem ILTIS} \] tells us that \( T \) is invertible. Just as we can use the inverse of the coefficient matrix to find the unique solution of any linear system with a nonsingular coefficient matrix (\[\text{Theorem SNSCM} \]), we can use the inverse of the linear transformation to construct the unique element of any pre-image (proof of \[\text{Theorem ILTIS} \]).

The executive summary of this discussion is that to every coefficient matrix of a system of linear equations we can associate a natural linear transformation. Solution sets for systems with this coefficient matrix are preimages of elements of the codomain of the linear transformation. For every theorem about systems of linear equations there is an analogue about linear transformations. The theory of linear transformations provides all the tools to recreate the theory of solutions to linear systems of equations.

We will continue this adventure in \[\text{Chapter R} \].

**Subsection READ**

**Reading Questions**

1. What conditions allow us to easily determine if a linear transformation is invertible?
2. What does it mean to say two vector spaces are isomorphic? Both technically, and informally?
3. How do linear transformations relate to systems of linear equations?
Subsection IVLT.EXC  Exercises

C50  Consider the linear transformation $S: M_{12} \mapsto P_1$ from the set of $1 \times 2$ matrices to the set of polynomials of degree at most 1, defined by

$$S \left( \begin{bmatrix} a & b \end{bmatrix} \right) = (3a + b) + (5a + 2b)x$$

Prove that $S$ is invertible. Then show that the linear transformation

$$R: P_1 \mapsto M_{12}, \quad R(r + sx) = \begin{bmatrix} (2r - s) & -5r + 3s \\ 3r - s & 5r + 3s \end{bmatrix}$$

is the inverse of $S$, that is $S^{-1} = R$.

Contributed by Robert Beezer  Solution 503

T15  Suppose that $T: U \mapsto V$ is a surjective linear transformation and $\dim(U) = \dim(V)$. Prove that $T$ is injective.

Contributed by Robert Beezer  Solution 503

T16  Suppose that $T: U \mapsto V$ is an injective linear transformation and $\dim(U) = \dim(V)$. Prove that $T$ is surjective.

Contributed by Robert Beezer
Determine the kernel of $S$ first. The condition that $S\begin{pmatrix} a \\ b \end{pmatrix} = 0$ becomes $(3a + b) + (5a + 2b)x = 0 + 0x$. Equating coefficients of these polynomials yields the system

\[
\begin{align*}
3a + b &= 0 \\
5a + 2b &= 0
\end{align*}
\]

This homogeneous system has a nonsingular coefficient matrix, so the only solution is $a = 0$, $b = 0$ and thus

\[K(S) = \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right\}\]

By Theorem KILT, we know $S$ is injective. With $n(S) = 0$ we employ Theorem RP-NDD to find

\[r(S) = r(S) + 0 = r(S) + n(S) = \dim(M_{12}) = 2 = \dim(P_1)\]

Since $R(S) \subseteq P_1$ and $\dim(R(S)) = \dim(P_1)$, we can apply Theorem EDYES to obtain the set equality $R(S) = P_1$ and therefore $S$ is surjective.

One of the two defining conditions of an invertible linear transformation is (Definition IVLT)

\[(S \circ R)\begin{pmatrix} a \\ b \end{pmatrix} = S(R(a + bx)) = S\begin{pmatrix} (2a - b) \\ -5a + 3b \end{pmatrix} = (3(2a - b) + (-5a + 3b)) + (5(2a - b) + 2(-5a + 3b)) x = ((6a - 3b) + (-5a + 3b)) + ((10a - 5b) + (-10a + 6b)) x = a + bx = I_{P_1}(a + bx)\]

That $(R \circ S)\begin{pmatrix} a \\ b \end{pmatrix} = I_{M_{12}}\begin{pmatrix} a \\ b \end{pmatrix}$ is similar.

If $T$ is surjective, then Theorem RSLT says $R(T) = V$, so $r(T) = \dim(V)$. In turn, the hypothesis gives $r(T) = \dim(U)$. Then, using Theorem RP-NDD, $n(T) = (r(T) + n(T)) - r(T) = \dim(U) - \dim(U) = 0$

With a null space of zero dimension, $K(T) = \{0\}$, and by Theorem KILT, we see that $T$ is injective. $T$ is both injective and surjective so by Theorem ILTIS, $T$ is invertible.
R: Representations

Section VR
Vector Representations

Previous work with linear transformations may have convinced you that we can convert most questions about linear transformations into questions about systems of equations or properties of subspaces of $\mathbb{C}^m$. In this section we begin to make these vague notions precise. First we establish an invertible linear transformation between any vector space $V$ of dimension $m$ and $\mathbb{C}^m$. This will allow us to “go back and forth” between the two vector spaces, no matter how abstract the definition of $V$ might be.

Definition VR
Vector Representation

Suppose that $V$ is a vector space with a basis $B = \{v_1, v_2, v_3, \ldots, v_n\}$. Define a function $\rho_B: V \mapsto \mathbb{C}^n$ as follows. For $w \in V$, find scalars $a_1, a_2, a_3, \ldots, a_n$ so that

$$w = a_1v_1 + a_2v_2 + a_3v_3 + \cdots + a_nv_n$$

then

$$\rho_B(w) = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_n \end{bmatrix} \triangleq$$

We need to show that $\rho_B$ is really a function (since “find scalars” sounds like it could be accomplished in many ways, or perhaps not at all) and right now we want to establish that $\rho_B$ is a linear transformation. We will wrap up both objectives in one theorem, even though the first part is working backwards to make sure that $\rho_B$ is well-defined.

Theorem VRLT
Vector Representation is a Linear Transformation

The function $\rho_B$ (Definition VR [505]) is a linear transformation. □

Proof The definition of $\rho_B$ (Definition VR [505]) appears to allow considerable latitude in selecting the scalars $a_1, a_2, a_3, \ldots, a_n$. However, since $B$ is a basis for $V$, Theorem VRRB [324] says this can be done, and done uniquely. So despite appearances, $\rho_B$ is indeed a function.
Suppose that \( x \) and \( y \) are two vectors in \( V \) and \( \alpha \in \mathbb{C} \). Then the vector space axioms (Definition VS 275) assure us that the vectors \( x + y \) and \( \alpha x \) are also vectors in \( V \). Theorem VRRB 324 then provides the follow sets of scalars for the four vectors \( x, y, x + y \) and \( \alpha x \), and tells us that each set of scalars is the only way to express the given vector as a linear combination of the basis vectors in \( B \):

\[
\begin{align*}
x &= a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_n v_n \\
y &= b_1 v_1 + b_2 v_2 + b_3 v_3 + \cdots + b_n v_n \\
x + y &= c_1 v_1 + c_2 v_2 + c_3 v_3 + \cdots + c_n v_n \\
\alpha x &= d_1 v_1 + d_2 v_2 + d_3 v_3 + \cdots + d_n v_n
\end{align*}
\]

Then

\[
\begin{align*}
c_1 v_1 + c_2 v_2 + c_3 v_3 + \cdots + c_n v_n \\
&= x + y \\
&= (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_n v_n) \\
&\quad + (b_1 v_1 + b_2 v_2 + b_3 v_3 + \cdots + b_n v_n) \\
&= a_1 v_1 + b_1 v_1 + a_2 v_2 + b_2 v_2 \\
&\quad + a_3 v_3 + b_3 v_3 + \cdots + a_n v_n + b_n v_n & \text{(Property AC 275)} \\
&= (a_1 + b_1) v_1 + (a_2 + b_2) v_2 \\
&\quad + (a_3 + b_3) v_3 + \cdots + (a_n + b_n) v_n & \text{(Property DSA 276)}
\end{align*}
\]

By the uniqueness of the expression of \( x + y \) as a linear combination of the vectors in \( B \) (Theorem VRRB 324), we conclude that \( c_i = a_i + b_i \), \( 1 \leq i \leq n \). So employing our definition of vector addition in \( \mathbb{C}^n \) (Definition CVA 89), we have

\[
\begin{align*}
\rho_B (x + y) &= \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_n \end{bmatrix} \\
&= \begin{bmatrix} a_1 + b_1 \\ a_2 + b_2 \\ a_3 + b_3 \\ \vdots \\ a_n + b_n \end{bmatrix} & \text{Definition VR 505} \\
&= \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_n \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{bmatrix} & \text{Theorem VRRB 324} \\
&= \rho_B (x) + \rho_B (y) & \text{Definition CVA 89}
\end{align*}
\]
so we have the first necessary property for $\rho_B$ to be a linear transformation (Definition LT 429). Similarly,

\[
d_1 v_1 + d_2 v_2 + d_3 v_3 + \cdots + d_n v_n
= \alpha x
= \alpha (a_1 v_1 + a_2 v_2 + a_3 v_3 + \cdots + a_n v_n)
= \alpha (a_1 v_1) + \alpha (a_2 v_2) + \alpha (a_3 v_3) + \cdots + \alpha (a_n v_n)
= (\alpha a_1) v_1 + (\alpha a_2) v_2 + (\alpha a_3) v_3 + \cdots + (\alpha a_n) v_n
\]

Property DVA 276

Property SMA 276

By the uniqueness of the expression of $\alpha x$ as a linear combination of the vectors in $B$ (Theorem VRRB 324), we conclude that $d_i = \alpha a_i$, $1 \leq i \leq n$. So employing our definition of scalar multiplication in $\mathbb{C}^m$ (Definition CVSM 90), we have

\[
\rho_B (\alpha x) = \begin{bmatrix}
d_1 \\
d_2 \\
d_3 \\
\vdots \\
d_n \\
\end{bmatrix}
\begin{bmatrix}
\alpha a_1 \\
\alpha a_2 \\
\alpha a_3 \\
\vdots \\
\alpha a_n \\
\end{bmatrix}
= \alpha
\begin{bmatrix}
a_1 \\
a_2 \\
a_3 \\
\vdots \\
a_n \\
\end{bmatrix}
= \alpha \rho_B (x)
\]

Definition VR 505

Theorem VRRB 324

Definition CVSM 90

and so, with the second property of a linear transformation (Definition LT 429) confirmed we can conclude that $\rho_B$ is a linear transformation.

Example VRC4

Vector representation in $\mathbb{C}^4$

Consider the vector $y \in \mathbb{C}^4$

\[
y = \begin{bmatrix}
6 \\
14 \\
6 \\
7 \\
\end{bmatrix}
\]

We will find several coordinate representations of $y$ in this example. Notice that $y$ never changes, but the representations of $y$ do change.
One basis for $\mathbb{C}^4$ is

$$B = \{ \mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \mathbf{u}_4 \} = \left\{ \begin{bmatrix} -2 \\ 1 \\ 2 \\ -3 \end{bmatrix}, \begin{bmatrix} 3 \\ -6 \\ 2 \\ -4 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 0 \\ 5 \end{bmatrix}, \begin{bmatrix} 4 \\ 3 \\ 1 \\ 6 \end{bmatrix} \right\}$$

as can be seen by making these vectors the column of a matrix, checking that the matrix is nonsingular and applying Theorem CNSMB \[323\]. To find $\rho_B(\mathbf{y})$, we need to find scalars, $a_1, a_2, a_3, a_4$ such that

$$\mathbf{y} = a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2 + a_3 \mathbf{u}_3 + a_4 \mathbf{u}_4$$

By Theorem SLSLC \[103\] the desired scalars are a solution to the linear system of equations with a coefficient matrix whose columns are the vectors in $B$ and with a vector of constants $\mathbf{y}$. With a nonsingular coefficient matrix, the solution is unique, but this is no surprise as this is the content of Theorem VRRB \[324\]. This unique solution is

$$a_1 = 2 \quad a_2 = -1 \quad a_3 = -3 \quad a_4 = 4$$

Then by Definition VR \[505\], we have

$$\rho_B(\mathbf{y}) = \begin{bmatrix} 2 \\ -1 \\ -3 \\ 4 \end{bmatrix}$$

Suppose now that we construct a representation of $\mathbf{y}$ relative to another basis of $\mathbb{C}^4$,

$$C = \left\{ \begin{bmatrix} -15 \\ 9 \\ -4 \\ -2 \end{bmatrix}, \begin{bmatrix} 16 \\ -14 \\ 5 \\ 2 \end{bmatrix}, \begin{bmatrix} -26 \\ 14 \\ -6 \\ -3 \end{bmatrix}, \begin{bmatrix} 14 \\ -13 \\ 4 \\ 6 \end{bmatrix} \right\}$$

As with $B$, it is easy to check that $C$ is a basis. Writing $\mathbf{y}$ as a linear combination of the vectors in $C$ leads to solving a system of four equations in the four unknown scalars with a nonsingular coefficient matrix. The unique solution can be expressed as

$$\mathbf{y} = \begin{bmatrix} -6 \\ -14 \\ -6 \\ -7 \end{bmatrix} = (-28) \begin{bmatrix} -15 \\ 9 \\ -4 \\ -2 \end{bmatrix} + (-8) \begin{bmatrix} 16 \\ -14 \\ 5 \\ 2 \end{bmatrix} + 11 \begin{bmatrix} -26 \\ 14 \\ -6 \\ -3 \end{bmatrix} + 0 \begin{bmatrix} 14 \\ -13 \\ 4 \\ 6 \end{bmatrix}$$

so that Definition VR \[505\] gives

$$\rho_C(\mathbf{y}) = \begin{bmatrix} -28 \\ -8 \\ 11 \\ 0 \end{bmatrix}$$

We often perform representations relative to standard bases, but for vectors in $\mathbb{C}^m$ its a little silly. Let’s find the vector representation of $\mathbf{y}$ relative to the standard basis (Theorem SUVB \[318\]),

$$D = \{ \mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_4 \}$$
Then, without any computation, we can check that

\[
y = \begin{bmatrix} 6 \\ 14 \\ 6 \\ 7 \end{bmatrix} = 6e_1 + 14e_2 + 6e_3 + 7e_4
\]

so by Definition VR 505,

\[
\rho_C(y) = \begin{bmatrix} 6 \\ 14 \\ 6 \\ 7 \end{bmatrix}
\]

which is not very exciting. Notice however that the order in which we place the vectors in the basis is critical to the representation. Let’s keep the standard unit vectors as our basis, but rearrange the order we place them in the basis. So a fourth basis is

\[
E = \{e_3, e_4, e_2, e_1\}
\]

Then,

\[
y = \begin{bmatrix} 6 \\ 14 \\ 6 \\ 7 \end{bmatrix} = 6e_3 + 7e_4 + 14e_2 + 6e_1
\]

so by Definition VR 505,

\[
\rho_E(y) = \begin{bmatrix} 6 \\ 7 \\ 14 \\ 6 \end{bmatrix}
\]

So for every basis we could find for \( \mathbb{C}^4 \) we could construct a representation of \( y \).

Vector representations are most interesting for vector spaces that are not \( \mathbb{C}^m \).

**Example VRP2**

**Vector representations in \( P_2 \)**

Consider the vector \( u = 15 + 10x - 6x^2 \) from the vector space of polynomials with degree at most 2 (Example VSP 277). A nice basis for \( P_2 \) is

\[
B = \{1, x, x^2\}
\]

so that

\[
u = 15 + 10x - 6x^2 = 15(1) + 10(x) + (-6)(x^2)
\]

so by Definition VR 505

\[
\rho_B(u) = \begin{bmatrix} 15 \\ 10 \\ -6 \end{bmatrix}
\]

Another nice basis for \( P_2 \) is

\[
B = \{1, 1 + x, 1 + x + x^2\}
\]
so that now it takes a bit of computation to determine the scalars for the representation. We want \( a_1, a_2, a_3 \) so that

\[
15 + 10x - 6x^2 = a_1(1) + a_2(1 + x) + a_3(1 + x + x^2)
\]

Performing the operations in \( P_2 \) on the right-hand side, and equating coefficients, gives the three equations in the three unknown scalars,

\[
\begin{align*}
15 &= a_1 + a_2 + a_3 \\
10 &= a_2 + a_3 \\
-6 &= a_3
\end{align*}
\]

The coefficient matrix of this system is nonsingular, leading to a unique solution (no surprise there, see Theorem VRRB [324]),

\[
\begin{align*}
a_1 &= 5 \\
a_2 &= 16 \\
a_3 &= -6
\end{align*}
\]

so by Definition VR [505],

\[
\rho_C(u) = \begin{bmatrix} 5 \\ 16 \\ -6 \end{bmatrix}
\]

While we often form vector representations relative to “nice” bases, nothing prevents us from forming representations relative to “nasty” bases. For example, the set

\[
D = \{ -2 - x + 3x^2, 1 - 2x^2, 5 + 4x + x^2 \}
\]

can be verified as a basis of \( P_2 \) by checking linear independence with Definition LI [309] and then arguing that 3 vectors from \( P_2 \), a vector space of dimension 3 (Theorem DP [336]), must also be a spanning set (Theorem G [348]). Now we desire scalars \( a_1, a_2, a_3 \) so that

\[
15 + 10x - 6x^2 = a_1(-2 - x + 3x^2) + a_2(1 - 2x^2) + a_3(5 + 4x + x^2)
\]

Performing the operations in \( P_2 \) on the right-hand side, and equating coefficients, gives the three equations in the three unknown scalars,

\[
\begin{align*}
15 &= -2a_1 + a_2 + 5a_3 \\
10 &= -a_1 + 4a_3 \\
-6 &= 3a_1 - 2a_2 + a_3
\end{align*}
\]

The coefficient matrix of this system is nonsingular, leading to a unique solution (no surprise there, see Theorem VRRB [324]),

\[
\begin{align*}
a_1 &= -2 \\
a_2 &= 1 \\
a_3 &= 2
\end{align*}
\]

so by Definition VR [505],

\[
\rho_D(u) = \begin{bmatrix} -2 \\ 1 \\ 2 \end{bmatrix}
\]
Theorem VRI
Vector Representation is Injective
The function \( \rho_B \) (Definition VR [505]) is an injective linear transformation.

Proof We will appeal to Theorem KILT [460]. Suppose \( U \) is a vector space of dimension \( n \), so vector representation is of the form \( \rho_B : U \to \mathbb{C}^n \). Let \( B = \{ u_1, u_2, u_3, \ldots, u_n \} \) be the basis of \( U \) used in the definition of \( \rho_B \). Suppose \( u \in \mathcal{K}(\rho_B) \). Finally, since \( B \) is a basis for \( U \), by Theorem VRRB [324] there are (unique) scalars, \( a_1, a_2, a_3, \ldots, a_n \) such that
\[
\begin{align*}
u &= a_1 u_1 + a_2 u_2 + a_3 u_3 + \cdots + a_n u_n
\end{align*}
\]
Then
\[
\begin{bmatrix}
  a_1 \\
  a_2 \\
  a_3 \\
  \vdots \\
  a_n
\end{bmatrix} = \rho_B(u) \quad \text{Definition VR [505]}
\]
\[
= 0 \quad u \in \mathcal{K}(\rho_B)
\]
\[
= \begin{bmatrix}
  0 \\
  0 \\
  0 \\
  \vdots \\
  0
\end{bmatrix}
\]
From this vector equality (Definition CVE [88]) we find that \( a_i = 0 \), \( 1 \leq i \leq n \). So
\[
\begin{align*}
u &= a_1 u_1 + a_2 u_2 + a_3 u_3 + \cdots + a_n u_n \\
&= 0 u_1 + 0 u_2 + 0 u_3 + \cdots + 0 u_n \\
&= 0 + 0 + 0 + \cdots + 0 \\
&= 0
\end{align*}
\]
Thus an arbitrary vector, \( u \), from the kernel \( \mathcal{K}(\rho_B) \), must equal the zero vector of \( U \). So \( \mathcal{K}(\rho_B) = \{ 0 \} \) and by Theorem KILT [460], \( \rho_B \) is injective.

Theorem VRS
Vector Representation is Surjective
The function \( \rho_B \) (Definition VR [505]) is a surjective linear transformation.

Proof We will appeal to Theorem RSLT [476]. Suppose \( U \) is a vector space of dimension \( n \), so vector representation is of the form \( \rho_B : U \to \mathbb{C}^n \). Let \( B = \{ u_1, u_2, u_3, \ldots, u_n \} \) be the basis of \( U \) used in the definition of \( \rho_B \). Suppose \( v \in \mathbb{C}^n \). Write
\[
v = \begin{bmatrix}
v_1 \\
v_2 \\
v_3 \\
\vdots \\
v_n
\end{bmatrix}
\]
and define
\[ u = v_1 u_1 + v_2 u_2 + v_3 u_3 + \cdots + v_n u_n \]
Then
\[ \rho_B(u) = \rho_B(v_1 u_1 + v_2 u_2 + v_3 u_3 + \cdots + v_n u_n) \]
\[ = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_n \end{bmatrix} \]
this demonstrates that \( v \in \mathcal{R}(\rho_B) \), so \( \mathbb{C}^n \subseteq \mathcal{R}(\rho_B) \). Since \( \mathcal{R}(\rho_B) \subseteq \mathbb{C}^n \) by Definition RLT \[473\], we have \( \mathcal{R}(\rho_B) = \mathbb{C}^n \) and Theorem RSLT \[476\] says \( \rho_B \) is surjective. \( \blacksquare \)

We will have many occasions later to employ the inverse of vector representation, so we will record the fact that vector representation is an invertible linear transformation.

**Theorem VRILT**

**Vector Representation is an Invertible Linear Transformation**
The function \( \rho_B \) (Definition VR \[505\]) is an invertible linear transformation. \( \square \)

**Proof** The function \( \rho_B \) (Definition VR \[505\]) is a linear transformation (Theorem VRLT \[505\]) that is injective (Theorem VRI \[511\]) and surjective (Theorem VRS \[511\]) with domain \( V \) and codomain \( \mathbb{C}^n \). By Theorem ILTIS \[491\] we then know that \( \rho_B \) is an invertible linear transformation. \( \blacksquare \)

Informally, we will refer to the application of \( \rho_B \) as *coordinatizing* a vector, while the application of \( \rho_B^{-1} \) will be referred to as *un-coordinatizing* a vector.

### Subsection CVS

**Characterization of Vector Spaces**

Limiting our attention to vector spaces with finite dimension, we now describe every possible vector space. All of them. Really.

**Theorem CFDVS**

**Characterization of Finite Dimensional Vector Spaces**
Suppose that \( V \) is a vector space with dimension \( n \). Then \( V \) is isomorphic to \( \mathbb{C}^n \). \( \square \)

**Proof** Since \( V \) has dimension \( n \) we can find a basis of \( V \) of size \( n \) (Definition D \[331\]) which we will call \( B \). The linear transformation \( \rho_B \) is an invertible linear transformation from \( V \) to \( \mathbb{C}^n \), so by Definition IVS \[493\], we have that \( V \) and \( \mathbb{C}^n \) are isomorphic. \( \blacksquare \)

Theorem CFDVS \[512\] is the first of several surprises in this chapter, though it might be a bit demoralizing too. It says that there really are not all that many different (finite dimensional) vector spaces, and none are really any more complicated than \( \mathbb{C}^n \). Hmmm. The following examples should make this point.
Example TIVS
Two isomorphic vector spaces
The vector space of polynomials with degree 8 or less, \( P_8 \), has dimension 9 (Theorem DF [336]). By Theorem CFDVS [512], \( P_8 \) is isomorphic to \( \mathbb{C}^9 \).

Example CVSR
Crazy vector space revealed
The crazy vector space, \( C \) of Example CVS [280], has dimension 2 (can you prove this?). By Theorem CFDVS [512], \( C \) is isomorphic to \( \mathbb{C}^2 \).

Example ASC
A subspace charaterized
In Example DSP4 [337] we determined that a certain subspace \( W \) of \( P_4 \) has dimension 4. By Theorem CFDVS [512], \( W \) is isomorphic to \( \mathbb{C}^4 \).

Theorem IFDVS
Isomorphism of Finite Dimensional Vector Spaces
Suppose \( U \) and \( V \) are both finite-dimensional vector spaces. Then \( U \) and \( V \) are isomorphic if and only if \( \dim(U) = \dim(V) \).

Proof (\( \Rightarrow \)) This is just the statement proved in Theorem IVSED [495].

(\( \Leftarrow \)) This is the advertised converse of Theorem IVSED [495]. We will assume \( U \) and \( V \) have equal dimension and discover that they are isomorphic vector spaces. Let \( n \) be the common dimension of \( U \) and \( V \). Then by Theorem CFDVS [512] there are isomorphisms \( T: U \mapsto \mathbb{C}^n \) and \( S: V \mapsto \mathbb{C}^n \).

\( T \) is therefore an invertible linear transformation by Definition IVS [493]. Similarly, \( S \) is an invertible linear transformation, and so \( S^{-1} \) is an invertible linear transformation (Theorem IILT [490]). The composition of invertible linear transformations is again invertible (Theorem CIVLT [492]) so the composition of \( S^{-1} \) with \( T \) is invertible. Then \( (S^{-1} \circ T): U \mapsto V \) is an invertible linear transformation from \( U \) to \( V \) and Definition IVS [493] says \( U \) and \( V \) are isomorphic.

Example MIVS
Multiple isomorphic vector spaces
\( \mathbb{C}^{10} \), \( P_9 \), \( M_{2,5} \) and \( M_{5,2} \) are all vector spaces and each has dimension 10. By Theorem IFDVS [513] each is isomorphic to any other.

The subspace of \( M_{4,4} \) that contains all the symmetric matrices (Definition SYM [183]) has dimension 10, so this subspace is also isomorphic to each of the four vector spaces above.

Subsection CP
Coordinatization Principle

With \( \rho_B \) available as an invertible linear transformation, we can translate between vectors in a vector space \( U \) of dimension \( m \) and \( \mathbb{C}^m \). Furthermore, as a linear transformation, \( \rho_B \) respects the addition and scalar multiplication in \( U \), while \( \rho_B^{-1} \) respects the addition and scalar multiplication in \( \mathbb{C}^m \). Since our definitions of linear independence, spans,
bases and dimension are all built up from linear combinations, we will finally be able to translate fundamental properties between abstract vector spaces \((U)\) and concrete vector spaces \((\mathbb{C}^n)\).

**Theorem CLI**

**Coordination and Linear Independence**

Suppose that \(U\) is a vector space with a basis \(B\) of size \(n\). Then \(S = \{u_1, u_2, u_3, \ldots, u_k\}\) is a linearly independent subset of \(U\) if and only if \(R = \{\rho_B(u_1), \rho_B(u_2), \rho_B(u_3), \ldots, \rho_B(u_k)\}\) is a linearly independent subset of \(\mathbb{C}^n\).

**Proof** The linear transformation \(\rho_B\) is an isomorphism between \(U\) and \(\mathbb{C}^n\) (Theorem VRILT [512]). As an invertible linear transformation, \(\rho_B\) is an injective linear transformation (Theorem ILTIS [491]), and \(\rho_B^{-1}\) is also an injective linear transformation (Theorem ILT [490], Theorem ILTIS [491]).

\((\Rightarrow)\) Since \(\rho_B\) is an injective linear transformation and \(S\) is linearly independent, Theorem ILTLI [461] says that \(R\) is linearly independent.

\((\Leftarrow)\) If we apply \(\rho_B^{-1}\) to each element of \(R\), we will create the set \(S\). Since we are assuming \(R\) is linearly independent and \(\rho_B^{-1}\) is injective, Theorem ILTLI [461] says that \(S\) is linearly independent.

**Theorem CSS**

**Coordination and Spanning Sets**

Suppose that \(U\) is a vector space with a basis \(B\) of size \(n\). Then \(u \in \mathcal{S}p(\{u_1, u_2, u_3, \ldots, u_k\})\) if and only if \(\rho_B(u) \in \mathcal{S}p(\{\rho_B(u_1), \rho_B(u_2), \rho_B(u_3), \ldots, \rho_B(u_k)\})\).

**Proof** \((\Rightarrow)\) Suppose \(u \in \mathcal{S}p(\{u_1, u_2, u_3, \ldots, u_k\})\). Then there are scalars, \(a_1, a_2, a_3, \ldots, a_k\), such that

\[
u = a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_ku_k
\]

Then,

\[
\rho_B(u) = \rho_B(a_1u_1 + a_2u_2 + a_3u_3 + \cdots + a_ku_k) \\
= a_1\rho_B(u_1) + a_2\rho_B(u_2) + a_3\rho_B(u_3) + \cdots + a_k\rho_B(u_k)
\]

which says that \(\rho_B(u) \in \mathcal{S}p(\{\rho_B(u_1), \rho_B(u_2), \rho_B(u_3), \ldots, \rho_B(u_k)\})\).

\((\Leftarrow)\) Suppose that \(\rho_B(u) \in \mathcal{S}p(\{\rho_B(u_1), \rho_B(u_2), \rho_B(u_3), \ldots, \rho_B(u_k)\})\). Then there are scalars \(b_1, b_2, b_3, \ldots, b_k\) such that

\[
\rho_B(u) = b_1\rho_B(u_1) + b_2\rho_B(u_2) + b_3\rho_B(u_3) + \cdots + b_k\rho_B(u_k)
\]

Recall that \(\rho_B\) is invertible (Theorem VRILT [512]), so

\[
u = I_U(u) \\
= (\rho_B^{-1} \circ \rho_B)(u) \\
= \rho_B^{-1}(\rho_B(u)) \\
= \rho_B^{-1}(b_1\rho_B(u_1) + b_2\rho_B(u_2) + b_3\rho_B(u_3) + \cdots + b_k\rho_B(u_k)) \\
= b_1\rho_B^{-1}(\rho_B(u_1)) + b_2\rho_B^{-1}(\rho_B(u_2)) + b_3\rho_B^{-1}(\rho_B(u_3)) + \cdots + b_k\rho_B^{-1}(\rho_B(u_k)) \\
= b_1I_U(u_1) + b_2I_U(u_2) + b_3I_U(u_3) + \cdots + b_kI_U(u_k) \\
= b_1u_1 + b_2u_2 + b_3u_3 + \cdots + b_ku_k
\]

which says that \(u \in \mathcal{S}p(\{u_1, u_2, u_3, \ldots, u_k\})\).
Here’s a fairly simple example that illustrates a very, very important idea.

**Example CP2**

**Coordinatizing in** \( P_2 \)

In Example VRP2\(^{509}\) we needed to know that

\[
D = \{-2 - x + 3x^2, 1 - 2x^2, 5 + 4x + x^2\}
\]

is a basis for \( P_2 \). With Theorem CLI\(^{514}\) and Theorem CSS\(^{514}\) this task is much easier. First, choose a known basis for \( P_2 \), a basis that forms vector representations easily. We will choose

\[
B = \{1, x, x^2\}
\]

Now, form the subset of \( \mathbb{C}^3 \) that is the result of applying \( \rho_B \) to each element of \( D \),

\[
F = \{\rho_B (-2 - x + 3x^2), \rho_B (1 - 2x^2), \rho_B (5 + 4x + x^2)\} = \left\{ \begin{bmatrix} -2 \\ -1 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}, \begin{bmatrix} 5 \\ 4 \\ 1 \end{bmatrix} \right\}
\]

and ask if \( F \) is a linearly independent spanning set for \( \mathbb{C}^3 \). This is easily seen to be the case by forming a matrix \( A \) whose columns are the vectors of \( F \), row-reducing \( A \) to the identity matrix \( I_3 \), and then using the nonsingularity of \( A \) to assert that \( F \) is a basis for \( \mathbb{C}^3 \) (Theorem CNSMB\(^{323}\)). Now, since \( F \) is a basis for \( \mathbb{C}^3 \), Theorem CLI\(^{514}\) and Theorem CSS\(^{514}\) tell us that \( D \) is also a basis for \( P_2 \).

Example CP2\(^{515}\) illustrates the broad notion that computations in abstract vector spaces can be reduced to computations in \( \mathbb{C}^n \). You may have noticed this phenomenon as you worked through examples in Chapter VS\(^{275}\) or Chapter LT\(^{429}\) employing vector spaces of matrices or polynomials. These computations seemed to invariably result in systems of equations or the like from Chapter SLE\(^{3}\), Chapter V\(^{87}\) and Chapter M\(^{179}\). It is vector representation, \( \rho_B \), that allows us to make this connection formal and precise.

Knowing that vector representation allows us to translate questions about linear combinations, linear independence and spans from general vector spaces to \( \mathbb{C}^n \) allows us to prove a great many theorems about how to translate other properties. Rather than prove these theorems, each of the same style as the other, we will offer some general guidance about how to best employ Theorem VRLT\(^{505}\), Theorem CLI\(^{514}\) and Theorem CSS\(^{514}\). This comes in the form of a “principle”: a basic truth, but most definitely not a theorem (hence, no proof).

The **Coordinatization Principle** Suppose that \( U \) is a vector space with a basis \( B \) of size \( n \). Then any question about \( U \), or its elements, which depends on the vector addition or scalar multiplication in \( U \), or depends on linear independence or spanning, may be translated into the same question in \( \mathbb{C}^n \) by application of the linear transformation \( \rho_B \) to the relevant vectors. Once the question is answered in \( \mathbb{C}^n \), the answer may be translated back to \( U \) (if necessary) through application of the inverse linear transformation \( \rho_B^{-1} \).

**Example CM32**

**Coordinatization in** \( M_{32} \)

This is a simple example of the Coordinatization Principle\(^{515}\), depending only on the
fact that coordinatizing is an invertible linear transformation (Theorem VRILT 512).
Suppose we have a linear combination to perform in $M_{32}$, the vector space of $3 \times 2$ matrices, but we are adverse to doing the operations of $M_{32}$ (Definition MA 180, Definition MSM 180). More specifically, suppose we are faced with the computation

$$
6 \begin{bmatrix}
3 & 7 \\
-2 & 4 \\
0 & -3
\end{bmatrix} + 2 \begin{bmatrix}
-1 & 3 \\
4 & 8 \\
-2 & 5
\end{bmatrix}
$$

We choose a nice basis for $M_{32}$ (or a nasty basis if we are so inclined),

\[ B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} \]

and apply $\rho_B$ to each vector in the linear combination. This gives us a new computation, now in the vector space $C^6$,

$$
6 \begin{bmatrix}
3 \\
-2 \\
0 \\
7 \\
4 \\
-3
\end{bmatrix} + 2 \begin{bmatrix}
-1 \\
4 \\
-2 \\
3 \\
8 \\
5
\end{bmatrix}
$$

which we can compute with the operations of $C^6$ (Definition CVA 89, Definition CVSM 90), to arrive at

$$
\begin{bmatrix}
16 \\
-4 \\
-4 \\
48 \\
40 \\
-8
\end{bmatrix}
$$

We are after the result of a computation in $M_{32}$, so we now can apply $\rho_B^{-1}$ to obtain a $3 \times 2$ matrix,

$$
16 \begin{bmatrix}
1 & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix} + (-4) \begin{bmatrix}
0 & 0 \\
1 & 0 \\
0 & 0
\end{bmatrix} + (48) \begin{bmatrix}
0 & 0 \\
0 & 1 \\
0 & 0
\end{bmatrix} + (40) \begin{bmatrix}
0 & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix} + (-8) \begin{bmatrix}
0 & 0 \\
0 & 0 \\
0 & 1
\end{bmatrix} = \begin{bmatrix}
16 & 48 \\
-4 & 40 \\
-4 & -8
\end{bmatrix}
$$

which is exactly the matrix we would have computed had we just performed the matrix operations in the first place.

Subsection READ

Reading Questions

1. The vector space of $3 \times 5$ matrices, $M_{3,5}$ is isomorphic to what fundamental vector space?
2. A basis for $\mathbb{C}^3$ is

$$B = \left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right\}$$

Compute $\rho_B \left( \begin{bmatrix} 5 \\ 8 \\ -1 \end{bmatrix} \right)$.

3. What is the first “surprise,” and why is it surprising?
Subsection EXC
Exercises

C10  In the vector space $\mathbb{C}^3$, compute the vector representation $\rho_B(v)$ for the basis $B$ and vector $v$ below.

$$B = \left\{ \begin{bmatrix} 2 \\ -2 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 5 \\ 2 \end{bmatrix} \right\}$$

$$v = \begin{bmatrix} 11 \\ 5 \\ 8 \end{bmatrix}$$

Contributed by Robert Beezer  Solution

C20  Rework Example CM32 replacing the basis $B$ by the basis

$$C = \left\{ \begin{bmatrix} -14 & -9 \\ 10 & 10 \end{bmatrix}, \begin{bmatrix} -7 & -4 \\ 5 & 5 \end{bmatrix}, \begin{bmatrix} -3 & -1 \\ 0 & -2 \end{bmatrix}, \begin{bmatrix} -7 & -4 \\ 3 & 2 \end{bmatrix}, \begin{bmatrix} -3 & -3 \\ -1 & -1 \end{bmatrix}, \begin{bmatrix} 4 & 2 \\ 2 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} \right\}$$

Contributed by Robert Beezer  Solution

M10  Prove that the set $S$ below is a basis for the vector space of $2 \times 2$ matrices, $M_{22}$. Do this choosing a natural basis for $M_{22}$ and coordinatizing the elements of $S$ with respect to this basis. Examine the resulting set of column vectors from $\mathbb{C}^4$ and apply the Coordinatization Principle.

$$S = \left\{ \begin{bmatrix} 33 & 99 \\ 78 & -9 \end{bmatrix}, \begin{bmatrix} -16 & -47 \\ -36 & 2 \end{bmatrix}, \begin{bmatrix} 10 & 27 \\ 17 & 3 \end{bmatrix}, \begin{bmatrix} -2 & -7 \\ -6 & 4 \end{bmatrix} \right\}$$

Contributed by Andy Zimmer
Subsection SOL
Solutions

C10 Contributed by Robert Beezer Statement 519
We need to express the vector $v$ as a linear combination of the vectors in $B$. Theorem VRRB 324 tells us we will be able to do this, and do it uniquely. The vector equation

$$a_1 \begin{bmatrix} 2 \\ -2 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 3 \end{bmatrix} + a_3 \begin{bmatrix} 3 \\ 5 \end{bmatrix} = \begin{bmatrix} 11 \\ 5 \end{bmatrix}$$

becomes (via Theorem SLSLC 103) a system of linear equations with augmented matrix,

$$\begin{bmatrix} 2 & 1 & 3 & 11 \\ -2 & 3 & 5 & 5 \\ 2 & 1 & 2 & 8 \end{bmatrix}$$

This system has the unique solution $a_1 = 2$, $a_2 = -2$, $a_3 = 3$. So by Definition VR 505,

$$\rho_B(v) = \rho_B \left( \begin{bmatrix} 11 \\ 5 \\ 8 \end{bmatrix} \right) = \rho_B \left( 2 \begin{bmatrix} 2 \\ -2 \\ 2 \end{bmatrix} + (-2) \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} + 3 \begin{bmatrix} 3 \\ 5 \\ 2 \end{bmatrix} \right) = \begin{bmatrix} 2 \\ -2 \\ 3 \end{bmatrix}$$

C20 Contributed by Robert Beezer Statement 519
The following computations replicate the computations given in Example CM32 515, only using the basis $C$.

$$\rho_C \left( \begin{bmatrix} 3 & 7 \\ -2 & 4 \\ 0 & -3 \end{bmatrix} \right) = \begin{bmatrix} -9 \\ 12 \\ -6 \\ 7 \\ -2 \\ -1 \end{bmatrix} \quad \rho_C \left( \begin{bmatrix} -1 & 3 \\ 4 & 8 \end{bmatrix} \right) = \begin{bmatrix} -6 \\ 24 \\ 1 \\ -6 \\ 11 \\ 5 \end{bmatrix}$$

$$\begin{bmatrix} -9 \\ 12 \\ -6 \\ 7 \\ -2 \\ -1 \end{bmatrix} + 2 \begin{bmatrix} -6 \\ 24 \\ 1 \\ -6 \\ 11 \\ 5 \end{bmatrix} = \begin{bmatrix} -66 \\ 120 \\ -34 \\ 30 \\ 10 \\ 4 \end{bmatrix} \quad \rho_C^{-1} \left( \begin{bmatrix} -66 \\ 120 \\ -34 \\ 30 \\ 10 \\ 4 \end{bmatrix} \right) = \begin{bmatrix} 16 & 48 \\ 120 & -4 \\ -34 & 30 \\ 30 & 10 \\ 10 & 4 \\ -4 & -8 \end{bmatrix}$$
We have seen that linear transformations whose domain and codomain are vector spaces of columns vectors have a close relationship with matrices (Theorem MBLT [435], Theorem MLTCV [437]). In this section, we will extend the relationship between matrices and linear transformations to the setting of linear transformations between abstract vector spaces.

**Definition MR**
**Matrix Representation**
Suppose that $T: U \rightarrow V$ is a linear transformation, $B = \{u_1, u_2, u_3, \ldots, u_n\}$ is a basis for $U$ of size $n$, and $C$ is a basis for $V$ of size $m$. The matrix representation of $T$ relative to $B$ and $C$ is the $m \times n$ matrix,

$$M^T_{B,C} = [\rho_C(T(u_1)) | \rho_C(T(u_2)) | \rho_C(T(u_3)) | \ldots | \rho_C(T(u_n))]$$

**Example OLTTR**
**One linear transformation, three representations**
Consider the linear transformation

$$S: P_3 \rightarrow M_{22}, \quad S(a + bx + cx^2 + dx^3) = \begin{bmatrix} 3a + 7b - 2c - 5d & 8a + 14b - 2c - 11d \\ -4a - 8b + 2c + 6d & 12a + 22b - 4c - 17d \end{bmatrix}$$

First, we build a representation relative to the bases,

$$B = \{1 + 2x + x^2 - x^3, 1 + 3x + x^2 + x^3, -1 - 2x + 2x^3, 2 + 3x + 2x^2 - 5x^3\}$$

$$C = \begin{bmatrix} [1 \ 1] & [2 \ 3] & [-1 \ -1] & [-1 \ -4] \\ [1 \ 2] & [2 \ 5] & [0 \ -2] & [-2 \ -4] \end{bmatrix}$$
We evaluate $S$ with each element of the basis for the domain, $B$, and coordinatize the result relative to the vectors in the basis for the codomain, $C$.

\[
\rho_C \left( S \left( 1 + 2x + x^2 - x^3 \right) \right) = \rho_C \left( \begin{bmatrix} 20 & 45 \\ -24 & 69 \end{bmatrix} \right) = \begin{bmatrix} -90 \\ 37 \\ -40 \\ 4 \end{bmatrix}
\]

\[
\rho_C \left( S \left( 1 + 3x + x^2 + x^3 \right) \right) = \rho_C \left( \begin{bmatrix} 17 & 37 \\ -20 & 57 \end{bmatrix} \right) = \begin{bmatrix} -72 \\ 29 \\ -34 \\ 3 \end{bmatrix}
\]

\[
\rho_C \left( S \left( -1 - 2x + 2x^3 \right) \right) = \rho_C \left( \begin{bmatrix} -27 & -58 \\ 32 & -90 \end{bmatrix} \right) = \begin{bmatrix} 114 \\ -46 \\ 54 \\ -5 \end{bmatrix}
\]

\[
\rho_C \left( S \left( 2 + 3x + 2x^2 - 5x^3 \right) \right) = \rho_C \left( \begin{bmatrix} 48 & 109 \\ -58 & 167 \end{bmatrix} \right) = \begin{bmatrix} -220 \\ 91 \\ -96 \\ 10 \end{bmatrix}
\]

Thus, employing Definition MR 523

\[
M_{B,C}^S = \begin{bmatrix} -90 & -72 & 114 & -220 \\ 37 & 29 & -46 & 91 \\ -40 & -34 & 54 & -96 \\ 4 & 3 & -5 & 10 \end{bmatrix}
\]

Often we use “nice” bases to build matrix representations and the work involved is much easier. Suppose we take bases

\[
D = \{ 1, x, x^2, x^3 \} \quad \quad E = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}
\]
The evaluation of $S$ at the elements of $D$ is easy and coordinatization relative to $E$ can be done on sight,

$$\rho_E(S(1)) = \rho_E\left(\begin{bmatrix} 3 & 8 \\ -4 & 12 \end{bmatrix}\right)$$

$$= \rho_E\left(3 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 8 \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + (-4) \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + 12 \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right) = \begin{bmatrix} 3 \\ 8 \\ -4 \\ 12 \end{bmatrix}$$

$$\rho_E(S(x)) = \rho_E\left(\begin{bmatrix} 7 & 14 \\ -8 & 22 \end{bmatrix}\right)$$

$$= \rho_E\left(7 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + 14 \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + (-8) \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + 22 \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right) = \begin{bmatrix} 7 \\ 14 \\ -8 \\ 22 \end{bmatrix}$$

$$\rho_E(S(x^2)) = \rho_E\left(\begin{bmatrix} -2 & -2 \\ 2 & -4 \end{bmatrix}\right)$$

$$= \rho_E\left((-2) \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + (-2) \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + 2 \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + (-4) \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right) = \begin{bmatrix} -2 \\ -2 \\ 2 \\ -4 \end{bmatrix}$$

$$\rho_E(S(x^3)) = \rho_E\left(\begin{bmatrix} -5 & -11 \\ 6 & -17 \end{bmatrix}\right)$$

$$= \rho_E\left((-5) \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + (-11) \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + 6 \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + (-17) \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}\right) = \begin{bmatrix} -5 \\ -11 \\ 6 \\ -17 \end{bmatrix}$$

So the matrix representation of $S$ relative to $D$ and $E$ is

$$M_{D,E}^S = \begin{bmatrix} 3 & 7 & -2 & -5 \\ 8 & 14 & -2 & -11 \\ -4 & -8 & 2 & 6 \\ 12 & 22 & -4 & -17 \end{bmatrix}$$

One more time, but now let’s use bases

$$F = \{1 + x - x^2 + 2x^3, -1 + 2x + 2x^3, 2 + x - 2x^2 + 3x^3, 1 + x + 2x^3\}$$

$$G = \left\{\begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}\right\}$$
and evaluate $S$ with the elements of $F$, then coordinatize the results relative to $G$,

$$
\rho_G \left( S \left( 1 + x - x^2 + 2x^3 \right) \right) = \rho_G \left( \begin{bmatrix} 2 & 2 \\ -2 & 4 \end{bmatrix} \right) = \rho_G \left( 2 \begin{bmatrix} 1 & 1 \\ -1 & 2 \end{bmatrix} \right) = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}
$$

$$
\rho_G \left( S \left( -1 + 2x + 2x^3 \right) \right) = \rho_G \left( \begin{bmatrix} 1 & -2 \\ 0 & -2 \end{bmatrix} \right) = \rho_G \left( (-1) \begin{bmatrix} -1 & 2 \\ 0 & 2 \end{bmatrix} \right) = \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix}
$$

$$
\rho_G \left( S \left( 2 + x - 2x^2 + 3x^3 \right) \right) = \rho_G \left( \begin{bmatrix} 2 & 1 \\ -2 & 3 \end{bmatrix} \right) = \rho_G \left( \begin{bmatrix} 2 & 1 \\ -2 & 3 \end{bmatrix} \right) = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}
$$

$$
\rho_G \left( S \left( 1 + x + 2x^3 \right) \right) = \rho_G \left( \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \right) = \rho_G \left( \begin{bmatrix} 0 & 1 \\ 0 & 2 \end{bmatrix} \right) = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}
$$

So we arrive at an especially economical matrix representation,

$$
M_{F,G}^S = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}
$$

We may choose to use whatever terms we want when we make a definition. Some are arbitrary, while others make sense, but only in light of subsequent theorems. Matrix representation is in the latter category. We begin with a linear transformation and produce a matrix. So what? Here’s the theorem that justifies the term “matrix representation.”

**Theorem FTMR**

**Fundamental Theorem of Matrix Representation**

Suppose that $T: U \rightarrow V$ is a linear transformation, $B$ is a basis for $U$, $C$ is a basis for $V$ and $M_{B,C}^T$ is the matrix representation of $T$ relative to $B$ and $C$. Then, for any $u \in U$,

$$
\rho_C (T (u)) = M_{B,C}^T (\rho_B (u))
$$

or equivalently

$$
T (u) = \rho_C^{-1} (M_{B,C}^T (\rho_B (u)))
$$

**Proof** Let $B = \{ u_1, u_2, u_3, \ldots, u_n \}$ be the basis of $U$. Since $u \in U$, there are scalars $a_1, a_2, a_3, \ldots, a_n$ such that

$$
u = a_1 u_1 + a_2 u_2 + a_3 u_3 + \cdots + a_n u_n$$
Then,
\[
M_{B,C}^T (\rho_B (u))
= [\rho_C (T (u_1)) \mid \rho_C (T (u_2)) \mid \rho_C (T (u_3)) \mid \ldots \mid \rho_C (T (u_n))] u
\]
\[
= [\rho_C (T (u_1)) \mid \rho_C (T (u_2)) \mid \rho_C (T (u_3)) \mid \ldots \mid \rho_C (T (u_n))]
\]
\[
= a_1 \rho_C (T (u_1)) + a_2 \rho_C (T (u_2)) + a_3 \rho_C (T (u_3)) + \cdots + a_n \rho_C (T (u_n))
\]
\[
= \rho_C (T (a_1 u_1 + a_2 u_2 + a_3 u_3 + \cdots + a_n u_n))
= \rho_C (T (u))
\]

The alternative conclusion is obtained from

\[
T (u) = I_V (T (u))
= (\rho_C^{-1} \circ \rho_C) (T (u))
= \rho_C^{-1} (\rho_C (T (u)))
= \rho_C^{-1} (M_{B,C}^T (\rho_B (u)))
\]

This theorem says that we can apply \( T \) to \( u \) and coordinatize the result relative to \( C \) in \( V \), or we can first coordinatize \( u \) relative to \( B \) in \( U \), then multiply by the matrix representation. Either way, the result is the same. So the effect of a linear transformation can always be accomplished by a matrix-vector product (Definition MVP \[187\]). That’s important enough to say again. The effect of a linear transformation is a matrix-vector product.

\[
\begin{pmatrix}
  a_1 \\
  a_2 \\
  a_3 \\
  \vdots \\
  a_n
\end{pmatrix}
\]

The alternative conclusion of this result might be even more striking. It says that to effect a linear transformation \( T \) of a vector \( u \), coordinatize the input (with \( \rho_B \)), do a matrix-vector product (with \( M_{B,C}^T \)), and un-coordinatize the result (with \( \rho_C^{-1} \)). So, absent some bookkeeping about vector representations, a linear transformation is a matrix.

Here’s an example to illustrate how the “action” of a linear transformation can be effected by matrix multiplication.

**Example ALTMM**

A linear transformation as matrix multiplication

In Example OLTTR \[523\] we found three representations of the linear transformation \( S \). In this example, we will compute a single output of \( S \) in four different ways. First “normally,” then three times over using Theorem FTMR \[526\].
Choose \( p(x) = 3 - x + 2x^2 - 5x^3 \), for no particular reason. Then the straightforward application of \( S \) to \( p(x) \) yields

\[
S(p(x)) = S(3 - x + 2x^2 - 5x^3) = \begin{bmatrix}
3(3) + 7(-1) - 2(2) - 5(-5) & 8(3) + 14(-1) - 2(2) - 11(-5) \\
-4(3) - 8(-1) + 2(2) + 6(-5) & 12(3) + 22(-1) - 4(2) - 17(-5)
\end{bmatrix}
= \begin{bmatrix}
23 & 61 \\
-30 & 91
\end{bmatrix}
\]

Now use the representation of \( S \) relative to the bases \( B \) and \( C \) and Theorem FTMR\[526\],

\[
S(p(x)) = \rho_C^{-1}(M_{B,C}^S \rho_B(p(x)))
= \rho_C^{-1}(M_{B,C}^S \rho_B(3 - x + 2x^2 - 5x^3))
= \rho_C^{-1}(M_{B,C}^S \rho_B(48(1 + 2x + x^2 - x^3) - 20(1 + 3x + x^2 + x^3) - (-1 - 2x + 2x^3) - 13(2 + x^3)))
= \rho_C^{-1} \begin{pmatrix}
48 \\
-20 \\
-1 \\
-13
\end{pmatrix}
= \rho_C^{-1} \begin{pmatrix}
-134 \\
59 \\
-46 \\
7
\end{pmatrix}
= (-134)\begin{pmatrix}
1 & 1 \\
1 & 2
\end{pmatrix} + 59\begin{pmatrix}
2 & 3 \\
2 & 5
\end{pmatrix} + (-46)\begin{pmatrix}
-1 & -1 \\
0 & -2
\end{pmatrix} + 7\begin{pmatrix}
-1 & -4 \\
-2 & -4
\end{pmatrix}
= \begin{bmatrix}
23 & 61 \\
-30 & 91
\end{bmatrix}
\]

Again, but now with “nice” bases like \( D \) and \( E \), and the computations are more trans-
parent.

\[ S(p(x)) = \rho_E^{-1}(M_{D,E}^S \rho_D(p(x))) \]
\[ = \rho_E^{-1}(M_{D,E}^S \rho_D(3 - x + 2x^2 - 5x^3)) \]
\[ = \rho_E^{-1}(M_{D,E}^S \rho_D(3(1) + (-1)(x) + 2(x^2) + (-5)(x^3))) \]
\[ = \rho_E^{-1}\left( M_{D,E}^S \begin{bmatrix} 3 & -1 & 0 \\ 2 & 2 & -5 \end{bmatrix} \right) \]
\[ = \rho_E^{-1}\left( \begin{bmatrix} 3 & 7 & -2 & -5 \\ 8 & 14 & -2 & -11 \\ -4 & -8 & 2 & 6 \\ 12 & 22 & -4 & -17 \end{bmatrix} \begin{bmatrix} 3 \\ -1 \\ 2 \\ -5 \end{bmatrix} \right) \]
\[ = \left( \begin{bmatrix} 23 \\ 61 \\ -30 \\ 91 \end{bmatrix} \right) \]
\[ = 23 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + 61 \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + (-30) \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} + 91 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \]
\[ = \begin{bmatrix} 23 \\ 61 \\ -30 \\ 91 \end{bmatrix} \]

OK, last time, now with the bases \( F \) and \( G \). The coordinatzations will take some work this time, but the matrix-vector product (Definition MVP \[187\]) (which is the actual action of the linear transformation) will be especially easy, given the diagonal nature of the matrix representation, \( M_{F,G}^S \). Here we go,

\[ S(p(x)) = \rho_G^{-1}(M_{F,G}^S \rho_F(p(x))) \]
\[ = \rho_G^{-1}(M_{F,G}^S \rho_F(3 - x + 2x^2 - 5x^3)) \]
\[ = \rho_G^{-1}(M_{F,G}^S \rho_F(32(1 + x - x^2 + 2x^3) - 7(-1 + 2x + 2x^3) - 17(2 + x - 2x^2 + 3x^3) - 2(1 + x + 2x) \]
\[ = \rho_G^{-1}\left( M_{F,G}^S \begin{bmatrix} 32 \\ -7 \\ -17 \\ -2 \end{bmatrix} \right) \]
\[ = \rho_G^{-1}\left( \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} 32 \\ -7 \\ -17 \\ -2 \end{bmatrix} \right) \]
\[ = \rho_G^{-1}\left( \begin{bmatrix} 64 \\ 7 \\ -17 \\ 0 \end{bmatrix} \right) \]
\[ = 64 \begin{bmatrix} 1 \\ 1 \\ 2 \\ -1 \end{bmatrix} + 7 \begin{bmatrix} -1 \\ 2 \\ -2 \\ 3 \end{bmatrix} + (17) \begin{bmatrix} 2 \\ 1 \\ 0 \\ 2 \end{bmatrix} \]
\[ = \begin{bmatrix} 23 \\ 61 \\ -30 \\ 91 \end{bmatrix} \]
This example is not meant to necessarily illustrate that any one of these four computations is simpler than the others. Instead, it is meant to illustrate the many different ways we can arrive at the same result, with the last three all employing a matrix representation to effect the linear transformation.

We will use Theorem FTMR \[526\] frequently in the next few sections. A typical application will feel like the linear transformation $T$ “commutes” with a vector representation, $\rho_C$, and as it does the transformation morphs into a matrix, $M_{B,C}^T$, while the vector representation changes to a new basis, $\rho_B$. Or vice-versa.

Subsection NRFO
New Representations from Old

In Subsection LT.NLTFO \[444\] we built new linear transformations from other linear transformations. Sums, scalar multiples and compositions. These new linear transformations will have matrix representations as well. How do the new matrix representations relate to the old matrix representations? Here are the three theorems.

**Theorem MRSLT**
Matrix Representation of a Sum of Linear Transformations
Suppose that $T: U \rightarrow V$ and $S: U \rightarrow V$ are linear transformations, $B$ is a basis of $U$ and $C$ is a basis of $V$. Then

$$M_{B,C}^{T+S} = M_{B,C}^T + M_{B,C}^S$$

**Proof** Let $x$ be any vector in $\mathbb{C}^n$. Define $u \in U$ by $u = \rho_B^{-1}(x)$, so $x = \rho_B(u)$. Then,

$$M_{B,C}^{T+S}x = M_{B,C}^{T+S}\rho_B(u)$$

Substitution

$$= \rho_C((T + S)(u))$$

Definition FTMR \[526\]

$$= \rho_C(T(u) + S(u))$$

Definition LTA \[444\]

$$= \rho_C(T(u)) + \rho_C(S(u))$$

Definition LT \[429\]

$$= M_{B,C}^T(\rho_B(u)) + M_{B,C}^S(\rho_B(u))$$

Theorem FTMR \[526\]

$$= (M_{B,C}^T + M_{B,C}^S)\rho_B(u)$$

Theorem MMDAA \[195\]

$$= (M_{B,C}^T + M_{B,C}^S)x$$

Substitution

Since the matrices $M_{B,C}^{T+S}$ and $M_{B,C}^T + M_{B,C}^S$ have equal matrix-vector products for every vector in $\mathbb{C}^n$, by Theorem EMMVP \[190\] they are equal matrices. (Now would be a good time to double-back and study the proof of Theorem EMMVP \[190\]. You did promise, didn’t you?)

**Theorem MRMLT**
Matrix Representation of a Multiple of a Linear Transformation
Suppose that $T: U \rightarrow V$ is a linear transformation, $\alpha \in \mathbb{C}$, $B$ is a basis of $U$ and $C$ is a basis of $V$. Then

$$M_{B,C}^{\alpha T} = \alpha M_{B,C}^T$$

\[\square\]
Proof Let \( x \) be any vector in \( \mathbb{C}^n \). Define \( u \in U \) by \( u = \rho_B^{-1}(x) \), so \( x = \rho_B(u) \). Then,

\[
M^a_T B_C^T x = M^S_T B_C^T \rho_B(u)
\]

Substitution

\[
= \rho_C((\alpha T)(u))
\]

Theorem FTMR 526

\[
= \rho_C(\alpha T(u))
\]

Definition LTSM 445

\[
= \alpha(T(u))
\]

Definition LT 429

\[
= \alpha(M^T_B C \rho_B(u))
\]

Theorem FTMR 526

\[
= (\alpha M^T_B C) \rho_B(u)
\]

Theorem MMSMM 196

\[
= (\alpha M^T_B C) x
\]

Substitution

Since the matrices \( M^a_T B_C^T \) and \( \alpha M^T_B C \) have equal matrix-vector products for every vector in \( \mathbb{C}^n \), by Theorem EMMVP 190 they are equal matrices. ■

The vector space of all linear transformations from \( U \) to \( V \) is now isomorphic to the vector space of all \( m \times n \) matrices.

Theorem MRCLT

Matrix Representation of a Composition of Linear Transformations

Suppose that \( T: U \rightarrow V \) and \( S: V \rightarrow W \) are linear transformations, \( B \) is a basis of \( U \), \( C \) is a basis of \( V \), and \( D \) is a basis of \( W \). Then

\[
M^S_T B_C D = M^S_C D M^T_B C
\]

□

Proof Let \( x \) be any vector in \( \mathbb{C}^n \). Define \( u \in U \) by \( u = \rho_B^{-1}(x) \), so \( x = \rho_B(u) \). Then,

\[
M^S_T B_C D x = M^S_T B_C D \rho_B(u)
\]

Substitution

\[
= \rho_D((S \circ T)(u))
\]

Theorem FTMR 526

\[
= \rho_D(S(T(u)))
\]

Definition LTC 446

\[
= M^S_C D \rho_C(T(u))
\]

Theorem FTMR 526

\[
= M^S_C D (M^T_B C \rho_B(u))
\]

Theorem FTMR 526

\[
= (M^S_C D M^T_B C) \rho_B(u)
\]

Theorem MMA 196

\[
= (M^S_C D M^T_B C) x
\]

Substitution

Since the matrices \( M^S_T B_C D \) and \( M^S_C D M^T_B C \) have equal matrix-vector products for every vector in \( \mathbb{C}^n \), by Theorem EMMVP 190 they are equal matrices. ■

This is the second great surprise of introductory linear algebra. Matrices are linear transformations (functions, really), and matrix multiplication is function composition! We can form the composition of two linear transformations, then form the matrix representation of the result. Or we can form the matrix representation of each linear transformation separately, then multiply the two representations together via Definition MM 191. In either case, we arrive at the same result.

Example MPMR

Matrix product of matrix representations
Consider the two linear transformations,

\[ T : \mathbb{C}^2 \rightarrow P_2 \quad T \left( \begin{bmatrix} a \\ b \end{bmatrix} \right) = (-a + 3b) + (2a + 4b)x + (a - 2b)x^2 \]

\[ S : P_2 \rightarrow M_{22} \quad S \left( a + bx + cx^2 \right) = \begin{bmatrix} 2a + b + 2c & a + 4b - c \\ -a + 3c & 3a + b + 2c \end{bmatrix} \]

and bases for \( \mathbb{C}^2 \), \( P_2 \) and \( M_{22} \) (respectively),

\[ B = \left\{ \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right\} \]

\[ C = \left\{ 1 - 2x + x^2, -1 + 3x, 2x + 3x^2 \right\} \]

\[ D = \left\{ \begin{bmatrix} 1 & -2 \\ 1 & -1 \end{bmatrix}, \begin{bmatrix} 1 & -1 \\ 1 & 2 \end{bmatrix}, \begin{bmatrix} -1 & 2 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 2 & -3 \\ 0 & 0 \end{bmatrix} \right\} \]

Begin by computing the new linear transformation that is the composition of \( T \) and \( S \) (Definition LTC [446], Theorem CLTLT [447]), \( (S \circ T) : \mathbb{C}^2 \rightarrow M_{22} \),

\[
(S \circ T) \left( \begin{bmatrix} a \\ b \end{bmatrix} \right) = S \left( T \left( \begin{bmatrix} a \\ b \end{bmatrix} \right) \right) \\
= S \left( (-a + 3b) + (2a + 4b)x + (a - 2b)x^2 \right) \\
= \begin{bmatrix} 2(-a + 3b) + (2a + 4b) + 2(a - 2b) & (-a + 3b) + 4(2a + 4b) - (a - 2b) \\ -(a - 3b + 3(a - 2b)) & 3(-a + 3b) + (2a + 4b) + 2(a - 2b) \end{bmatrix} \\
= \begin{bmatrix} 2a + 6b & 6a + 21b \\ 4a - 9b & a + 9b \end{bmatrix}
\]

Now compute the matrix representations (Definition MR [523]) for each of these three linear transformations \( (T, S, S \circ T) \), relative to the appropriate bases. First for \( T \),

\[
\rho_C \left( T \left( \begin{bmatrix} 3 \\ 1 \end{bmatrix} \right) \right) = \rho_C \left( 10x + x^2 \right) \\
= \rho_C \left( 28(1 - 2x + x^2) + 28(-1 + 3x) + (-9)(2x + 3x^2) \right) = \begin{bmatrix} 28 \\ -9 \end{bmatrix}
\]

\[
\rho_C \left( T \left( \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right) \right) = \rho_C \left( 1 + 8x \right) \\
= \rho_C \left( 33(1 - 2x + x^2) + 32(-1 + 3x) + (-11)(2x + 3x^2) \right) = \begin{bmatrix} 33 \\ 32 \\ -11 \end{bmatrix}
\]

So we have the matrix representation of \( T \),

\[
M^T_{B,C} = \begin{bmatrix} 28 & 33 \\ 28 & 32 \\ -9 & -11 \end{bmatrix}
\]
Now, a representation of $S$, 

$$
\rho_D \left( S (1 - 2x + x^2) \right) = \rho_D \left( \begin{bmatrix} 2 & -8 \\ 2 & 3 \end{bmatrix} \right) \\
= \rho_D \left( (-11) \begin{bmatrix} 1 & -2 \\ 1 & -1 \end{bmatrix} + (-21) \begin{bmatrix} 1 & -1 \\ 1 & 2 \end{bmatrix} + 0 \begin{bmatrix} -1 & 2 \\ 0 & 0 \end{bmatrix} + (17) \begin{bmatrix} 2 & -3 \\ 2 & 2 \end{bmatrix} \right) \\
= \begin{bmatrix} -11 \\ -21 \\ 0 \\ 17 \end{bmatrix}
$$

$$
\rho_D (S (-1 + 3x)) = \rho_D \left( \begin{bmatrix} 1 & 11 \\ 1 & 0 \end{bmatrix} \right) \\
= \rho_D \left( 26 \begin{bmatrix} 1 & -2 \\ 1 & -1 \end{bmatrix} + 51 \begin{bmatrix} 1 & -1 \\ 1 & 2 \end{bmatrix} + 0 \begin{bmatrix} -1 & 2 \\ 0 & 0 \end{bmatrix} + (-38) \begin{bmatrix} 2 & -3 \\ 2 & 2 \end{bmatrix} \right) \\
= \begin{bmatrix} 26 \\ 51 \\ 0 \\ -38 \end{bmatrix}
$$

$$
\rho_D (S (2x + 3x^2)) = \rho_D \left( \begin{bmatrix} 8 & 5 \\ 9 & 8 \end{bmatrix} \right) \\
= \rho_D \left( 34 \begin{bmatrix} 1 & -2 \\ 1 & -1 \end{bmatrix} + 67 \begin{bmatrix} 1 & -1 \\ 1 & 2 \end{bmatrix} + 1 \begin{bmatrix} -1 & 2 \\ 0 & 0 \end{bmatrix} + (-46) \begin{bmatrix} 2 & -3 \\ 2 & 2 \end{bmatrix} \right) \\
= \begin{bmatrix} 34 \\ 67 \\ 1 \\ -46 \end{bmatrix}
$$

So we have the matrix representation of $S$, 

$$
M_S^{C,D} = \begin{bmatrix} -11 & 26 & 34 \\ -21 & 51 & 67 \\ 0 & 0 & 1 \\ 17 & -38 & -46 \end{bmatrix}
$$
Finally, a representation of $S \circ T$,

\[
\rho_D \left( (S \circ T) \left( \begin{bmatrix} 3 \\ 1 \end{bmatrix} \right) \right) = \rho_D \left( \begin{bmatrix} 12 \\ 3 \\ 39 \\ 12 \end{bmatrix} \right) = \rho_D \left( \begin{bmatrix} 114 \\ 237 \\ -9 \\ -174 \end{bmatrix} \right)
\]

\[
\rho_D \left( (S \circ T) \left( \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right) \right) = \rho_D \left( \begin{bmatrix} 10 \\ -1 \\ 33 \\ 11 \end{bmatrix} \right) = \rho_D \left( \begin{bmatrix} 95 \\ 202 \\ -11 \\ -149 \end{bmatrix} \right)
\]

So we have the matrix representation of $S \circ T$,

\[
M^{S \circ T}_{B,D} = \begin{bmatrix} 114 & 95 \\ 237 & 202 \\ -9 & -11 \\ -174 & -149 \end{bmatrix}
\]

Now, we are all set to verify the conclusion of Theorem MRCLT [531],

\[
M^S_{C,D} M^T_{B,C} = \begin{bmatrix} -11 & 26 & 34 \\ -21 & 51 & 67 \\ 0 & 0 & 1 \\ 17 & -38 & -46 \end{bmatrix} \begin{bmatrix} 28 & 33 \\ 28 & 32 \\ -9 & -11 \end{bmatrix} = \begin{bmatrix} 114 & 95 \\ 237 & 202 \\ -9 & -11 \\ -174 & -149 \end{bmatrix} = M^{S \circ T}_{B,D}
\]

We have intentionally used non-standard bases. If you were to choose “nice” bases for the three vector spaces, then the result of the theorem might be rather transparent. But this would still be a worthwhile exercise — give it a go.

A diagram, similar to ones we have seen earlier, might make the importance of this theorem clearer,
One of our goals in the first part of this book is to make the definition of matrix multiplication \(\text{Definition MVP}[187], \text{Definition MM}[191]\) seem as natural as possible. However, many are brought up with an entry-by-entry description of matrix multiplication \(\text{Theorem ME}[406]\) as the definition of matrix multiplication, and then theorems about columns of matrices and linear combinations follow from that definition. With this unmotivated definition, the realization that matrix multiplication is function composition is quite remarkable. It is an interesting exercise to begin with the question, “What is the matrix representation of the composition of two linear transformations?” and then, without using any theorems about matrix multiplication, finally arrive at the entry-by-entry description of matrix multiplication. Try it yourself.

### Subsection PMR

#### Properties of Matrix Representations

It will not be a surprise to discover that the kernel and range of a linear transformation are closely related to the null space and column space of the transformation’s matrix representation. Perhaps this idea has been bouncing around in your head already, even before seeing the definition of a matrix representation. However, with a formal definition of a matrix representation \(\text{Definition MR}[523]\), and a fundamental theorem to go with it \(\text{Theorem FTMR}[526]\) we can be formal about the relationship, using the idea of isomorphic vector spaces \(\text{Definition IVS}[493]\). Here are the twin theorems.

#### Theorem KNSI

**Kernel and Null Space Isomorphism**

Suppose that \(T: U \mapsto V\) is a linear transformation, \(B\) is a basis for \(U\) of size \(n\), and \(C\) is a basis for \(V\). Then the kernel of \(T\) is isomorphic to the null space of \(M_{T,B,C}^T\):

\[
\mathcal{K}(T) \cong \mathcal{N}(M_{B,C}^T)
\]

**Proof** To establish that two vector spaces are isomorphic, we must find an isomorphism between them, an invertible linear transformation \(\text{Definition IVS}[493]\). The kernel of the linear transformation \(T, \mathcal{K}(T)\), is a subspace of \(U\), while the null space of the matrix representation, \(\mathcal{N}(M_{B,C}^T)\) is a subspace of \(\mathbb{C}^n\). The function \(\rho_B\) is defined as a function from \(U\) to \(\mathbb{C}^n\), but we can just as well employ the definition of \(\rho_B\) as a function from \(\mathcal{K}(T)\) to \(\mathcal{N}(M_{B,C}^T)\).

The restriction in the size of the domain and codomain will not affect the fact that \(\rho_B\) is a linear transformation \(\text{Theorem VRLT}[505]\), nor will it affect the fact that \(\rho_B\) is injective \(\text{Theorem VRI}[511]\). Something must done though to verify that \(\rho_B\) is surjective. To this end, appeal to the definition of surjective \(\text{Definition SLT}[469]\), and suppose that we have an element of the codomain, \(x \in \mathcal{N}(M_{B,C}^T) \subseteq \mathbb{C}^n\) and we wish to find an element of the domain with \(x\) as its image. We now show that the desired
element of the domain is $u = \rho_B^{-1}(x)$. First, verify that $u \in K(T)$,

$$T(u) = T(\rho_B^{-1}(x))$$

$$= \rho_C^{-1}(M_{B,C}^T(\rho_B(\rho_B^{-1}(x))))$$

$$= \rho_C^{-1}(M_{B,C}(I_{C^n}(x)))$$

$$= \rho_C^{-1}(M_{B,C}x)$$

$$= \rho_C^{-1}(0_{C^n})$$

$$= 0_V$$

Second, verify that the proposed isomorphism, $\rho_B$, takes $u$ to $x$,

$$\rho_B(u) = \rho_B(\rho_B^{-1}(x))$$

$$= I_{C^n}(x)$$

$$= x$$

With $\rho_B$ demonstrated to be an injective and surjective linear transformation from $K(T)$ to $N(M_{B,C}^T)$, Theorem ILTIS [491] tells us $\rho_B$ is invertible, and so by Definition IVS [493], we say $K(T)$ and $N(M_{B,C})$ are isomorphic.

Example KVMR
Kernel via matrix representation
Consider the kernel of the linear transformation

$$T: M_{22} \rightarrow P_2, \quad T\left(\begin{bmatrix} a & b \\ c & d \end{bmatrix}\right) = (2a - b + c - 5d) + (a + 4b + 5b + 2d)x + (3a - 2b + c - 8d)x^2$$

We will begin with a matrix representation of $T$ relative to the bases for $M_{22}$ and $P_2$ (respectively),

$$B = \left\{ \begin{bmatrix} 1 & 2 \\ -1 & -1 \end{bmatrix}, \begin{bmatrix} 1 & 3 \\ -1 & -4 \end{bmatrix}, \begin{bmatrix} 1 & 2 \\ 0 & -2 \end{bmatrix}, \begin{bmatrix} 2 & 5 \\ -2 & -4 \end{bmatrix} \right\}$$

$$C = \{1 + x + x^2, 2 + 3x, -1 - 2x^2\}$$
Then,
\[
\rho_C \left( T \left( \begin{bmatrix} 1 & 2 \\ -1 & -1 \end{bmatrix} \right) \right) = \rho_C \left( 4 + 2x + 6x^2 \right) = 2(1+x+x^2) + 0(2+3x) + (-2)(-1-2x^2) = \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix}
\]
\[
\rho_C \left( T \left( \begin{bmatrix} 1 & 3 \\ -1 & -4 \end{bmatrix} \right) \right) = \rho_C \left( 18 + 28x^2 \right) = (-24)(1+x+x^2) + 8(2+3x) + (-26)(-1-2x^2) = \begin{bmatrix} -24 \\ 8 \\ -26 \end{bmatrix}
\]
\[
\rho_C \left( T \left( \begin{bmatrix} 1 & 2 \\ 0 & -2 \end{bmatrix} \right) \right) = \rho_C \left( 10 + 5x + 15x^2 \right) = 5(1+x+x^2) + 0(2+3x) + (-5)(-1-2x^2) = \begin{bmatrix} 5 \\ 0 \\ -5 \end{bmatrix}
\]
\[
\rho_C \left( T \left( \begin{bmatrix} 2 & 5 \\ -2 & -4 \end{bmatrix} \right) \right) = \rho_C \left( 17 + 4x + 26x^2 \right) = (-8)(1+x+x^2) + (4)(2+3x) + (-17)(-1-2x^2) = \begin{bmatrix} -8 \\ 4 \\ -17 \end{bmatrix}
\]

So the matrix representation of \( T \) (relative to \( B \) and \( C \)) is
\[
M_{B,C}^T = \begin{bmatrix} 2 & -24 & 5 & -8 \\ 0 & 8 & 0 & 4 \\ -2 & -26 & -5 & -17 \end{bmatrix}
\]

We know from Theorem KNSI [535] that the kernel of the linear transformation \( T \) is isomorphic to the null space of the matrix representation \( M_{B,C}^T \) and by studying the proof of Theorem KNSI [535] we learn that \( \rho_B \) is an isomorphism between these null spaces. Rather than trying to compute the kernel of \( T \) using definitions and techniques from Chapter LT [429] we will instead analyze the null space of \( M_{B,C}^T \) using techniques from way back in Chapter V [87]. First row-reduce \( M_{B,C}^T \),
\[
\begin{bmatrix} 2 & -24 & 5 & -8 \\ 0 & 8 & 0 & 4 \\ -2 & -26 & -5 & -17 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & \frac{5}{2} & 2 \\ 0 & 1 & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 0 \end{bmatrix}
\]
So, by Theorem BNS, a basis for $\mathcal{N}(M^T_{B,C})$ is

$$S_p \left( \left\{ \begin{pmatrix} -\frac{5}{2} \\ 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} -2 \\ -\frac{1}{2} \\ 0 \\ 1 \end{pmatrix} \right\} \right)$$

We can now convert this basis of $\mathcal{N}(M^T_{B,C})$ into a basis of $\mathcal{K}(T)$ by applying $\rho^{-1}_B$ to each element of the basis,

$$\rho^{-1}_B \left( \begin{pmatrix} -\frac{5}{2} \\ 0 \\ 1 \\ 0 \end{pmatrix} \right) = \left( -\frac{5}{2} \right) \begin{pmatrix} 1 \\ -1 \\ -1 \\ 0 \end{pmatrix} + 0 \begin{pmatrix} 1 \\ -1 \\ -4 \\ 0 \end{pmatrix} + 1 \begin{pmatrix} 2 \\ -2 \\ 0 \\ 1 \end{pmatrix} + 0 \begin{pmatrix} 2 \\ -2 \\ -4 \end{pmatrix}$$

$$= \begin{pmatrix} -\frac{5}{2} \\ -3 \\ -\frac{1}{2} \end{pmatrix}$$

$$\rho^{-1}_B \left( \begin{pmatrix} -\frac{1}{2} \\ 0 \\ 1 \end{pmatrix} \right) = \left( -2 \right) \begin{pmatrix} 1 \\ -1 \\ -1 \\ 0 \end{pmatrix} + \left( -\frac{1}{2} \right) \begin{pmatrix} 1 \\ -1 \\ -4 \\ 0 \end{pmatrix} + 0 \begin{pmatrix} 1 \\ 0 \\ -2 \end{pmatrix} + 1 \begin{pmatrix} 2 \\ -2 \\ -4 \end{pmatrix}$$

$$= \begin{pmatrix} -\frac{1}{2} \\ -\frac{1}{2} \\ 0 \end{pmatrix}$$

So the set

$$\left\{ \begin{pmatrix} -\frac{5}{2} \\ -3 \\ -\frac{1}{2} \end{pmatrix}, \begin{pmatrix} -\frac{1}{2} \\ -\frac{1}{2} \\ 0 \end{pmatrix} \right\}$$

is a basis for $\mathcal{K}(T)$.

An entirely similar result applies to the range of a linear transformation and the column space of a matrix representation of the linear transformation.

**Theorem RCSI**

**Range and Column Space Isomorphism**

Suppose that $T : U \mapsto V$ is a linear transformation, $B$ is a basis for $U$ of size $n$, and $C$ is a basis for $V$ of size $m$. Then the range of $T$ is isomorphic to the column space of $M^T_{B,C}$,

$$\mathcal{R}(T) \cong \mathcal{C}(M^T_{B,C})$$

**Proof** To establish that two vector spaces are isomorphic, we must find an isomorphism between them, an invertible linear transformation (Definition IVS). The range of the linear transformation $T$, $\mathcal{R}(T)$, is a subspace of $V$, while the column space of the matrix representation, $\mathcal{C}(M^T_{B,C})$ is a subspace of $\mathbb{C}^m$. The function $\rho_C$ is defined as a function from $V$ to $\mathbb{C}^m$, but we can just as well employ the definition of $\rho_C$ as a function from $\mathcal{R}(T)$ to $\mathcal{C}(M^T_{B,C})$.

The restriction in the size of the domain and codomain will not affect the fact that $\rho_C$ is a linear transformation (Theorem VRLT), nor will it affect the fact that $\rho_C$ is injective (Theorem VRI). Something must done though to verify that $\rho_C$ is surjective. This all gets a bit confusing, since the domain of our isomorphism is the range of the linear transformation, so think about your objects as you go. To establish that $\rho_C$ is surjective,
appeal to the definition of a surjective linear transformation (Definition SLT [469]), and suppose that we have an element of the codomain, $y \in C(M_{B,C}) \subseteq \mathbb{C}^m$ and we wish to find an element of the domain with $y$ as its image. Since $y \in C(M_{B,C})$, there exists a vector, $x \in \mathbb{C}^n$ with $M_{B,C}^T x = y$. We now show that the desired element of the domain is $v = \rho_C^{-1}(y)$. First, verify that $v \in R(T)$ by applying $T$ to $u = \rho_B^{-1}(x)$,

$$T(u) = T\left(\rho_B^{-1}(x)\right) = \rho_C^{-1}(M_{B,C}^T(\rho_B(\rho_B^{-1}(x)))) = \rho_C^{-1}(M_{B,C}^T(I_{C^n}(x))) = \rho_C^{-1}(M_{B,C}^T x) = \rho_C^{-1}(y) = y \in C(M_{B,C}^T)$$

Substitution

Second, verify that the proposed isomorphism, $\rho_C$, takes $v$ to $y$,

$$\rho_C(v) = \rho_C(\rho_C^{-1}(y)) = I_{C^m}(y) = y$$

With $\rho_C$ demonstrated to be an injective and surjective linear transformation from $R(T)$ to $C(M_{B,C}^T)$, Theorem ILTIS [491] tells us $\rho_C$ is invertible, and so by Definition IVS [493], we say $R(T)$ and $C(M_{B,C}^T)$ are isomorphic.

Example RVMR

Range via matrix representation

In this example, we will recycle the linear transformation $T$ and the bases $B$ and $C$ of Example KVMR [536] but now we will compute the range of $T$,

$$T: M_{22} \mapsto P_2, \quad T\left(\begin{bmatrix} a & b \\ c & d \end{bmatrix}\right) = (2a-b+c-5d)+(a+4b+5b+2d)x+(3a-2b+c-8d)x^2$$

With bases $B$ and $C$,

$$B = \left\{ \begin{bmatrix} 1 & 2 \\ -1 & -1 \end{bmatrix}, \begin{bmatrix} 1 & 3 \\ -1 & -4 \end{bmatrix}, \begin{bmatrix} 1 & 2 \\ 0 & -2 \end{bmatrix}, \begin{bmatrix} 2 & 5 \\ -2 & -4 \end{bmatrix} \right\}$$

$$C = \{1 + x + x^2, 2 + 3x, -1 - 2x^2\}$$

we obtain the matrix representation

$$M_{B,C}^T = \begin{bmatrix} 2 & -24 & 5 & -8 \\ 0 & 8 & 0 & 4 \\ -2 & -26 & -5 & -17 \end{bmatrix}$$

We know from Theorem RCSI [538] that the range of the linear transformation $T$ is isomorphic to the column space of the matrix representation $M_{B,C}^T$ and by studying the proof of Theorem RCSI [538] we learn that $\rho_C$ is an isomorphism between these subspaces. Notice that since the range is a subspace of the codomain, we will employ $\rho_C$ as the isomorphism, rather than $\rho_B$, which was the correct choice for an isomorphism between the null spaces of Example KVMR [536].
Rather than trying to compute the range of $T$ using definitions and techniques from Chapter LT \[429\], we will instead analyze the column space of $M_{B,C}^T$ using techniques from way back in Chapter M \[179\]. First row-reduce $(M_{B,C}^T)^t$,

\[
\begin{bmatrix}
2 & 0 & -2 \\
-24 & 8 & -26 \\
5 & 0 & -5 \\
-8 & 4 & -17 \\
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 0 & -1 \\
0 & 1 & -\frac{25}{4} \\
0 & 0 & 0 \\
0 & 0 & 0 \\
\end{bmatrix}
\]

Now employ Theorem CSRST \[246\] and Theorem BRS \[245\] (there are other methods we could choose here to compute the column space, such as Theorem BCSOC \[238\]) to obtain the basis for $C(M_{B,C}^T)$,

\[
\left\{ \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -\frac{25}{4} \end{bmatrix} \right\}
\]

We can now convert this basis of $C(M_{B,C}^T)$ into a basis of $\mathcal{R}(T)$ by applying $\rho_C^{-1}$ to each element of the basis,

\[
\rho_C^{-1}\left( \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \right) = (1 + x + x^2) - (-1 - 2x^2) = 2 + x + 3x^2
\]

\[
\rho_C^{-1}\left( \begin{bmatrix} 0 \\ 1 \\ -\frac{25}{4} \end{bmatrix} \right) = (2 + 3x) - \frac{25}{4}(-1 - 2x^2) = \frac{33}{4} + 3x + \frac{31}{2}x^2
\]

So the set

\[
\left\{ 2 + 3x + 3x^2, \frac{33}{4} + 3x + \frac{31}{2}x^2 \right\}
\]

is a basis for $\mathcal{R}(T)$.\[\circ\]

Theorem KNSI \[535\] and Theorem RCSI \[538\] can be viewed as further formal evidence for the Coordinatization Principle \[515\], though they are not direct consequences.

Subsection IVLT

Invertible Linear Transformations

We have seen, both in theorems and in examples, that questions about linear transformations are often equivalent to questions about matrices. It is the matrix representation of a linear transformation that makes this idea precise. Here’s our final theorem that solidifies this connection. TODO: theorem below as “T invertible iff $M_{B,C}^T$ invertible.”

When invertible, matrix rep of inverse is as given.

**Theorem IMR**

**Invertible Matrix Representations**

Suppose that $T : U \rightarrow V$ is an invertible linear transformation, $B$ is a basis for $U$ and $C$ is a basis for $V$. Then the matrix representation of $T$ relative to $B$ and $C$, $M_{B,C}^T$ is an invertible matrix, and

\[
M_{C,B}^{T^{-1}} = (M_{B,C}^T)^{-1}
\]

\[\square\]
Proof This theorem states that the matrix representation of $T^{-1}$ can be found by finding the matrix inverse of the matrix representation of $T$ (with suitable bases in the right places). It also says that the matrix representation of $T$ is an invertible matrix. We can establish the invertibility, and precisely what the inverse is, by appealing to the definition of a matrix inverse, [Definition MI 208]. To this end, let $B = \{u_1, u_2, u_3, \ldots, u_n\}$ and $C = \{v_1, v_2, v_3, \ldots, v_n\}$. Then

$$M_{C,B}^{T^{-1}} M_{B,C}^T = M_{B,B}^{T^{-1} \circ T}$$

= $M_{B,B}^{I}$

= $[\rho_B (I_U (u_1)) | \rho_B (I_U (u_2)) | \ldots | \rho_B (I_U (u_n))]$

= $[\rho_B (u_1) | \rho_B (u_2) | \rho_B (u_3) | \ldots | \rho_B (u_n)]$

= $[v_1 | v_2 | v_3 | \ldots | v_n]$

= $I_n$

and

$$M_{B,C}^T M_{C,B}^{T^{-1}} = M_{C,C}^{T \circ T^{-1}}$$

= $M_{C,C}^{I}$

= $[\rho_C (I_V (v_1)) | \rho_C (I_V (v_2)) | \ldots | \rho_C (I_V (v_n))]$

= $[\rho_C (v_1) | \rho_C (v_2) | \rho_C (v_3) | \ldots | \rho_C (v_n)]$

= $[e_1 | e_2 | e_3 | \ldots | e_n]$

= $I_n$

So by [Definition MI 208], the matrix $M_{B,C}^T$ has an inverse, and that inverse is $M_{C,B}^{T^{-1}}$. \[\Box\]

Example I LTVR
Inverse of a linear transformation via a representation
Consider the linear transformation

$$R: P_3 \mapsto M_{22}, \quad R \left( a + bx + cx^2 + x^3 \right) = \begin{bmatrix} a + b - c + 2d & 2a + 3b - 2c + 3d \\ a + b + 2d & -a + b + 2c - 5d \end{bmatrix}$$

If we wish to quickly find a formula for the inverse of $R$ (assuming it exists), then choosing “nice” bases will work best. So build a matrix representation of $R$ relative to the bases $B$ and $C$,

$$B = \{1, x, x^2, x^3\}$$

$$C = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \right\}$$
Then,

\[
\rho_C(R(1)) = \rho_C\left(\begin{bmatrix} 1 & 2 \\ 1 & -1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 2 \\ 1 \\ -1 \end{bmatrix}
\]

\[
\rho_C(R(x)) = \rho_C\left(\begin{bmatrix} 1 & 3 \\ 1 & 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 3 \\ 1 \\ 1 \end{bmatrix}
\]

\[
\rho_C(R(x^2)) = \rho_C\left(\begin{bmatrix} -1 & -2 \\ 0 & 2 \end{bmatrix}\right) = \begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \end{bmatrix}
\]

\[
\rho_C(R(x^3)) = \rho_C\left(\begin{bmatrix} 2 & 3 \\ 2 & -5 \end{bmatrix}\right) = \begin{bmatrix} 2 \\ 3 \\ 2 \\ -5 \end{bmatrix}
\]

So a representation of \( R \) is

\[
M_{B,C}^R = \begin{bmatrix} 1 & 1 & -1 & 2 \\ 2 & 3 & -2 & 3 \\ 1 & 1 & 0 & 2 \\ -1 & 1 & 2 & -5 \end{bmatrix}
\]

The matrix \( M_{B,C}^R \) is invertible (as you can check) so we know by Theorem IMR [540]. Furthermore,

\[
M_{C,B}^{R^{-1}} = (M_{B,C}^R)^{-1} = \begin{bmatrix} 1 & 1 & -1 & 2 \\ 2 & 3 & -2 & 3 \\ 1 & 1 & 0 & 2 \\ -1 & 1 & 2 & -5 \end{bmatrix}^{-1} = \begin{bmatrix} 20 & -7 & -2 & 3 \\ -8 & 3 & 1 & -1 \\ -1 & 0 & 1 & 0 \\ -6 & 2 & 1 & -1 \end{bmatrix}
\]
We can use this representation of the inverse linear transformation, in concert with Theorem FTMR [526], to determine an explicit formula for the inverse itself,

\[ R^{-1} \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) = \rho_B^{-1} \left( M_{C,B}^{-1} \rho_C \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) \right) \]

Theorem FTMR [526]

\[ = \rho_B^{-1} \left( (M_{B,C}^R)^{-1} \rho_C \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) \right) \]

Theorem IMR [540]

\[ = \rho_B^{-1} \left( (M_{B,C}^R)^{-1} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \right) \]

Definition VR [505]

\[ = \rho_B^{-1} \left( \begin{bmatrix} 20 & -7 & -2 & 3 \\ -8 & 3 & 1 & -1 \\ -1 & 0 & 1 & 0 \\ -6 & 2 & 1 & -1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \right) \]

Definition MI [208]

\[ = \rho_B^{-1} \left( \begin{bmatrix} 20a - 7b - 2c + 3d \\ -8a + 3b + c - d \\ -a + c \\ -6a + 2b + c - d \end{bmatrix} \right) \]

Definition MVP [187]

\[ = (20a - 7b - 2c + 3d) + (-8a + 3b + c - d)x \\
+ (-a + c)x^2 + (-6a + 2b + c - d)x^3 \]

Definition VR [505]

You might look back at Example AIVLT [487], where we first witnessed the inverse of a linear transformation and recognize that the inverse (S) was built from using the method of this example on a matrix representation of T.

TODO: NSMEExx! \( T(x) = Ax \) is invertible. Proof: matrix rep with standard basis is just A.

Subsection READ

Reading Questions

1. Why does Theorem FTMR [526] deserve the moniker “fundamental”?

2. Find the matrix representation, \( M_{B,C}^T \) of the linear transformation

\[ T: \mathbb{C}^2 \rightarrow \mathbb{C}^2, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right) = \begin{bmatrix} 2x_1 - x_2 \\ 3x_1 + 2x_2 \end{bmatrix} \]

relative to the bases

\[ B = \left\{ \begin{bmatrix} 2 \\ 3 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \end{bmatrix} \right\} \quad C = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \]

3. What is the second “surprise,” and why is it surprising?
Subsection EXC

Exercises

C20  Compute the matrix representation of $T$ relative to the bases $B$ and $C$.

$$T : P_3 \rightarrow \mathbb{C}^3, \quad T (a + bx + cx^2 + dx^3) = \begin{bmatrix} 2a - 3b + 4c - 2d \\ a + b - c + d \\ 3a + 2c - 3d \end{bmatrix}$$

$B = \{1, x, x^2, x^3\}$  $C = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$

Contributed by Robert Beezer

C30  Find bases for the kernel and range of the linear transformation $S$ below.

$$S : M_{22} \rightarrow P_2, \quad S \left( \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right) = (a + 2b + 5c - 4d) + (3a - b + 8c + 2d)x + (a + b + 4c - 2d)x^2$$

Contributed by Robert Beezer

C40  Let $S_{22}$ be the set of $2 \times 2$ symmetric matrices. Verify that the linear transformation $R$ is invertible and find $R^{-1}$.

$$R : S_{22} \rightarrow P_2, \quad R \left( \begin{bmatrix} a & b \\ b & c \end{bmatrix} \right) = (a - b) + (2a - 3b - 2c)x + (a - b + c)x^2$$

Contributed by Robert Beezer

T80  Suppose that $T : U \rightarrow V$ and $S : V \rightarrow W$ are linear transformations, and that $B$, $C$ and $D$ are bases for $U$, $V$, and $W$. Using only Definition MR define matrix representations for $T$ and $S$. Using these two definitions, and Definition MR derive a matrix representation for the composition $S \circ T$ in terms of the entries of the matrices $M_B^T$ and $M_C^S$. Explain how you would use this result to motivate a definition for matrix multiplication that is strikingly similar to Theorem ME.

Contributed by Robert Beezer
Subsection SOL
Solutions

C20  Contributed by Robert Beezer  Statement 545
Apply Definition MR 523,

\[
\rho_C(T(1)) = \rho_C\left(\begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}\right) = \rho_C\left(\begin{bmatrix} 1 & 1 \\ 0 & -2 \\ 0 & 3 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 2 \\ -3 \end{bmatrix}
\]

\[
\rho_C(T(x)) = \rho_C\left(\begin{bmatrix} -3 \\ 1 \\ 0 \end{bmatrix}\right) = \rho_C\left(\begin{bmatrix} 1 \\ -4 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ 4 \\ 0 \end{bmatrix}
\]

\[
\rho_C(T(x^2)) = \rho_C\left(\begin{bmatrix} 4 \\ -1 \\ 2 \end{bmatrix}\right) = \rho_C\left(\begin{bmatrix} 1 \\ 5 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ -3 \end{bmatrix} + \begin{bmatrix} 1 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 5 \\ 2 \end{bmatrix}
\]

\[
\rho_C(T(x^3)) = \rho_C\left(\begin{bmatrix} -2 \\ 1 \\ -3 \end{bmatrix}\right) = \rho_C\left(\begin{bmatrix} 1 \\ -3 \end{bmatrix} + \begin{bmatrix} 0 \\ 4 \end{bmatrix} + \begin{bmatrix} -3 \\ 1 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ -3 \end{bmatrix}
\]

These four vectors are the columns of the matrix representation,

\[
M_{B,C}^T = \begin{bmatrix} 1 & -4 & 5 & -3 \\ -2 & 1 & -3 & 4 \\ 3 & 0 & 2 & -3 \end{bmatrix}
\]

C30  Contributed by Robert Beezer  Statement 545
These subspaces will be easiest to construct by analyzing a matrix representation of \( S \). Since we can use any matrix representation, we might as well use natural bases that allow us to construct the matrix representation quickly and easily,

\[
B = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\} \quad C = \left\{ 1, x, x^2 \right\}
\]

then we can practically build the matrix representation on sight,

\[
M_{B,C}^S = \begin{bmatrix} 1 & 2 & 5 & -4 \\ 3 & -1 & 8 & 2 \\ 1 & 1 & 4 & -2 \end{bmatrix}
\]

The first step is to find bases for the null space and column space of the matrix representation. Row-reducing the matrix representation we find,

\[
\begin{bmatrix} 1 & 0 & 3 & 0 \\ 0 & 1 & 1 & -2 \\ 0 & 0 & 0 & 0 \end{bmatrix}
\]

So by Theorem SSNS 122, Theorem BNS 141 and Theorem BCSOC 238, we have

\[
\mathcal{N}(M_{B,C}^S) = \mathcal{S}_p\left(\begin{bmatrix} -3 \\ -1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 2 \\ 1 \end{bmatrix}\right) \quad \mathcal{C}(M_{B,C}^S) = \mathcal{S}_p\left(\begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \end{bmatrix}\right)
\]
Now, the proofs of Theorem KNSI \[535\] and Theorem RCSI \[538\] tell us that we can apply \(\rho_B^{-1}\) and \(\rho_C^{-1}\) (respectively) to "un-coordinatize" and get bases for the kernel and range of the linear transformation \(S\) itself,

\[
\mathcal{K}(S) = S\rho \left\{ \begin{bmatrix} -3 & -1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 2 \\ 0 & 1 \end{bmatrix} \right\} \quad \mathcal{R}(S) = S\rho \left\{ 1 + 3x + x^2, 2 - x + x^2 \right\}
\]

\[\text{C40} \quad \text{Contributed by Robert Beezer} \quad \text{Statement} \quad \text{545}\]

The analysis of \(R\) will be easiest if we analyze a matrix representation of \(R\). Since we can use any matrix representation, we might as well use natural bases that allow us to construct the matrix representation quickly and easily,

\[
B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} \quad C = \{ 1, x, x^2 \}
\]

then we can practically build the matrix representation on sight,

\[
M_{B,C}^R = \begin{bmatrix} 1 & -1 & 0 \\ 2 & -3 & -2 \\ 1 & -1 & 1 \end{bmatrix}
\]

This matrix representation is invertible (it has a nonzero determinant of \(-1\), Theorem SMZD \[366\], Theorem NSI \[225\]) so Theorem IMR \[540\] tells us that the linear transformation \(S\) is also invertible. To find a formula for \(R^{-1}\) we compute,

\[
R^{-1} (a + bx + cx^2) = \rho_B^{-1} \left( M_{C,B}^R \rho_C^{-1} (a + bx + cx^2) \right) \quad \text{Theorem FTMR} \quad \text{526}
\]

\[
= \rho_B^{-1} \left( (M_{B,C}^R)^{-1} \rho_C (a + bx + cx^2) \right) \quad \text{Theorem IMR} \quad \text{540}
\]

\[
= \rho_B^{-1} \left( (M_{B,C}^R)^{-1} \begin{bmatrix} a \\ b \\ c \end{bmatrix} \right) \quad \text{Definition VR} \quad \text{505}
\]

\[
= \rho_B^{-1} \left( \begin{bmatrix} 5a - b - 2c \\ 4a - b - 2c \\ -a + c \end{bmatrix} \right) \quad \text{Definition MVP} \quad \text{187}
\]

\[
= \begin{bmatrix} 5a - b - 2c & 4a - b - 2c \\ 4a - b - 2c & -a + c \end{bmatrix} \quad \text{Definition VR} \quad \text{505}
\]
Section CB
Change of Basis

We have seen in Section MR that a linear transformation can be represented by a matrix, once we pick bases for the domain and codomain. How does the matrix representation change if we choose different bases? Which bases lead to especially nice representations? From the infinite possibilities, what is the best possible representation? This section will begin to answer these questions. But first we need to define eigenvalues for linear transformations and the change-of-basis matrix.

Subsection EELT
Eigenvalues and Eigenvectors of Linear Transformations

We now define the notion of an eigenvalue and eigenvector of a linear transformation. It should not be too surprising, especially if you remind yourself of the close relationship between matrices and linear transformations.

Definition EELT
Eigenvalue and Eigenvector of a Linear Transformation
Suppose that \( T : V \rightarrow V \) is a linear transformation. Then a nonzero vector \( v \in V \) is an eigenvector of \( T \) for the eigenvalue \( \lambda \) if \( T(v) = \lambda v \).

We will see shortly the best method for computing the eigenvalues and eigenvectors of a linear transformation, but for now, here are some examples to verify that such things do exist.

(TODO: Examples here for abstract vector space eigenvectors.)

Subsection CBM
Change-of-Basis Matrix

Definition CBM
Change-of-Basis Matrix
Suppose that \( V \) is a vector space, and \( I_V : V \rightarrow V \) is the identity linear transformation on \( V \). Let \( B = \{v_1, v_2, v_3, \ldots, v_n\} \) and \( C \) be two bases of \( V \). Then the change-of-basis matrix from \( B \) to \( C \) is the matrix representation of \( I_V \) relative to \( B \) and \( C \),

\[
C_{B,C} = M^{I_V}_{B,C} = [\rho_C(I_V(v_1)) | \rho_C(I_V(v_2)) | \rho_C(I_V(v_3)) | \ldots | \rho_C(I_V(v_n))] = [\rho_C(v_1) | \rho_C(v_2) | \rho_C(v_3) | \ldots | \rho_C(v_n)]
\]

△
Notice that this definition is primarily about a single vector space \((V)\) and two bases of \(V\) \((B, C)\). The linear transformation \((I_V)\) is necessary but not critical. As you might expect, this matrix has something to do with changing bases. Here is the theorem that gives the matrix its name (not the other way around).

**Theorem CB**  
**Change-of-Basis**  
Suppose that \(u\) is a vector in the vector space \(V\) and \(B\) and \(C\) are bases of \(V\). Then

\[ C_{B,C}\rho_B (v) = \rho_C (v) \]

**Proof**

\[ C_{B,C}\rho_B (v) = M^{I_V}_{B,C}\rho_B (v) = \rho_C (I_V (v)) = \rho_C (v) \]

So the change-of-basis matrix can be used with matrix multiplication to convert a vector representation of a vector \((v)\) relative to one basis \((\rho_B (v))\) to a representation of the same vector relative to a second basis \((\rho_C (v))\).

**Theorem ICBM**  
**Inverse of Change-of-Basis Matrix**  
Suppose that \(V\) is a vector space, and \(B\) and \(C\) are bases of \(V\). Then the change-of-basis matrix \(C_{B,C}\) is nonsingular and

\[ C^{-1}_{B,C} = C_{C,B} \]

**Proof** The linear transformation \(I_V: V \mapsto V\) is invertible, and its inverse is itself, \(I_V\) (check this!). So by **Theorem IMR** 540, the matrix \(M^{I_V}_{B,C} = C_{B,C}\) is invertible. **Theorem NSI** 225 says an invertible matrix is nonsingular.

Then

\[ C^{-1}_{B,C} = (M^{I_V}_{B,C})^{-1} = M^{-1}_{C,B} = M_{C,B} = C_{C,B} \]

**Subsection MRS**  
**Matrix Representations and Similarity**  

Here is the main theorem of this section. It looks a bit involved at first glance, but the proof should make you realize it is not all that complicated. In any event, we are more interested in a special case.
Theorem MRCB
Matrix Representation and Change of Basis
Suppose that \( T: U \mapsto V \) is a linear transformation, \( B \) and \( C \) are bases for \( U \), and \( D \) and \( E \) are bases for \( V \). Then

\[
M_{B,D}^T = C_{E,D}M_{C,E}^TM_{B,C}^T
\]

\( \square \)

Proof

\[
C_{E,D}M_{C,E}^TM_{B,C} = M_{E,D}^IM_{B,E}^T
\]

Definition CBM \[549\]

\[
= M_{E,D}^IM_{B,E}^T
\]

Theorem MRCLT \[531\]

\[
= M_{E,D}^IM_{B,E}^T
\]

Definition IDLT \[487\]

\[
= C_{B,D}M_{C,C}^T
\]

Theorem MRCLT \[531\]

\[
= C_{B,D}M_{C,C}^T
\]

Definition IDLT \[487\]

\( \square \)

Here is a special case of the previous theorem, where we choose \( U \) and \( V \) to be the same vector space, so the matrix representations and the change-of-basis matrices are all square of the same size.

Theorem SCB
Similarity and Change of Basis
Suppose that \( T: V \mapsto V \) is a linear transformation and \( B \) and \( C \) are bases of \( V \). Then

\[
M_{B,B}^T = C_{B,C}^{-1}M_{C,C}^TC_{B,C}
\]

\( \square \)

Proof In the conclusion of Theorem MRCB \[551\], replace \( D \) by \( B \), and replace \( E \) by \( C \),

\[
M_{B,B}^T = C_{B,C}^{-1}M_{C,C}^TC_{B,C}
\]

Theorem MRCB \[551\]

\( \square \)

This is the third surprise of this chapter. Theorem SCB \[551\] considers the special case where a linear transformation has the same vector space for the domain and codomain (\( V \)). We build a matrix representation of \( T \) using the basis \( B \) simultaneously for both the domain and codomain (\( M_{B,B}^T \)), and then we build a second matrix representation of \( T \), now using the basis \( C \) for both the domain and codomain (\( M_{B,C}^T \)). Then these two representations are related via a similarity transformation (Definition SIM \[411\]) using a change-of-basis matrix (\( C_{B,C} \))!

We can now return to the question of computing an eigenvalue or eigenvector of a linear transformation. For a linear transformation of the form \( T: V \mapsto V \), we know that representations relative to different bases are similar matrices. We also know that similar matrices have equal characteristic polynomials by Theorem SMEE \[414\]. We will now show that eigenvalues of a linear transformation \( T \) are precisely the eigenvalues of any matrix representation of \( T \). Since the choice of a different matrix representation leads to a similar matrix, there will be no “new” eigenvalues obtained from this second representation. Similarly, the change-of-basis matrix can be used to show that eigenvectors obtained from one matrix representation will be precisely those obtained from any other representation. So we can determine the eigenvalues and eigenvectors of a linear transformation by forming one matrix representation, using any basis we please, and analyzing the matrix in the manner of Chapter E \[373\].
Theorem EER  
Eigenvalues, Eigenvectors, Representations

Suppose that $T : V \rightarrow V$ is a linear transformation and $B$ is a basis of $V$. Then $v \in V$ is an eigenvector of $T$ for the eigenvalue $\lambda$ if and only if $\rho_B(v)$ is an eigenvector of $M_{B,B}^T$ for the eigenvalue $\lambda$.

Proof ($\Rightarrow$) Assume that $v \in V$ is an eigenvector of $T$ for the eigenvalue $\lambda$. Then

$$M_{B,B}^T\rho_B(v) = \rho_B(T(v)) = \rho_B(\lambda v) = \lambda \rho_B(v)$$

which by Definition EEM says that $\rho_B(v)$ is an eigenvector of the matrix $M_{B,B}^T$ for the eigenvalue $\lambda$.

($\Leftarrow$) Assume that $\rho_B(v)$ is an eigenvector of $M_{B,B}^T$ for the eigenvalue $\lambda$. Then

$$T(v) = \rho_B^{-1}(\rho_B(T(v))) = \rho_B^{-1}(\lambda \rho_B(v)) = \lambda \rho_B^{-1}(\rho_B(v)) = \lambda v$$

which by Definition EELT says $v$ is an eigenvector of $T$ for the eigenvalue $\lambda$.

Knowing that the eigenvalues of a linear transformation are the eigenvalues of any representation, no matter what the choice of the basis is, we could now unambiguously define items such as the characteristic polynomial of a linear transformation. But we won’t go to the trouble.

As a practical matter, how does one compute the eigenvalues and eigenvectors of a linear transformation of the form $T : V \rightarrow V$? Choose a nice basis $B$ for $V$, one where the vector representations of the values of the linear transformations necessary for the matrix representation are easy to compute. Construct the matrix representation relative to this basis, and find the eigenvalues and eigenvectors of this matrix using the techniques of Chapter E. The resulting eigenvalues of the matrix are precisely the eigenvalues of the linear transformation. The eigenvectors of the matrix are column vectors that need to be converted to vectors in $V$ through application of $\rho_B^{-1}$.

Now consider the case where the matrix representation of a linear transformation is diagonalizable. The $n$ linearly independent eigenvectors that must exist for the matrix (Theorem DC) can be converted (via $\rho_B^{-1}$) into eigenvectors of the linear transformation. A matrix representation of the linear transformation relative to a basis of eigenvectors will be a diagonal matrix — an especially nice representation! Though we did not know it at the time, the diagonalizations of Section SD were really finding especially pleasing matrix representations of linear transformations.
1. The change-of-basis matrix is a matrix representation of which linear transformation?

2. Find the change-of-basis matrix, $C_{B,C}$, for the two bases of $\mathbb{C}^2$

   $$B = \left\{ \begin{bmatrix} 2 \\ 3 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \end{bmatrix} \right\}$$

   $$C = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$$

3. What is the third “surprise,” and why is it surprising?
Subsection EXC
Exercises

C30 Find a basis for the vector space $P_3$ composed of eigenvectors of the linear transformation $T$. Then find a matrix representation of $T$ relative to this basis.

$$T: P_3 \rightarrow P_3, \quad T(a + bx + cx^2 + dx^3) = (a+c+d)+(b+c+d)x+(a+b+c)x^2+(a+b+d)x^3$$

Contributed by Robert Beezer Solution 557

T10 Suppose that $T: V \mapsto V$ is an invertible linear transformation with a nonzero eigenvalue $\lambda$. Prove that $\frac{1}{\lambda}$ is an eigenvalue of $T^{-1}$.
Contributed by Robert Beezer Solution 558
With the domain and codomain being identical, we will build a matrix representation using the same basis for both the domain and codomain. The eigenvalues of the matrix representation will be the eigenvalues of the linear transformation, and we can obtain the eigenvectors of the linear transformation by un-coordinatizing (Theorem EER 552). Since the method does not depend on which basis we choose, we can choose a natural basis for ease of computation, say,

\[ B = \{1, x, x^2, x^3\} \]

The matrix representation is then,

\[
M_{B,B}^T = \begin{bmatrix}
1 & 0 & 1 & 1 \\
0 & 1 & 1 & 1 \\
1 & 1 & 1 & 0 \\
1 & 1 & 0 & 1
\end{bmatrix}
\]

The eigenvalues and eigenvectors of this matrix were computed in Example ESMS4 385. A basis for \( \mathbb{C}^4 \), composed of eigenvectors of the matrix representation is,

\[
C = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \\ 1 \end{bmatrix} \right\}
\]

Applying \( \rho_B^{-1} \) to each vector of this set, yields a basis of \( P_3 \) composed of eigenvectors of \( T \),

\[ D = \{1 + x + x^2 + x^3, -1 + x, -x^2 + x^3, -1 - x + x^2 + x^3\} \]

The matrix representation of \( T \) relative to the basis \( D \) will be a diagonal matrix with the corresponding eigenvalues along the diagonal, so in this case we get

\[
M_{D,D}^T = \begin{bmatrix}
3 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & -1
\end{bmatrix}
\]
Let \( \mathbf{v} \) be an eigenvector of \( T \) for the eigenvalue \( \lambda \). Then,

\[
T^{-1}(\mathbf{v}) = \frac{1}{\lambda} \lambda T^{-1}(\mathbf{v}) \quad \lambda \neq 0
\]

\[
= \frac{1}{\lambda} T^{-1}(\lambda \mathbf{v}) \quad \text{Theorem ILTLT 490}
\]

\[
= \frac{1}{\lambda} T^{-1}(T(\mathbf{v})) \quad \mathbf{v} \text{ eigenvector of } T
\]

\[
= \frac{1}{\lambda} I_V(\mathbf{v}) \quad \text{Definition IVLT 487}
\]

\[
= \frac{1}{\lambda} \mathbf{v} \quad \text{Definition IDLT 487}
\]

which says that \( \frac{1}{\lambda} \) is an eigenvalue of \( T^{-1} \) with eigenvector \( \mathbf{v} \). Note that it is possible to prove that any eigenvalue of an invertible linear transformation is never zero. So the hypothesis that \( \lambda \) be nonzero is just a convenience for this problem.
A: Archetypes

The American Heritage Dictionary of the English Language (Third Edition) gives two definitions of the word “archetype”: 1. An original model or type after which other similar things are patterned; a prototype; and 2. An ideal example of a type; quintessence.

Either use might apply here. Our archetypes are typical examples of systems of equations, matrices and linear transformations. They have been designed to demonstrate the range of possibilities, allowing you to compare and contrast them. Several are of a size and complexity that is usually not presented in a textbook, but should do a better job of being “typical.”

We have made frequent reference to many of these throughout the text, such as the frequent comparisons between Archetype A [563] and Archetype B [568]. Some we have left for you to investigate, such as Archetype J [604], which parallels Archetype I [599].

How should you use the archetypes? First, consult the description of each one as it is mentioned in the text. See how other facts about the example might illuminate whatever property or construction is being described in the example. Second, Each property has a short description that usually includes references to the relevant theorems. Perform the computations and understand the connections to the listed theorems. Third, each property has a small checkbox in front of it. Use the archetypes like a workbook and chart your progress by “checking-off” those properties that you understand.

The next page has a chart that summarizes some (but not all) of the properties described for each archetype. Notice that while there are several types of objects, there are fundamental connections between them. That some lines of the table do double-duty is meant to convey some of these connections. Consult this table when you wish to quickly find an example of a certain phenomenon.
|          | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W |
| Type     | S | S | S | S | S | S | S | S | M | M | L | L | L | L | L | L | L | L | L | L | L | L |
| Vars, Cols, Domain | 3 | 3 | 4 | 4 | 4 | 4 | 2 | 2 | 7 | 9 | 5 | 5 | 5 | 5 | 3 | 3 | 5 | 5 | 3 | 5 | 6 | 4 | 3 |
| Eqns, Rows, CoDom | 3 | 3 | 3 | 3 | 3 | 4 | 5 | 5 | 4 | 6 | 5 | 5 | 3 | 3 | 5 | 5 | 5 | 5 | 4 | 6 | 4 | 4 | 3 |
| Consistent | I | U | I | I | N | U | U | N | I | I | I | I | I | I | I | I | I | I | I | I | I | I |
| Rank     | 2 | 3 | 3 | 2 | 2 | 4 | 2 | 2 | 3 | 4 | 5 | 3 | 2 | 3 | 2 | 3 | 4 | 5 | 2 | 0 | 2 | 4 | 3 |
| Nullity  | 1 | 0 | 1 | 2 | 2 | 0 | 0 | 0 | 4 | 5 | 0 | 2 | 3 | 2 | 1 | 0 | 1 | 0 | 2 | 5 | 4 | 3 |
| Injective | X | X | N | Y | N | Y | N | Y | X | Y | Y | Y | X | X | X | X | X | Y | Y | Y | Y | Y |
| Surjective | N | Y | X | X | N | Y | X | X | Y | Y | Y | Y | X | X | X | X | X | X | X | X | X | X |
| Full Rank | N | Y | Y | N | N | Y | Y | N | N | Y | N | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Nonsingular | N | Y | N | N | Y | Y | N | N | Y | N | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Invertible | N | Y | Y | Y | Y | N | N | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Determinant | 0 | -2 | -18 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Diagonalizable | N | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |

Archetype Facts
S=System of Equations, M=Matrix, L=Linear Transformation
U=Unique solution, I=Infinitely many solutions, N=No solutions
Y=Yes, N=No, X=Impossible, blank=Not Applicable
Archetype A

Summary  Linear system of three equations, three unknowns. Singular coefficient matrix with dimension 1 null space. Integer eigenvalues and a degenerate eigenspace for coefficient matrix.

- A system of linear equations (Definition SLE [14]):
  \[
  \begin{align*}
  x_1 - x_2 + 2x_3 &= 1 \\
  2x_1 + x_2 + x_3 &= 8 \\
  x_1 + x_2 &= 5
  \end{align*}
  \]

- Some solutions to the system of linear equations (not necessarily exhaustive):
  \[
  x_1 = 2, \quad x_2 = 3, \quad x_3 = 1 \\
  x_1 = 3, \quad x_2 = 2, \quad x_3 = 0
  \]

- Augmented matrix of the linear system of equations (Definition AM [31]):
  \[
  \begin{bmatrix}
  1 & -1 & 2 & 1 \\
  2 & 1 & 1 & 8 \\
  1 & 1 & 0 & 5
  \end{bmatrix}
  \]

- Matrix in reduced row-echelon form, row-equivalent to augmented matrix:
  \[
  \begin{bmatrix}
  1 & 0 & 1 & 3 \\
  0 & 1 & -1 & 2 \\
  0 & 0 & 0 & 0
  \end{bmatrix}
  \]

- Analysis of the augmented matrix (Notation RREFA [49]):
  \[
  r = 2 \quad D = \{1, 2\} \quad F = \{3, 4\}
  \]

- Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \(F\) for the larger examples.

  \[
  \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3
  \end{bmatrix} = \begin{bmatrix} 3 \\
  2 \\
  0 \end{bmatrix} + x_3 \begin{bmatrix} -1 \\
  1 \\
  1 \end{bmatrix}
  \]

- Given a system of equations we can always build a new, related, homogeneous system...
(Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[ x_1 - x_2 + 2x_3 = 0 \]
\[ 2x_1 + x_2 + x_3 = 0 \]
\[ x_1 + x_2 = 0 \]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

\[ x_1 = 0, \ x_2 = 0, \ x_3 = 0 \]
\[ x_1 = -1, \ x_2 = 1, \ x_3 = 1 \]
\[ x_1 = -5, \ x_2 = 5, \ x_3 = 5 \]

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 1 & 0 \\
0 & 1 & -1 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[ r = 2 \quad D = \{1, 2\} \quad F = \{3, 4\} \]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
1 & -1 & 2 \\
2 & 1 & 1 \\
1 & 1 & 0
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 1 \\
0 & 1 & -1 \\
0 & 0 & 0
\end{bmatrix}
\]
Analysis of the row-reduced matrix (Notation RREFA [49]):
\[ r = 2 \quad D = \{1, 2\} \quad F = \{3\} \]

Matrix (coefficient matrix) is nonsingular or singular? (Theorem NSRRI [77]) at the same time, examine the size of the set \( F \) above. Notice that this property does not apply to matrices that are not square.

Singular.

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[ \mathcal{S}_p \left( \left\{ \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \right\} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[ \mathcal{S}_p \left( \left\{ \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} , \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \right\} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = \begin{bmatrix} 1 & -2 & 3 \end{bmatrix} \]

\[ \mathcal{S}_p \left( \left\{ \begin{bmatrix} -3 \\ 0 \\ 1 \end{bmatrix} , \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} \right\} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into
reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.

\[ S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ -\frac{1}{3} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{2}{3} \end{bmatrix} \right\} \right) \]

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

\[ S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right\} \right) \]

Inverse matrix, if it exists. The inverse is not defined for matrices that are not square, and if the matrix is square, then the matrix must be nonsingular. (Definition MI [208], Theorem NSI [225])

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 3  \hspace{1cm} \text{Rank: 2}  \hspace{1cm} \text{Nullity: 1}

Determinant of the matrix, which is only defined for square matrices. The matrix is nonsingular if and only if the determinant is nonzero (Theorem SMZD [366]). (Product of all eigenvalues?)

Determinant = 0

Eigenvalues, and bases for eigenspaces. (Definition EEM [373], Definition EM [382])

\[ \lambda = 0 \quad E_A(0) = S_p \left( \left\{ \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \right\} \right) \]

\[ \lambda = 2 \quad E_A(2) = S_p \left( \left\{ \begin{bmatrix} 1 \\ 5 \\ 3 \end{bmatrix} \right\} \right) \]
Geometric and algebraic multiplicities. (Definition GME 384, Definition AME 384)

\[ \gamma_A(0) = 1 \quad \alpha_A(0) = 2 \]
\[ \gamma_A(2) = 1 \quad \alpha_A(2) = 1 \]

Diagonalizable? (Definition DZM 415)

No, \( \gamma_A(0) \neq \alpha_B(0) \). (Theorem DMLE 418)
Archetype B


A system of linear equations (Definition SLE [14]):

\[-7x_1 - 6x_2 - 12x_3 = -33\]
\[5x_1 + 5x_2 + 7x_3 = 24\]
\[x_1 + 4x_3 = 5\]

Some solutions to the system of linear equations (not necessarily exhaustive):

\[x_1 = -3, \quad x_2 = 5, \quad x_3 = 2\]

Augmented matrix of the linear system of equations (Definition AM [31]):

\[
\begin{bmatrix}
-7 & -6 & -12 & -33 \\
5 & 5 & 7 & 24 \\
1 & 0 & 4 & 5
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 0 & -3 \\
0 & 1 & 0 & 5 \\
0 & 0 & 1 & 2
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA [49]):

\[r = 3, \quad D = \{1, 2, 3\}, \quad F = \{4\}\]

Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \(F\) for the larger examples.

\[
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix} = \begin{bmatrix}
-3 \\
5 \\
2
\end{bmatrix}
\]

Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with
various properties of the original system.

\[-11x_1 + 2x_2 - 14x_3 = 0\]
\[23x_1 - 6x_2 + 33x_3 = 0\]
\[14x_1 - 2x_2 + 17x_3 = 0\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):
\[x_1 = 0, \quad x_2 = 0, \quad x_3 = 0\]

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA \[49\]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:
\[r = 3 \quad D = \{1, 2, 3\} \quad F = \{4\}\]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4 \\
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA \[49\]):
\[r = 3 \quad D = \{1, 2, 3\} \quad F = \{\} \]
Matrix (coefficient matrix) is nonsingular or singular? (Theorem NSRRI [77]) at the same time, examine the size of the set \( F \) above. Notice that this property does not apply to matrices that are not square.

Nonsingular.

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\( S_p(\{ \} ) \)

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[ \left( \begin{array}{c}
-7 \\
-6 \\
-12
\end{array} \right), \left( \begin{array}{c}
5 \\
5 \\
7
\end{array} \right), \left( \begin{array}{c}
1 \\
0 \\
4
\end{array} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = [\] \]

\[ S_p(\left( \begin{array}{c}
1 \\
0 \\
0
\end{array} \right), \left( \begin{array}{c}
0 \\
1 \\
0
\end{array} \right), \left( \begin{array}{c}
0 \\
0 \\
1
\end{array} \right) ) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.
Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

$S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \right)$

Inverse matrix, if it exists. The inverse is not defined for matrices that are not square, and if the matrix is square, then the matrix must be nonsingular. (Definition MI [208], Theorem NSI [225])

$$\begin{bmatrix} -10 & -12 & -9 \\ \frac{13}{2} & 8 & \frac{11}{2} \\ \frac{3}{2} & 3 & \frac{3}{2} \end{bmatrix}$$

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 3          Rank: 3          Nullity: 0

Determinant of the matrix, which is only defined for square matrices. The matrix is nonsingular if and only if the determinant is nonzero (Theorem SMZD [366]). (Product of all eigenvalues?)

Determinant = $-2$

Eigenvalues, and bases for eigenspaces. (Definition EEM [373], Definition EM [382])

$$\lambda = -1 \quad E_B (-1) = S_p \left( \begin{bmatrix} \frac{-5}{3} \\ 1 \end{bmatrix} \right)$$

$$\lambda = 1 \quad E_B (1) = S_p \left( \begin{bmatrix} \frac{-3}{2} \\ 1 \end{bmatrix} \right)$$

$$\lambda = 2 \quad E_B (2) = S_p \left( \begin{bmatrix} \frac{-2}{1} \\ 1 \end{bmatrix} \right)$$
Geometric and algebraic multiplicities. \( \text{(Definition GME 384 Definition AME 384)} \)

\[
\begin{align*}
\gamma_B (-1) &= 1 & \alpha_B (-1) &= 1 \\
\gamma_B (1) &= 1 & \alpha_B (1) &= 1 \\
\gamma_B (2) &= 1 & \alpha_B (2) &= 1 
\end{align*}
\]

Diagonalizable? \( \text{(Definition DZM 415)} \)

Yes, distinct eigenvalues, \( \text{Theorem DED 420} \).

The diagonalization. \( \text{(Theorem DC 415)} \)

\[
\begin{pmatrix}
-1 & -1 & -1 \\
2 & 3 & 1 \\
-1 & -2 & 1
\end{pmatrix}
\begin{pmatrix}
-7 & -6 & -12 \\
5 & 5 & 7 \\
1 & 0 & 4
\end{pmatrix}
\begin{pmatrix}
-5 & -3 & -2 \\
3 & 2 & 1 \\
1 & 1 & 1
\end{pmatrix}
= 
\begin{pmatrix}
-1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 2
\end{pmatrix}
\]
Archetype C

Summary  System with three equations, four variables. Consistent. Null space of coefficient matrix has dimension 1.

- A system of linear equations (Definition SLE [14]):
  
  \[
  \begin{align*}
  2x_1 - 3x_2 + x_3 - 6x_4 &= -7 \\
  4x_1 + x_2 + 2x_3 + 9x_4 &= -7 \\
  3x_1 + x_2 + x_3 + 8x_4 &= -8
  \end{align*}
  \]

- Some solutions to the system of linear equations (not necessarily exhaustive):

  \[
  \begin{align*}
  x_1 &= -7, & x_2 &= -2, & x_3 &= 7, & x_4 &= 1 \\
  x_1 &= -1, & x_2 &= -7, & x_3 &= 4, & x_4 &= -2
  \end{align*}
  \]

- Augmented matrix of the linear system of equations (Definition AM [31]):

  \[
  \begin{bmatrix}
  2 & -3 & 1 & -6 & -7 \\
  4 & 1 & 2 & 9 & -7 \\
  3 & 1 & 1 & 8 & -8
  \end{bmatrix}
  \]

- Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

  \[
  \begin{bmatrix}
  1 & 0 & 0 & 2 & -5 \\
  0 & 1 & 0 & 3 & 1 \\
  0 & 0 & 1 & -1 & 6
  \end{bmatrix}
  \]

- Analysis of the augmented matrix (Notation RREFA [49]):

  \[
  r = 3, \quad D = \{1, 2, 3\}, \quad F = \{4, 5\}
  \]

- Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \( F \) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \( F \) for the larger examples.

  \[
  \begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  x_4
  \end{bmatrix} = \begin{bmatrix}
  -5 \\
  1 \\
  6 \\
  0
  \end{bmatrix} + x_4 \begin{bmatrix}
  -2 \\
  -3 \\
  1 \\
  1
  \end{bmatrix}
  \]

- Given a system of equations we can always build a new, related, homogeneous system
by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
2x_1 - 3x_2 + x_3 - 6x_4 &= 0 \\
4x_1 + x_2 + 2x_3 + 9x_4 &= 0 \\
3x_1 + x_2 + x_3 + 8x_4 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

- \(x_1 = 0, \ x_2 = 0, \ x_3 = 0, \ x_4 = 0\)
- \(x_1 = -2, \ x_2 = -3, \ x_3 = 1, \ x_4 = 1\)
- \(x_1 = -4, \ x_2 = -6, \ x_3 = 2, \ x_4 = 2\)

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 0 & 2 & 0 \\
0 & 1 & 0 & 3 & 0 \\
0 & 0 & 1 & -1 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[r = 3 \quad D = \{1, 2, 3\} \quad F = \{4, 5\}\]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
2 & -3 & 1 & -6 \\
4 & 1 & 2 & 9 \\
3 & 1 & 1 & 8
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 0 & 2 \\
0 & 1 & 0 & 3 \\
0 & 0 & 1 & -1
\end{bmatrix}
\]
Analysis of the row-reduced matrix (Notation RREFA [49]):

\[ r = 3 \quad D = \{1, 2, 3\} \quad F = \{4\} \]

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[ S_p \left( \left\{ \begin{bmatrix} -2 \\ -3 \\ 1 \\ 1 \end{bmatrix} \right\} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[ S_p \left( \left\{ \begin{bmatrix} 2 \\ 4 \\ 3 \end{bmatrix}, \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \right\} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = [] \]

\[ S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRT [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.
Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 4  Rank: 3  Nullity: 1
Archetype D

Summary  System with three equations, four variables. Consistent. Null space of coefficient matrix has dimension 2. Coefficient matrix identical to that of Archetype E, vector of constants is different.

A system of linear equations (Definition SLE [14]):

\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 8 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= -12 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 4
\end{align*}

Some solutions to the system of linear equations (not necessarily exhaustive):

- \(x_1 = 0, \ x_2 = 1, \ x_3 = 2, \ x_4 = 1\)
- \(x_1 = 4, \ x_2 = 0, \ x_3 = 0, \ x_4 = 0\)
- \(x_1 = 7, \ x_2 = 8, \ x_3 = 1, \ x_4 = 3\)

Augmented matrix of the linear system of equations (Definition AM [31]):

\[
\begin{bmatrix}
2 & 1 & 7 & -7 & 8 \\
-3 & 4 & -5 & -6 & -12 \\
1 & 1 & 4 & -5 & 4
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 4 \\
0 & 1 & -3 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA [49]):

\(r = 2\)  \(D = \{1, 2\}\)  \(F = \{3, 4, 5\}\)

Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \(F\) for the larger examples.
Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 0 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= 0 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

\[
\begin{align*}
&x_1 = 0, \quad x_2 = 0, \quad x_3 = 0, \quad x_4 = 0 \\
&x_1 = -3, \quad x_2 = -1, \quad x_3 = 1, \quad x_4 = 0 \\
&x_1 = 2, \quad x_2 = 3, \quad x_3 = 0, \quad x_4 = 1 \\
&x_1 = -1, \quad x_2 = 2, \quad x_3 = 1, \quad x_4 = 1
\end{align*}
\]

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[
\begin{align*}
&\ r = 2 \\
&\ D = \{1, 2\} \\
&\ F = \{3, 4, 5\}
\end{align*}
\]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
2 & 1 & 7 & -7 \\
-3 & 4 & -5 & -6 \\
1 & 1 & 4 & -5
\end{bmatrix}
\]
Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 \\
0 & 1 & 1 & -3 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

\[r = 2 \quad D = \{1, 2\} \quad F = \{3, 4\}\]

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[\mathcal{S}_p\left(\left\{\begin{bmatrix}
-3 \\
-1 \\
1 \\
0
\end{bmatrix}, \begin{bmatrix}
2 \\
3 \\
0 \\
1
\end{bmatrix}\right\}\right)\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \(D\) above. (Theorem BCSOC [238])

\[\mathcal{S}_p\left(\left\{\begin{bmatrix}
2 \\
-3 \\
-1 \\
1
\end{bmatrix}, \begin{bmatrix}
1 \\
4 \\
1 \\
1
\end{bmatrix}\right\}\right)\]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \(L\) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \(L\), computed as according to Theorem FS [262] and Theorem BNS [141]. When \(r = m\), the matrix \(K\) has no rows and the column space is all of \(\mathbb{C}^m\).

\[L = \begin{bmatrix}
1 & 1 & -\frac{11}{7}
\end{bmatrix}\]

\[\mathcal{S}_p\left(\left\{\begin{bmatrix}
\frac{11}{7} \\
0 \\
0
\end{bmatrix}, \begin{bmatrix}
1 \\
\frac{1}{7} \\
0
\end{bmatrix}\right\}\right)\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into
reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST \[246\] and Theorem BRS \[245\], and in the style of Example CSROI \[246\], this yields a linearly independent set of vectors that span the column space.

### Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS \[245\])

\[
S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ \frac{7}{11} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{1}{11} \end{bmatrix} \right\} \right)
\]

### Subspace dimensions associated with the matrix. (Definition NOM \[338\], Definition ROM \[338\]) Verify Theorem RPNC \[339\]

Matrix columns: 4  
Rank: 2  
Nullity: 2
Archetype E

Summary  System with three equations, four variables. Inconsistent. Null space of coefficient matrix has dimension 2. Coefficient matrix identical to that of Archetype D, constant vector is different.

A system of linear equations (Definition SLE [14]):

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 2 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= 3 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 2
\end{align*}
\]

Some solutions to the system of linear equations (not necessarily exhaustive):

None. (Why?)

Augmented matrix of the linear system of equations (Definition AM [31]):

\[
\begin{bmatrix}
2 & 1 & 7 & -7 & 2 \\
-3 & 4 & -5 & -6 & 3 \\
1 & 1 & 4 & -5 & 2
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREF A [49]):

\[
r = 3 \quad D = \{1, 2, 5\} \quad F = \{3, 4\}
\]

Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \(F\) for the larger examples.

Inconsistent system, no solutions exist.

Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with
various properties of the original system.

\[
\begin{align*}
2x_1 + x_2 + 7x_3 - 7x_4 &= 0 \\
-3x_1 + 4x_2 - 5x_3 - 6x_4 &= 0 \\
x_1 + x_2 + 4x_3 - 5x_4 &= 0 \\
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

- \(x_1 = 0, \ x_2 = 0, \ x_3 = 0, \ x_4 = 0\)
- \(x_1 = 4, \ x_2 = 13, \ x_3 = 2, \ x_4 = 5\)

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 & 0 \\
0 & 1 & 1 & -3 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

- \(r = 2\)
- \(D = \{1, 2\}\)
- \(F = \{3, 4, 5\}\)

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
2 & 1 & 7 & -7 \\
-3 & 4 & -5 & -6 \\
1 & 1 & 4 & -5
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 3 & -2 \\
0 & 1 & 1 & -3 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

- \(r = 2\)
- \(D = \{1, 2\}\)
- \(F = \{3, 4\}\)
This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VFSLS [106]) to see these vectors arise.

\[ S_p \left( \begin{bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 0 \\ 1 \end{bmatrix} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[ S_p \left( \begin{bmatrix} 2 \\ -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 1 \end{bmatrix} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = \begin{bmatrix} 1 & \frac{1}{7} & -\frac{11}{7} \end{bmatrix} \]

\[ S_p \left( \begin{bmatrix} \frac{11}{7} \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -\frac{1}{7} \\ 1 \\ 0 \end{bmatrix} \right) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.

\[ S_p \left( \begin{bmatrix} 1 \\ 0 \\ \frac{7}{11} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{1}{11} \end{bmatrix} \right) \]

Row space of the matrix, expressed as a span of a set of linearly independent vectors,
obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS \[245\])

\[
S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ 3 \\ -2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ -3 \end{bmatrix} \right\} \right)
\]

Subspace dimensions associated with the matrix. (Definition NOM \[338\], Definition ROM \[338\]) Verify Theorem RPNC \[339\]

Matrix columns: 4 Rank: 2 Nullity: 2
Archetype F

Summary  System with four equations, four variables. Nonsingular coefficient matrix. Integer eigenvalues, one has “high” multiplicity.

A system of linear equations (Definition SLE 14):

\[
\begin{align*}
33x_1 - 16x_2 + 10x_3 - 2x_4 &= -27 \\
99x_1 - 47x_2 + 27x_3 - 7x_4 &= -77 \\
78x_1 - 36x_2 + 17x_3 - 6x_4 &= -52 \\
-9x_1 + 2x_2 + 3x_3 + 4x_4 &= 5
\end{align*}
\]

Some solutions to the system of linear equations (not necessarily exhaustive):

\(x_1 = 1, \quad x_2 = 2, \quad x_3 = -2, \quad x_4 = 4\)

Augmented matrix of the linear system of equations (Definition AM 31):

\[
\begin{bmatrix}
33 & -16 & 10 & -2 & -27 \\
99 & -47 & 27 & -7 & -77 \\
78 & -36 & 17 & -6 & -52 \\
-9 & 2 & 3 & 4 & 5
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 2 \\
0 & 0 & 1 & 0 & -2 \\
0 & 0 & 0 & 1 & 4
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA 49):

\(r = 4\) \quad \(D = \{1, 2, 3, 4\}\) \quad \(F = \{5\}\)

Vector form of the solution set to the system of equations (Theorem VFSLS 106). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set \(F\) for the larger examples.
Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{bmatrix}
33 & -16 & 10 & -2 \\
99 & -47 & 27 & -7 \\
78 & -36 & 17 & -6 \\
-9 & 2 & 3 & 4
\end{bmatrix}
\]

Some solutions to the associated homogeneous system of linear equations (not necessarily exhaustive):
\[
\begin{align*}
x_1 &= 0, \quad x_2 = 0, \quad x_3 = 0, \quad x_4 = 0
\end{align*}
\]

Form the augmented matrix of the homogeneous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogeneous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[
\begin{align*}
r &= 4 & D &= \{1, 2, 3, 4\} & F &= \{5\}
\end{align*}
\]

Coefficient matrix of original system of equations, and of associated homogeneous system. This matrix will be the subject of further analysis, rather than the systems of equations.
Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

\[r = 4 \quad D = \{1, 2, 3, 4\} \quad F = \{\}\]

Matrix (coefficient matrix) is nonsingular or singular? (Theorem NSRRI [77]) at the same time, examine the size of the set \(F\) above. Notice that this property does not apply to matrices that are not square.

Nonsingular.

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[S_p(\{\})\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \(D\) above. (Theorem BCSOC [238])

\[S_p\left(\left\{\begin{bmatrix}33 \\ 99 \\ 78 \\ -9\end{bmatrix}, \begin{bmatrix}-16 \\ -47 \\ -36 \\ 2\end{bmatrix}, \begin{bmatrix}10 \\ 27 \\ 17 \\ 3\end{bmatrix}, \begin{bmatrix}-2 \\ -7 \\ -6 \\ 4\end{bmatrix}\right\}\right)\]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \(L\) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \(L\), computed as according to Theorem FS [262] and Theorem BNS [141]. When \(r = m\), the matrix \(K\) has no rows and the column space is all of \(\mathbb{C}^m\).

\[L = \]
Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST 246 and Theorem BRS 245, and in the style of Example CSROI 246, this yields a linearly independent set of vectors that span the column space.

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS 245)

Inverse matrix, if it exists. The inverse is not defined for matrices that are not square, and if the matrix is square, then the matrix must be nonsingular. (Definition MI 208, Theorem NSI 225)

Subspace dimensions associated with the matrix. (Definition NOM 338, Definition ROM 338) Verify Theorem RPNC 339

Matrix columns: 4 Rank: 4 Nullity: 0
Determinant = \(-18\)

Eigenvalues, and bases for eigenspaces. (Definition EEM [373], Definition EM [382])

\[
\lambda = -1 \quad E_F(-1) = \mathcal{S}p\left(\begin{bmatrix} 1 \\ 2 \\ 0 \\ 1 \end{bmatrix}\right)
\]

\[
\lambda = 2 \quad E_F(2) = \mathcal{S}p\left(\begin{bmatrix} 2 \\ 5 \\ 2 \\ 1 \end{bmatrix}\right)
\]

\[
\lambda = 3 \quad E_F(3) = \mathcal{S}p\left(\begin{bmatrix} 1 \\ 0 \\ 7 \end{bmatrix}, \begin{bmatrix} 17 \\ 45 \\ 21 \end{bmatrix}\right)
\]

Geometric and algebraic multiplicities. (Definition GME [384], Definition AME [384])

\[
\gamma_F(-1) = 1 \quad \alpha_F(-1) = 1
\]
\[
\gamma_F(2) = 1 \quad \alpha_F(2) = 1
\]
\[
\gamma_F(3) = 2 \quad \alpha_F(3) = 2
\]

Diagonalizable? (Definition DZM [415])

Yes, large eigenspaces. Theorem DMLE [418].

The diagonalization. (Theorem DC [415])

\[
\begin{bmatrix}
12 & -5 & 1 & -1 \\
-39 & 18 & -7 & 3 \\
27 & -13 & 6 & -1 \\
36 & -18 & 6 & -1
\end{bmatrix}
= \begin{bmatrix}
1 & 2 & 1 & 17 \\
99 & -47 & 27 & -7 \\
78 & -36 & 17 & -6 \\
-9 & 2 & 3 & 4
\end{bmatrix}
\]

Version 0.52
Archetype G

Summary  System with five equations, two variables. Consistent. Null space of coefficient matrix has dimension 0. Coefficient matrix identical to that of Archetype H, constant vector is different.

A system of linear equations (Definition SLE [14]):

\[\begin{align*}
2x_1 + 3x_2 &= 6 \\
-x_1 + 4x_2 &= -14 \\
3x_1 + 10x_2 &= -2 \\
3x_1 - x_2 &= 20 \\
6x_1 + 9x_2 &= 18
\end{align*}\]

Some solutions to the system of linear equations (not necessarily exhaustive):

\[x_1 = 6, \quad x_2 = -2\]

Augmented matrix of the linear system of equations (Definition AM [31]):

\[
\begin{bmatrix}
2 & 3 & 6 \\
-1 & 4 & -14 \\
3 & 10 & -2 \\
3 & -1 & 20 \\
6 & 9 & 18
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 6 \\
0 & 1 & -2 \\
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA [49]):

\[r = 2 \quad D = \{1, 2\} \quad F = \{3\}\]

Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set.
$F$ for the larger examples.

\[
\begin{bmatrix}
x_1 \\
x_2
\end{bmatrix} = \begin{bmatrix} 6 \\ -2 \end{bmatrix}
\]

Given a system of equations we can always build a new, related, homogeneous system (Definition HS \[63\]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
2x_1 + 3x_2 &= 0 \\
-x_1 + 4x_2 &= 0 \\
3x_1 + 10x_2 &= 0 \\
3x_1 - x_2 &= 0 \\
6x_1 + 9x_2 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

$x_1 = 0, \quad x_2 = 0$

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA \[49\]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[
r = 2 \quad D = \{1, 2\} \quad F = \{3\}
\]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
2 & 3 \\
-1 & 4 \\
3 & 10 \\
3 & -1 \\
6 & 9
\end{bmatrix}
\]
Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

\[ r = 2 \quad D = \{1, 2\} \quad F = \{ \} \]

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[ Sp(\{ \} ) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[ Sp \left( \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \\ 6 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 10 \\ 9 \end{bmatrix} \right\} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = \begin{bmatrix}
1 & 0 & 0 & 0 & -\frac{1}{3} \\
0 & 1 & 0 & -\frac{1}{3} \\
0 & 0 & 1 & 1 & -1
\end{bmatrix} \]
Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 2 Rank: 2 Nullity: 0
Archetype H

Summary  System with five equations, two variables. Inconsistent, overdetermined. Null space of coefficient matrix has dimension 0. Coefficient matrix identical to that of Archetype G, constant vector is different.

A system of linear equations (Definition SLE [14]):

\[
\begin{align*}
2x_1 + 3x_2 &= 5 \\
-x_1 + 4x_2 &= 6 \\
3x_1 + 10x_2 &= 2 \\
3x_1 - x_2 &= -1 \\
6x_1 + 9x_2 &= 3
\end{align*}
\]

Some solutions to the system of linear equations (not necessarily exhaustive):
None. (Why?)

Augmented matrix of the linear system of equations (Definition AM [31]):

\[
\begin{bmatrix}
2 & 3 & 5 \\
-1 & 4 & 6 \\
3 & 10 & 2 \\
3 & -1 & -1 \\
6 & 9 & 3
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA [49]):

\[
r = 3 \quad D = \{1, 2, 3\} \quad F = \{\}
\]

Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set \(F\) above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set.
Inconsistent system, no solutions exist.

Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
2x_1 + 3x_2 &= 0 \\
-x_1 + 4x_2 &= 0 \\
3x_1 + 10x_2 &= 0 \\
3x_1 - x_2 &= 0 \\
6x_1 + 9x_2 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

\[x_1 = 0, \quad x_2 = 0\]

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[r = 2 \quad D = \{1, 2\} \quad F = \{3\}\]

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
2 & 3 \\
-1 & 4 \\
3 & 10 \\
3 & -1 \\
6 & 9
\end{bmatrix}
\]
Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 \\
0 & 1 \\
0 & 0 \\
0 & 0
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA 49):

\[ r = 2 \quad D = \{1, 2\} \quad F = \{\} \]

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS 122, Theorem BNS 141). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS 106) to see these vectors arise.

\[ S_p(\{\}) \]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC 238)

\[ S_p \left( \begin{pmatrix}
2 \\
-1 \\
3 \\
3 \\
6
\end{pmatrix}, \begin{pmatrix}
3 \\
4 \\
10 \\
-1 \\
9
\end{pmatrix} \right) \]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF 259. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS 262 and Theorem BNS 141. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[ L = \[] \]
Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By [Theorem CSRST][246] and [Theorem BRS][245], and in the style of [Example CSROI][246], this yields a linearly independent set of vectors that span the column space.

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix $L$ is computed as described in [Definition EEF][259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of $L$, computed as according to [Theorem FS][262] and [Theorem BNS][141]. When $r = m$, the matrix $K$ has no rows and the column space is all of $\mathbb{C}^m$.

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. ([Theorem BRS][245])

Subspace dimensions associated with the matrix. ([Definition NOM][338], [Definition ROM][338]) Verify [Theorem RPNC][339]

- Matrix columns: 2
- Rank: 2
- Nullity: 0
Archetype I

Summary  System with four equations, seven variables. Consistent. Null space of coefficient matrix has dimension 4.

- A system of linear equations (Definition SLE [14]):
  \[
  \begin{align*}
  x_1 + 4x_2 - x_4 + 7x_6 - 9x_7 &= 3 \\
  2x_1 + 8x_2 - x_3 + 3x_4 + 9x_5 - 13x_6 + 7x_7 &= 9 \\
  2x_3 - 3x_4 - 4x_5 + 12x_6 - 8x_7 &= 1 \\
  -x_1 - 4x_2 + 2x_3 + 4x_4 + 8x_5 - 31x_6 + 37x_7 &= 4 
  \end{align*}
  \]

- Some solutions to the system of linear equations (not necessarily exhaustive):
  \[
  \begin{align*}
  x_1 &= -25, \quad x_2 = 4, \quad x_3 = 22, \quad x_4 = 29, \quad x_5 = 1, \quad x_6 = 2, \quad x_7 = -3 \\
  x_1 &= -7, \quad x_2 = 5, \quad x_3 = 7, \quad x_4 = 15, \quad x_5 = -4, \quad x_6 = 2, \quad x_7 = 1 \\
  x_1 &= 4, \quad x_2 = 0, \quad x_3 = 2, \quad x_4 = 1, \quad x_5 = 0, \quad x_6 = 0, \quad x_7 = 0 
  \end{align*}
  \]

- Augmented matrix of the linear system of equations (Definition AM [31]):
  \[
  \begin{bmatrix}
  1 & 4 & 0 & -1 & 0 & 7 & -9 & 3 \\
  2 & 8 & -1 & 3 & 9 & -13 & 7 & 9 \\
  0 & 0 & 2 & -3 & -4 & 12 & -8 & 1 \\
  -1 & -4 & 2 & 4 & 8 & -31 & 37 & 4 
  \end{bmatrix}
  \]

- Matrix in reduced row-echelon form, row-equivalent to augmented matrix:
  \[
  \begin{bmatrix}
  1 & 4 & 0 & 0 & 2 & 1 & -3 & 4 \\
  0 & 0 & 1 & 0 & 1 & -3 & 5 & 2 \\
  0 & 0 & 0 & 1 & 2 & -6 & 6 & 1 \\
  0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 
  \end{bmatrix}
  \]

- Analysis of the augmented matrix (Notation RREFA [49]):
  \[
  r = 3 \quad D = \{1, 3, 4\} \quad F = \{2, 5, 6, 7, 8\} 
  \]

- Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set $F$ above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set $F$ for the larger examples.
Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
x_1 + 4x_2 - x_4 + 7x_6 - 9x_7 &= 0 \\
2x_1 + 8x_2 - x_3 + 3x_4 + 9x_5 - 13x_6 + 7x_7 &= 0 \\
2x_3 - 3x_4 - 4x_5 + 12x_6 - 8x_7 &= 0 \\
x_1 - 4x_2 + 2x_3 + 4x_4 + 8x_5 - 31x_6 + 37x_7 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

- \(x_1 = 0, x_2 = 0, x_3 = 0, x_4 = 0, x_5 = 0, x_6 = 0, x_7 = 0\)
- \(x_1 = 3, x_2 = 0, x_3 = -5, x_4 = -6, x_5 = 0, x_6 = 0, x_7 = 1\)
- \(x_1 = -1, x_2 = 0, x_3 = 3, x_4 = 6, x_5 = 0, x_6 = 1, x_7 = 0\)
- \(x_1 = -2, x_2 = 0, x_3 = -1, x_4 = -2, x_5 = 1, x_6 = 0, x_7 = 0\)
- \(x_1 = -4, x_2 = 1, x_3 = 0, x_4 = 0, x_5 = 0, x_6 = 0, x_7 = 0\)
- \(x_1 = -4, x_2 = 1, x_3 = -3, x_4 = -2, x_5 = 1, x_6 = 1, x_7 = 1\)

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain zeros:

\[
\begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 & 0 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 & 0 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 
\end{bmatrix}
\]

Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

\[
r = 3 \\
D = \{1, 3, 4\} \\
F = \{2, 5, 6, 7, 8\}
\]
Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

\[
\begin{bmatrix}
1 & 4 & 0 & -1 & 0 & 7 & -9 \\
2 & 8 & -1 & 3 & 9 & -13 & 7 \\
0 & 0 & 2 & -3 & -4 & 12 & -8 \\
-1 & -4 & 2 & 4 & 8 & -31 & 37 \\
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 4 & 0 & 0 & 2 & 1 & -3 \\
0 & 0 & 1 & 0 & 1 & -3 & 5 \\
0 & 0 & 0 & 1 & 2 & -6 & 6 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

\[r = 3\quad D = \{1, 3, 4\} \quad F = \{2, 5, 6, 7\}\]

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[
\begin{bmatrix}
-4 \\
1 \\
0 \\
0 \\
0 \\
-2 \\
0 \\
1 \\
0 \\
\end{bmatrix}, \begin{bmatrix}
-2 \\
0 \\
-1 \\
-2 \\
0 \\
3 \\
1 \\
0 \\
0 \\
\end{bmatrix}, \begin{bmatrix}
-1 \\
0 \\
3 \\
6 \\
0 \\
-5 \\
0 \\
0 \\
0 \\
\end{bmatrix}, \begin{bmatrix}
3 \\
0 \\
0 \\
0 \\
0 \\
-6 \\
0 \\
0 \\
1 \\
\end{bmatrix}
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \(D\) above. (Theorem BCSOC [238])
The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix $L$ is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of $L$, computed as according to Theorem FS [262] and Theorem BNS [141]. When $r = m$, the matrix $K$ has no rows and the column space is all of $\mathbb{C}^m$.

$L = \begin{bmatrix} 1 & -\frac{12}{31} & -\frac{13}{31} & \frac{7}{31} \end{bmatrix}$

$S_p \left( \left\{ \begin{bmatrix} \frac{1}{2} \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 2 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 3 \\ -3 \\ 4 \end{bmatrix} \right\} \right)$

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.

$S_p \left( \left\{ \begin{bmatrix} \frac{1}{7} \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} \frac{12}{31} \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} \frac{13}{31} \\ 1 \\ 0 \\ 0 \end{bmatrix} \right\} \right)$

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

$S_p \left( \left\{ \begin{bmatrix} 1 \\ 0 \\ -\frac{31}{7} \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \frac{12}{7} \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ \frac{13}{7} \end{bmatrix} \right\} \right)$

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 7 Rank: 3 Nullity: 4
Archetype J

Summary  System with six equations, nine variables. Consistent. Null space of coefficient matrix has dimension 5.

A system of linear equations (Definition SLE [14]):
\[
\begin{align*}
    x_1 + 2x_2 - 2x_3 + 9x_4 + 3x_5 - 5x_6 - 2x_7 + x_8 + 27x_9 &= -5 \\
    2x_1 + 4x_2 + 3x_3 + 4x_4 - x_5 + 4x_6 + 10x_7 + 2x_8 - 23x_9 &= 18 \\
    x_1 + 2x_2 + x_3 + 3x_4 + x_5 + x_6 + 5x_7 + 2x_8 - 7x_9 &= 6 \\
    2x_1 + 4x_2 + 3x_3 + 4x_4 - 7x_5 + 2x_6 + 4x_7 - 11x_9 &= 20 \\
    x_1 + 2x_2 + 5x_4 + 2x_5 - 4x_6 + 3x_7 + 8x_8 + 13x_9 &= -4 \\
    -3x_1 - 6x_2 - x_3 - 13x_4 + 2x_5 - 5x_6 - 4x_7 + 13x_8 + 10x_9 &= -29
\end{align*}
\]

Some solutions to the system of linear equations (not necessarily exhaustive):
\[
\begin{align*}
    x_1 &= 6, x_2 = 0, x_3 = -1, x_4 = 0, x_5 = -1, x_6 = 2, x_7 = 0, x_8 = 0, x_9 = 0 \\
    x_1 &= 4, x_2 = 1, x_3 = -1, x_4 = 0, x_5 = -1, x_6 = 2, x_7 = 0, x_8 = 0, x_9 = 0 \\
    x_1 &= -17, x_2 = 7, x_3 = 3, x_4 = 2, x_5 = -1, x_6 = 14, x_7 = -1, x_8 = 3, x_9 = 2 \\
    x_1 &= -11, x_2 = -6, x_3 = 1, x_4 = 5, x_5 = -4, x_6 = 7, x_7 = 3, x_8 = 1, x_9 = 1
\end{align*}
\]

Augmented matrix of the linear system of equations (Definition AM [31]):
\[
\begin{bmatrix}
    1 & 2 & -2 & 9 & 3 & -5 & -2 & 1 & 27 & -5 \\
    2 & 4 & 3 & 4 & -1 & 4 & 10 & 2 & -23 & 18 \\
    1 & 2 & 1 & 3 & 1 & 1 & 5 & 2 & -7 & 6 \\
    2 & 4 & 3 & 4 & -7 & 2 & 4 & 0 & -11 & 20 \\
    1 & 2 & 0 & 5 & 2 & -4 & 3 & 8 & 13 & -4 \\
    -3 & -6 & -1 & -13 & 2 & -5 & -4 & 13 & 10 & -29
\end{bmatrix}
\]

Matrix in reduced row-echelon form, row-equivalent to augmented matrix:
\[
\begin{bmatrix}
    1 & 2 & 0 & 5 & 0 & 0 & 0 & 1 & -2 & 3 & 6 \\
    0 & 0 & 1 & -2 & 0 & 0 & 3 & 5 & -6 & -1 \\
    0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & -1 & -1 \\
    0 & 0 & 0 & 0 & 0 & 1 & 0 & -2 & -3 & 2 \\
    0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the augmented matrix (Notation RREFA [49]):
\[
r = 4 \quad D = \{1, 3, 5, 6\} \quad F = \{2, 4, 7, 8, 9, 10\}
\]
Vector form of the solution set to the system of equations (Theorem VFSLS [106]). Notice the relationship between the free variables and the set $F$ above. Also, notice the pattern of 0’s and 1’s in the entries of the vectors corresponding to elements of the set $F$ for the larger examples.

\[
\begin{bmatrix}
 x_1 \\
 x_2 \\
 x_3 \\
 x_4 \\
 x_5 \\
 x_6 \\
 x_7 \\
 x_8 \\
 x_9 \\
\end{bmatrix} =
\begin{bmatrix}
 6 \\
 0 \\
 -1 \\
 0 \\
 -1 \\
 2 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 x_2 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 -2 \\
 0 \\
 0 \\
 0 \\
 -1 \\
 0 \\
 1 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 -5 \\
 0 \\
 2 \\
 1 \\
 -1 \\
 0 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 -1 \\
 2 \\
 0 \\
 0 \\
 0 \\
 1 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 -1 \\
 0 \\
 0 \\
 0 \\
 -1 \\
 0 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 2 \\
 0 \\
 0 \\
 1 \\
 0 \\
 0 \\
 0 \\
 0 \\
 1 \\
\end{bmatrix} +
\begin{bmatrix}
 -3 \\
 0 \\
 0 \\
 0 \\
 1 \\
 0 \\
 0 \\
 0 \\
 0 \\
\end{bmatrix} +
\begin{bmatrix}
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 0 \\
 1 \\
\end{bmatrix}
\]

Given a system of equations we can always build a new, related, homogeneous system (Definition HS [63]) by converting the constant terms to zeros and retaining the coefficients of the variables. Properties of this new system will have precise relationships with various properties of the original system.

\[
\begin{align*}
 x_1 + 2x_2 - 2x_3 + 9x_4 + 3x_5 - 5x_6 - 2x_7 + x_8 + 27x_9 &= 0 \\
 2x_1 + 4x_2 + 3x_3 + 4x_4 - x_5 + 4x_6 + 10x_7 + 2x_8 - 23x_9 &= 0 \\
 x_1 + 2x_2 + x_3 + 3x_4 + x_5 + x_6 + 5x_7 + 2x_8 - 7x_9 &= 0 \\
 2x_1 + 4x_2 + 3x_3 + 4x_4 - 7x_5 + 2x_6 + 4x_7 - 11x_9 &= 0 \\
 x_1 + 2x_2 + 5x_4 + 2x_5 - 4x_6 + 3x_7 + 8x_8 + 13x_9 &= 0 \\
 -3x_1 - 6x_2 - x_3 - 13x_4 + 2x_5 - 5x_6 - 4x_7 + 13x_8 + 10x_9 &= 0
\end{align*}
\]

Some solutions to the associated homogenous system of linear equations (not necessarily exhaustive):

\[
\begin{align*}
 x_1 &= 0, x_2 = 0, x_3 = 0, x_4 = 0, x_5 = 0, x_6 = 0, x_7 = 0, x_8 = 0, x_9 = 0 \\
 x_1 &= -2, x_2 = 1, x_3 = 0, x_4 = 0, x_5 = 0, x_6 = 0, x_7 = 0, x_8 = 0, x_9 = 0 \\
 x_1 &= -23, x_2 = 7, x_3 = 4, x_4 = 2, x_5 = 0, x_6 = 12, x_7 = -1, x_8 = 3, x_9 = 2 \\
 x_1 &= -17, x_2 = -6, x_3 = 2, x_4 = 5, x_5 = -3, x_6 = 5, x_7 = 3, x_8 = 1, x_9 = 1
\end{align*}
\]

Form the augmented matrix of the homogenous linear system, and use row operations to convert to reduced row-echelon form. Notice how the entries of the final column remain
Analysis of the augmented matrix for the homogenous system (Notation RREFA [49]). Notice the slight variation for the same analysis of the original system only when the original system was consistent:

$$r = 4 \quad D = \{1, 3, 5, 6\} \quad F = \{2, 4, 7, 8, 9, 10\}$$

Coefficient matrix of original system of equations, and of associated homogenous system. This matrix will be the subject of further analysis, rather than the systems of equations.

Matrix brought to reduced row-echelon form:

$$r = 4 \quad D = \{1, 3, 5, 6\} \quad F = \{2, 4, 7, 8, 9\}$$

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix.
(Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VF-SLS [106]) to see these vectors arise.

\[
\begin{pmatrix}
-2 & -5 & -1 & 2 & -3 \\
1 & 0 & 0 & 0 & 0 \\
0 & 2 & -3 & -5 & 6 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & -1 & -1 & 1 \\
0 & 0 & 0 & 2 & 3 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{pmatrix}
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])

\[
\begin{pmatrix}
1 & -2 & 3 & -1 & 3 \\
2 & 1 & -1 & 1 & 1 \\
1 & 3 & -7 & 2 & -4 \\
-3 & -1 & 2 & -4 & -5
\end{pmatrix}
\]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \( L \) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \( L \), computed as according to Theorem FS [262] and Theorem BNS [141]. When \( r = m \), the matrix \( K \) has no rows and the column space is all of \( \mathbb{C}^m \).

\[
L = \begin{bmatrix}
1 & 0 & 186/131 & 51/131 & -188/131 & 77/131 \\
0 & 1 & -272/131 & -45/131 & -58/131 & -14/131
\end{bmatrix}
\]

\[
\begin{pmatrix}
-77/131 & 188/131 & -51/131 & -186/131 \\
14/131 & -45/131 & 151/131 & 272/131 \\
0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
1 & 0 & 0 & 0
\end{pmatrix}
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span
the column space.

$$\mathcal{S}_p \left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \\ -1 \\ -\frac{29}{7} \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \\ -\frac{11}{7} \\ -\frac{94}{7} \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 10 \\ 22 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ \frac{3}{2} \\ \frac{3}{3} \end{pmatrix} \right\}$$

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. (Theorem BRS [245])

$$\mathcal{S}_p \left\{ \begin{pmatrix} 1 \\ 2 \\ 5 \\ 0 \\ 1 \\ -2 \\ 3 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 3 \\ -6 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ -1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ -2 \end{pmatrix} \right\}$$

Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 9  Rank: 4  Nullity: 5
**Archetype K**

**Summary**  Square matrix of size 5. Nonsingular. 3 distinct eigenvalues, 2 of multiplicity 2.

A matrix:

\[
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

Analysis of the row-reduced matrix (Notation RREFA [49]):

\[ r = 5 \quad D = \{1, 2, 3, 4, 5\} \quad F = \{\} \]

Matrix (coefficient matrix) is nonsingular or singular? (Theorem NSRRI [77]) at the same time, examine the size of the set \( F \) above. Notice that this property does not apply to matrices that are not square.

Nonsingular.

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix (Theorem SSNS [122], Theorem BNS [141]). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form (Theorem VFSLS [106]) to see these vectors arise.

\[ Sp(\{\} \} )\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the set \( D \) above. (Theorem BCSOC [238])
\[
S_p\left( \begin{pmatrix}
10 & 18 & 24 & 24 & -12 \\
-12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20 \\
\end{pmatrix} \right)
\]

The column space of the matrix, as it arises from the extended echelon form of the matrix. The matrix \(L\) is computed as described in Definition EEF [259]. This is followed by the column space described by a set of linearly independent vectors that span the null space of \(L\), computed as according to Theorem FS [262] and Theorem BNS [141]. When \(r = m\), the matrix \(K\) has no rows and the column space is all of \(\mathbb{C}^m\).

\[
L = \left[ \begin{matrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
\end{matrix} \right]
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By Theorem CSRST [246] and Theorem BRS [245], and in the style of Example CSROI [246], this yields a linearly independent set of vectors that span the column space.

\[
S_p\left( \begin{pmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
\end{matrix} \right)
\]

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. Theorem BRS [245]

\[
S_p\left( \begin{pmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
\end{matrix} \right)
\]

Inverse matrix, if it exists. The inverse is not defined for matrices that are not square, and if the matrix is square, then the matrix must be nonsingular. Definition MI [208], Theorem NSI [225]
Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 5 Rank: 5 Nullity: 0

Determinant of the matrix, which is only defined for square matrices. The matrix is nonsingular if and only if the determinant is nonzero (Theorem SMZD [366]). (Product of all eigenvalues?)

Determinant = 16

Eigenvalues, and bases for eigenspaces. (Definition EEM [373], Definition EM [382])

\[ \lambda = -2 \quad E_K(-2) = Sp \left( \begin{bmatrix} 2 \\ -2 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 2 \\ -2 \\ 1 \\ 0 \end{bmatrix} \right) \]

\[ \lambda = 1 \quad E_K(1) = Sp \left( \begin{bmatrix} 4 \\ -10 \\ 7 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} -4 \\ 18 \\ -17 \\ 5 \\ 0 \end{bmatrix} \right) \]

\[ \lambda = 4 \quad E_K(4) = Sp \left( \begin{bmatrix} 1 \\ -1 \\ 0 \\ 1 \\ 1 \end{bmatrix} \right) \]

Geometric and algebraic multiplicities. (Definition GME [384], Definition AME [384])

\[ \gamma_K(-2) = 2 \quad \alpha_K(-2) = 2 \]

\[ \gamma_K(1) = 2 \quad \alpha_K(1) = 2 \]

\[ \gamma_K(4) = 1 \quad \alpha_K(4) = 1 \]
Diagonalizable? (Definition DZM 415)

Yes, large eigenspaces, Theorem DMLE 418.

The diagonalization. (Theorem DC 415)

\[
\begin{bmatrix}
-4 & -3 & -4 & -6 & 7 \\
-7 & -5 & -6 & -8 & 10 \\
1 & -1 & -1 & 1 & -3 \\
1 & 0 & 0 & 1 & -2 \\
2 & 5 & 6 & 4 & 0 \\
\end{bmatrix}
= 
\begin{bmatrix}
10 & 18 & 24 & 24 & -12 \\
12 & -2 & -6 & 0 & -18 \\
-30 & -21 & -23 & -30 & 39 \\
27 & 30 & 36 & 37 & -30 \\
18 & 24 & 30 & 30 & -20 \\
\end{bmatrix}
\begin{bmatrix}
2 & -1 & 4 & -4 & 1 \\
-2 & 2 & -10 & 18 & -1 \\
1 & -2 & 7 & -17 & 0 \\
0 & 1 & 0 & 5 & 1 \\
1 & 0 & 2 & 0 & 1 \\
\end{bmatrix}
\]
Archetype L

Summary  Square matrix of size 5. Singular, nullity 2. 2 distinct eigenvalues, each of “high” multiplicity.

A matrix:
\[
\begin{bmatrix}
-2 & -1 & -2 & -4 & 4 \\
-6 & -5 & -4 & -4 & 6 \\
10 & 7 & 7 & 10 & -13 \\
-7 & -5 & -6 & -9 & 10 \\
-4 & -3 & -4 & -6 & 6
\end{bmatrix}
\]

Matrix brought to reduced row-echelon form:
\[
\begin{bmatrix}
1 & 0 & 0 & 1 & -2 \\
0 & 1 & 0 & -2 & 2 \\
0 & 0 & 1 & 2 & -1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

Analysis of the row-reduced matrix \( \text{Notation RREFA} \): 
\[ r = 5 \quad D = \{1, 2, 3\} \quad F = \{4, 5\} \]

Matrix (coefficient matrix) is nonsingular or singular? \( \text{Theorem NSRRI} \) at the same time, examine the size of the set \( F \) above. Notice that this property does not apply to matrices that are not square.

Singular.

This is the null space of the matrix. The set of vectors used in the span construction is a linearly independent set of column vectors that spans the null space of the matrix \( \text{Theorem SSNS} \). Solve the homogenous system with this matrix as the coefficient matrix and write the solutions in vector form \( \text{Theorem VF-SLS} \) to see these vectors arise.

\[
\mathcal{S}p \left\{ \begin{bmatrix} -1 \\ 2 \\ -2 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ 1 \\ 0 \\ 1 \end{bmatrix} \right\}
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors that are also columns of the matrix. These columns have indices that form the
set $D$ above. \(\text{(Theorem BCSOC 238)}\)

\[
S_p \left\{ \left[\begin{array}{c} -2 \\ -6 \\ 10 \\ -7 \\ -4 \end{array}\right], \left[\begin{array}{c} -1 \\ -5 \\ 7 \\ -5 \\ -3 \end{array}\right], \left[\begin{array}{c} -2 \\ -4 \\ 7 \\ -6 \\ -4 \end{array}\right] \right\}
\]

\[L = \begin{bmatrix} 1 & 0 & -2 & -6 & 5 \\ 0 & 1 & 4 & 10 & -9 \end{bmatrix}\]

\[
S_p \left\{ \left[\begin{array}{c} -5 \\ 9 \\ 0 \\ 1 \\ 1 \end{array}\right], \left[\begin{array}{c} 6 \\ -10 \\ 0 \\ 1 \\ 0 \end{array}\right], \left[\begin{array}{c} 2 \\ -4 \\ 0 \\ 0 \end{array}\right] \right\}
\]

Column space of the matrix, expressed as the span of a set of linearly independent vectors. These vectors are computed by row-reducing the transpose of the matrix into reduced row-echelon form, tossing out the zero rows, and writing the remaining nonzero rows as column vectors. By \text{Theorem CSRST 246} and \text{Theorem BRS 245}, and in the style of \text{Example CSROI 246}, this yields a linearly independent set of vectors that span the column space.

\[
S_p \left\{ \left[\begin{array}{c} 1 \\ 0 \\ 0 \\ 9 \end{array}\right], \left[\begin{array}{c} 0 \\ 1 \\ 0 \\ \frac{3}{2} \end{array}\right], \left[\begin{array}{c} 0 \\ 0 \\ 1 \\ \frac{1}{2} \end{array}\right] \right\}
\]

Row space of the matrix, expressed as a span of a set of linearly independent vectors, obtained from the nonzero rows of the equivalent matrix in reduced row-echelon form. \(\text{(Theorem BRS 245)}\)
$S_p \left( \left\{ \left[ \begin{array}{c} 1 \\ 0 \\ 0 \\ 1 \\ -2 \end{array} \right], \left[ \begin{array}{c} 0 \\ 1 \\ 0 \\ -2 \\ 2 \end{array} \right], \left[ \begin{array}{c} 0 \\ 0 \\ 1 \\ 2 \\ -1 \end{array} \right] \right\} \right)$

- Inverse matrix, if it exists. The inverse is not defined for matrices that are not square, and if the matrix is square, then the matrix must be nonsingular. (Definition MI [208], Theorem NSI [225])

- Subspace dimensions associated with the matrix. (Definition NOM [338], Definition ROM [338]) Verify Theorem RPNC [339]

Matrix columns: 5    Rank: 3    Nullity: 2

- Determinant of the matrix, which is only defined for square matrices. The matrix is nonsingular if and only if the determinant is nonzero (Theorem SMZD [366]). (Product of all eigenvalues?)

Determinant = 0

- Eigenvalues, and bases for eigenspaces. (Definition EEM [373], Definition EM [382])

$\lambda = -1$  $E_L(-1) = S_p \left( \left\{ \left[ \begin{array}{c} -5 \\ 9 \\ 0 \\ 0 \\ 1 \end{array} \right], \left[ \begin{array}{c} 6 \\ -10 \\ 0 \\ 1 \\ 0 \end{array} \right], \left[ \begin{array}{c} 2 \\ -4 \\ -2 \\ 0 \\ 0 \end{array} \right] \right\} \right)$

$\lambda = 0$  $E_L(0) = S_p \left( \left\{ \left[ \begin{array}{c} 0 \\ -2 \\ 1 \\ 2 \\ 1 \end{array} \right], \left[ \begin{array}{c} 0 \\ -2 \\ 1 \\ 1 \\ 0 \end{array} \right] \right\} \right)$

- Geometric and algebraic multiplicities. (Definition GME [384], Definition AME [384])

$\gamma_L(-1) = 3$  $\alpha_L(-1) = 3$
$\gamma_L(0) = 2$  $\alpha_L(0) = 2$
Diagonalizable? \( \text{Definition DZM 415} \)

Yes, large eigenspaces, \( \text{Theorem DMLE 418} \).

The diagonalization. \( \text{Theorem DC 415} \)

\[
\begin{bmatrix}
4 & 3 & 4 & 6 & -6 \\
7 & 5 & 6 & 9 & -10 \\
-10 & -7 & -7 & -10 & 13 \\
-4 & -3 & -4 & -6 & 7 \\
-7 & -5 & -6 & -8 & 10
\end{bmatrix}
\begin{bmatrix}
-2 & -1 & -2 & -4 & 4 \\
-6 & -5 & -4 & -4 & 6 \\
10 & 7 & 7 & 10 & -13 \\
-7 & -5 & -6 & -9 & 10 \\
-4 & -3 & -4 & -6 & 6
\end{bmatrix}
\begin{bmatrix}
-5 & 6 & 2 & 2 & -1 \\
9 & -10 & -4 & -2 & 2 \\
0 & 0 & 1 & 1 & -2 \\
0 & 1 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 & 0
\end{bmatrix}
= \begin{bmatrix}
-1 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]
Archetype M

Summary  Linear transformation with bigger domain than codomain, so it is guaranteed to not be injective. Happens to not be surjective.

A linear transformation:  \( T: \mathbb{C}^5 \rightarrow \mathbb{C}^3 \),  
\[
T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} x_1 + 2x_2 + 3x_3 + 4x_4 + 4x_5 \\ 3x_1 + x_2 + 4x_3 - 3x_4 + 7x_5 \\ x_1 - x_2 - 5x_4 + x_5 \end{pmatrix}
\]

A basis for the null space of the linear transformation:  
\[
\left\{ \begin{pmatrix} -2 \\ -1 \\ 0 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ -3 \\ 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \\ 0 \\ 0 \end{pmatrix} \right\}
\]

Injective: No.  
Since the kernel is nontrivial \( \text{Theorem KILT} \) tells us that the linear transformation is not injective. Also, since the rank can not exceed 3, we are guaranteed to have a nullity of at least 2, just from checking dimensions of the domain and the codomain. In particular, verify that
\[
T \begin{pmatrix} 1 \\ 2 \\ -1 \\ 4 \\ 5 \end{pmatrix} = \begin{pmatrix} 38 \\ 24 \\ -16 \end{pmatrix}
\]
\[
T \begin{pmatrix} 0 \\ -3 \\ 0 \\ 5 \\ 6 \end{pmatrix} = \begin{pmatrix} 38 \\ 24 \\ -16 \end{pmatrix}
\]

This demonstration that \( T \) is not injective is constructed with the observation that
\[
\begin{pmatrix} 0 \\ -3 \\ 0 \\ 5 \\ 6 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ -1 \\ 4 \\ 5 \end{pmatrix} - \begin{pmatrix} 1 \\ 2 \\ -1 \\ 4 \\ 5 \end{pmatrix}
\]

and
\[
z = \begin{pmatrix} -1 \\ -5 \\ 1 \\ 1 \\ 1 \end{pmatrix} \in \mathcal{K}(T)
\]
so the vector \( z \) effectively “does nothing” in the evaluation of \( T \).

A basis for the range of the linear transformation: (Definition RLT [473])

Evaluate the linear transformation on a standard basis to get a spanning set for the range (Theorem SSRLT [478]):

\[
\left\{ \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 4 \\ 3 \\ 1 \\ 4 \\ -3 \\ 7 \\ 4 \\ -1 \\ 0 \\ -5 \\ 1 \end{bmatrix} \right\}
\]

If the linear transformation is injective, then the set above is guaranteed to be linearly independent (Theorem ILTLI [461]). This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows (Theorem BRS [245]). A basis for the range is:

\[
\left\{ \begin{bmatrix} 1 \\ 0 \\ -4 \\ 5 \\ 3 \\ 5 \end{bmatrix} \right\}
\]

Surjective: No. (Definition SLT [469])

Notice that the range is not all of \( \mathbb{C}^3 \) since its dimension 2, not 3. In particular, verify that \( \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix} \notin \mathcal{R}(T) \), by setting the output equal to this vector and seeing that the resulting system of linear equations has no solution, i.e. is inconsistent. So the preimage, \( T^{-1} \left( \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix} \right) \), is nonempty. This alone is sufficient to see that the linear transformation is not onto.

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD [496].

- Domain dimension: 5
- Rank: 2
- Nullity: 3

Invertible: No.

Not injective or surjective.

Matrix representation (Theorem MLTCV [437]):

\[ T : \mathbb{C}^5 \rightarrow \mathbb{C}^3, \quad T(x) = Ax, \quad A = \begin{bmatrix} 1 & 2 & 3 & 4 & 4 \\ 3 & 1 & 4 & -3 & 7 \\ 1 & -1 & 0 & -5 & 1 \end{bmatrix} \]
Archetype N

Summary  Linear transformation with domain larger than its codomain, so it is guaranteed to not be injective. Happens to be onto.

A linear transformation: (Definition LT [429])

\[ T : \mathbb{C}^5 \rightarrow \mathbb{C}^3, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} 2x_1 + x_2 + 3x_3 - 4x_4 + 5x_5 \\ x_1 - 2x_2 + 3x_3 - 9x_4 + 3x_5 \\ 3x_1 + 4x_3 - 6x_4 + 5x_5 \end{pmatrix} \]

A basis for the null space of the linear transformation: (Definition KLT [457])

\[ \left\{ \begin{pmatrix} 1 \\ -1 \\ -2 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -2 \\ -1 \\ 3 \\ 1 \\ 0 \end{pmatrix} \right\} \]

Injective: No. (Definition ILT [453])

Since the kernel is nontrivial, Theorem KILT [460] tells us that the linear transformation is not injective. Also, since the rank can not exceed 3, we are guaranteed to have a nullity of at least 2, just from checking dimensions of the domain and the codomain. In particular, verify that

\[ T \begin{pmatrix} -3 \\ 1 \\ -2 \\ -3 \\ 1 \end{pmatrix} = \begin{pmatrix} 6 \\ 19 \\ 6 \end{pmatrix} \quad T \begin{pmatrix} -4 \\ -4 \\ -2 \\ -1 \\ 4 \end{pmatrix} = \begin{pmatrix} 6 \\ 19 \\ 6 \end{pmatrix} \]

This demonstration that \( T \) is not injective is constructed with the observation that

\[ \begin{pmatrix} -4 \\ -4 \\ -2 \\ -1 \\ 4 \end{pmatrix} = \begin{pmatrix} -3 \\ 1 \\ -2 \\ -3 \\ 1 \end{pmatrix} + \begin{pmatrix} -1 \\ -5 \\ 0 \\ 2 \\ 3 \end{pmatrix} \]

and

\[ z = \begin{pmatrix} -1 \\ -5 \\ 0 \\ 2 \\ 3 \end{pmatrix} \in \mathcal{K}(T) \]
so the vector \( z \) effectively “does nothing” in the evaluation of \( T \).

A basis for the range of the linear transformation: (Definition RLT 473)

Evaluate the linear transformation on a standard basis to get a spanning set for the range (Theorem SSRLT 478):

\[
\begin{align*}
\begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}, & \begin{bmatrix} 1 \\ -2 \\ 0 \end{bmatrix}, & \begin{bmatrix} 3 \\ 3 \\ 4 \end{bmatrix}, & \begin{bmatrix} -4 \\ -9 \\ -6 \end{bmatrix}, & \begin{bmatrix} 5 \\ 3 \end{bmatrix} \\
\end{align*}
\]

If the linear transformation is injective, then the set above is guaranteed to be linearly independent (Theorem ILTLI 461). This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows (Theorem BRS 245). A basis for the range is:

\[
\begin{align*}
\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, & \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, & \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\
\end{align*}
\]

Surjective: Yes. (Definition SLT 469)

Notice that the basis for the range above is the standard basis for \( \mathbb{C}^3 \). So the range is all of \( \mathbb{C}^3 \) and thus the linear transformation is surjective.

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD 496.

Domain dimension: 5 Rank: 3 Nullity: 2

Invertible: No.

Not surjective, and the relative sizes of the domain and codomain mean the linear transformation cannot be injective.

Matrix representation (Theorem MLTCV 437):

\[
T: \mathbb{C}^5 \rightarrow \mathbb{C}^3, \quad T(x) = Ax, \quad A = \begin{bmatrix} 2 & 1 & 3 & -4 & 5 \\ 1 & -2 & 3 & -9 & 3 \\ 3 & 0 & 4 & -6 & 5 \end{bmatrix}
\]
Archetype O

**Summary**  Linear transformation with a domain smaller than the codomain, so it is guaranteed to not be onto. Happens to not be one-to-one.

- A linear transformation: (Definition LT 429)
  \[ T: \mathbb{C}^3 \to \mathbb{C}^5, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} -x_1 + x_2 - 3x_3 \\ -x_1 + 2x_2 - 4x_3 \\ x_1 + x_2 + x_3 \\ 2x_1 + 3x_2 + x_3 \\ x_1 + 2x_3 \end{pmatrix} \]

- A basis for the null space of the linear transformation: (Definition KLT 457)
  \[ \left\{ \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix} \right\} \]

- Injective: No. (Definition ILT 453)
  Since the kernel is nontrivial Theorem KILT 460 tells us that the linear transformation is not injective. Also, since the rank can not exceed 3, we are guaranteed to have a nullity of at least 2, just from checking dimensions of the domain and the codomain. In particular, verify that
  \[ T \begin{pmatrix} 5 \\ -1 \\ 3 \end{pmatrix} = \begin{pmatrix} -15 \\ -19 \\ 7 \\ 10 \\ 11 \end{pmatrix} \]
  \[ T \begin{pmatrix} 1 \\ 1 \\ 5 \end{pmatrix} = \begin{pmatrix} -15 \\ -19 \\ 7 \\ 10 \\ 11 \end{pmatrix} \]
  This demonstration that \( T \) is not injective is constructed with the observation that
  \[ \begin{pmatrix} 1 \\ 1 \\ 5 \end{pmatrix} = \begin{pmatrix} 5 \\ -1 \\ 3 \end{pmatrix} + \begin{pmatrix} -4 \\ 2 \\ 2 \end{pmatrix} \]
  and
  \[ z = \begin{pmatrix} -4 \\ 2 \\ 2 \end{pmatrix} \in \ker(T) \]
  so the vector \( z \) effectively “does nothing” in the evaluation of \( T \).

- A basis for the range of the linear transformation: (Definition RLT 473)
Evaluate the linear transformation on a standard basis to get a spanning set for the range (Theorem SSRLT 478):

\[
\{ \begin{bmatrix} -1 \\ -1 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 1 \\ 3 \\ 0 \end{bmatrix}, \begin{bmatrix} -3 \\ -4 \\ 1 \\ 1 \\ 2 \end{bmatrix} \}
\]

If the linear transformation is injective, then the set above is guaranteed to be linearly independent (Theorem ILTLI 461). This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows (Theorem BRS 245). A basis for the range is:

\[
\{ \begin{bmatrix} 1 \\ 0 \\ -3 \\ -7 \\ -2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 2 \\ 5 \\ 1 \end{bmatrix} \}
\]

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD 496.

Domain dimension: 3   Rank: 2   Nullity: 1

Surjective: No. (Definition SLT 469)

The dimension of the range is 2, and the codomain (C^5) has dimension 5. So the transformation is not onto. Notice too that since the domain C^3 has dimension 3, it is impossible for the range to have a dimension greater than 3, and no matter what the actual definition of the function, it cannot possibly be onto.

To be more precise, verify that \( \begin{bmatrix} 2 \\ 3 \\ 1 \\ 1 \\ 1 \end{bmatrix} \not\in R(T) \), by setting the output equal to this vector and seeing that the resulting system of linear equations has no solution, i.e. is inconsistent. So the preimage, \( T^{-1} \left( \begin{bmatrix} 2 \\ 3 \\ 1 \\ 1 \\ 1 \end{bmatrix} \right) \), is nonempty. This alone is sufficient to see that the linear transformation is not onto.

Invertible: No.
Not injective, and the relative dimensions of the domain and codomain prohibit any possibility of being surjective.

Matrix representation (Theorem MLTCV [437]):

\[ T : \mathbb{C}^3 \rightarrow \mathbb{C}^5, \quad T(x) = Ax, \quad A = \begin{bmatrix} -1 & 1 & -3 \\ -1 & 2 & -4 \\ 1 & 1 & 1 \\ 2 & 3 & 1 \\ 1 & 0 & 2 \end{bmatrix} \]
Archetype P

Summary  Linear transformation with a domain smaller that its codomain, so it is guaranteed to not be surjective. Happens to be injective.

- A linear transformation: (Definition LT [429])
  \[ T: \mathbb{C}^3 \rightarrow \mathbb{C}^5, \quad T \left( \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \right) = \begin{bmatrix} -x_1 + x_2 + x_3 \\ -x_1 + 2x_2 + 2x_3 \\ x_1 + x_2 + 3x_3 \\ 2x_1 + 3x_2 + x_3 \\ -2x_1 + x_2 + 3x_3 \end{bmatrix} \]

- A basis for the null space of the linear transformation: (Definition KLT [457])
  \{ \}

- Injective: Yes. (Definition ILT [453])
  Since \( \mathcal{K}(T) = \{0\} \), Theorem KILT [460] tells us that \( T \) is injective.

- A basis for the range of the linear transformation: (Definition RLT [473])
  Evaluate the linear transformation on a standard basis to get a spanning set for the range (Theorem SSRLT [478]):
  \[
  \begin{cases}
  \begin{bmatrix} -1 \\ -1 \\ 1 \\ 2 \\ -2 \end{bmatrix}, \\
  \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \\ 1 \end{bmatrix}
  \end{cases}
  \]
  If the linear transformation is injective, then the set above is guaranteed to be linearly independent (Theorem ILTLI [461]). This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows (Theorem BRS [245]). A basis for the range is:
  \[
  \begin{cases}
  \begin{bmatrix} 1 \\ 0 \\ -10 \\ 6 \end{bmatrix}, \\
  \begin{bmatrix} 0 \\ 1 \\ 7 \\ -3 \end{bmatrix}, \\
  \begin{bmatrix} 1 \\ 0 \\ -1 \\ 1 \end{bmatrix}
  \end{cases}
  \]

- Surjective: No. (Definition SLT [469])
The dimension of the range is 3, and the codomain ($\mathbb{C}^5$) has dimension 5. So the transformation is not surjective. Notice too that since the domain $\mathbb{C}^3$ has dimension 3, it is impossible for the range to have a dimension greater than 3, and no matter what the actual definition of the function, it cannot possibly be surjective in this situation.

To be more precise, verify that

$$\begin{bmatrix} 2 \\ 1 \\ -3 \\ 2 \\ 6 \end{bmatrix} \not\in \mathcal{R}(T),$$

by setting the output equal to this vector and seeing that the resulting system of linear equations has no solution, i.e. is inconsistent. So the preimage, $T^{-1}\left(\begin{bmatrix} 2 \\ 1 \\ -3 \\ 2 \\ 6 \end{bmatrix}\right)$, is nonempty. This alone is sufficient to see that the linear transformation is not onto.

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD [496].

Domain dimension: 3 \hspace{1cm} Rank: 3 \hspace{1cm} Nullity: 0

Invertible: No.

Not surjective.

Matrix representation (Theorem MLTCV [437]):

$$T: \mathbb{C}^3 \rightarrow \mathbb{C}^5, \quad T(x) = Ax, \quad A = \begin{bmatrix} -1 & 1 & 1 \\ -1 & 2 & 2 \\ 1 & 1 & 3 \\ 2 & 3 & 1 \\ -2 & 1 & 3 \end{bmatrix}$$
Archetype Q

Summary  Linear transformation with equal-sized domain and codomain, so it has the potential to be invertible, but in this case is not. Neither injective nor surjective. Diagonalizable, though.

A linear transformation: (Definition LT [429])

\[ T : \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T \left( \begin{array}{c} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{array} \right) = \left( \begin{array}{c} -2x_1 + 3x_2 + 3x_3 - 6x_4 + 3x_5 \\ -16x_1 + 9x_2 + 12x_3 - 28x_4 + 28x_5 \\ -19x_1 + 7x_2 + 14x_3 - 32x_4 + 37x_5 \\ -21x_1 + 9x_2 + 15x_3 - 35x_4 + 39x_5 \\ -9x_1 + 5x_2 + 7x_3 - 16x_4 + 16x_5 \end{array} \right) \]

A basis for the null space of the linear transformation: (Definition KLT [457])

\[ \left\{ \begin{bmatrix} 3 \\ 4 \\ 1 \\ 3 \\ 3 \end{bmatrix} \right\} \]

Injective: No. (Definition ILT [453])

Since the kernel is nontrivial, Theorem KILT [460] tells us that the linear transformation is not injective. Also, since the rank can not exceed 3, we are guaranteed to have a nullity of at least 2, just from checking dimensions of the domain and the codomain. In particular, verify that

\[ T \left( \begin{array}{c} 1 \\ 3 \\ -1 \\ 2 \\ 4 \end{array} \right) = \left( \begin{array}{c} 4 \\ 55 \\ 72 \\ 77 \\ 31 \end{array} \right) \quad T \left( \begin{array}{c} 4 \\ 7 \\ 0 \\ 5 \\ 7 \end{array} \right) = \left( \begin{array}{c} 4 \\ 55 \\ 72 \\ 77 \\ 31 \end{array} \right) \]

This demonstration that \( T \) is not injective is constructed with the observation that

\[ \left( \begin{array}{c} 4 \\ 7 \\ 0 \\ 5 \\ 7 \end{array} \right) = \left( \begin{array}{c} 1 \\ 3 \\ -1 \\ 2 \\ 4 \end{array} \right) + \left( \begin{array}{c} 3 \\ 4 \\ 1 \\ 3 \\ 3 \end{array} \right) \]
and

\[ z = \begin{bmatrix} 3 \\ 4 \\ 1 \\ 3 \\ 3 \end{bmatrix} \in \mathcal{K}(T) \]

so the vector \( z \) effectively “does nothing” in the evaluation of \( T \).

A basis for the range of the linear transformation: [Definition RLT 473]

Evaluate the linear transformation on a standard basis to get a spanning set for the range [Theorem SSRLT 478]:

\[
\left\{ \begin{bmatrix} -2 \\ -16 \\ -19 \\ -21 \\ -9 \end{bmatrix}, \begin{bmatrix} 3 \\ 9 \\ 7 \\ 9 \\ 5 \end{bmatrix}, \begin{bmatrix} 3 \\ 12 \\ 14 \\ 15 \\ 7 \end{bmatrix}, \begin{bmatrix} -6 \\ -28 \\ -32 \\ -35 \\ -16 \end{bmatrix}, \begin{bmatrix} 3 \\ 28 \\ 37 \\ 39 \\ 16 \end{bmatrix} \right\}
\]

If the linear transformation is injective, then the set above is guaranteed to be linearly independent [Theorem ILTLI 461]. This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows [Theorem BRS 245]. A basis for the range is:

\[
\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -1 \\ 0 \end{bmatrix} \right\}
\]

Surjective: No. [Definition SLT 469]

The dimension of the range is 4, and the codomain (\( \mathbb{C}^5 \)) has dimension 5. So \( \mathcal{R}(T) \neq \mathbb{C}^5 \) and by [Theorem RSLT 476] the transformation is not surjective.

To be more precise, verify that \( \begin{bmatrix} -1 \\ 2 \\ 3 \\ -1 \\ 4 \end{bmatrix} \not\in \mathcal{R}(T) \), by setting the output equal to this vector and seeing that the resulting system of linear equations has no solution, i.e. is inconsistent. So the preimage, \( T^{-1} \left( \begin{bmatrix} -1 \\ 2 \\ 3 \\ -1 \\ 4 \end{bmatrix} \right) \), is nonempty. This alone is sufficient to see
that the linear transformation is not onto.

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD 496.

Domain dimension: 5
Rank: 4
Nullity: 1

Invertible: No.

Neither injective nor surjective. Notice that since the domain and codomain have the same dimension, either the transformation is both onto and one-to-one (making it invertible) or else it is both not onto and not one-to-one (as in this case) by Theorem RPNDD 496.

Matrix representation (Theorem MLTCV 437):

\[
T: \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T(x) = Ax, \quad A = \begin{bmatrix}
-2 & 3 & 3 & -6 & 3 \\
-16 & 9 & 12 & -28 & 28 \\
-19 & 7 & 14 & -32 & 37 \\
-21 & 9 & 15 & -35 & 39 \\
-9 & 5 & 7 & -16 & 16
\end{bmatrix}
\]

Eigenvalues and eigenvectors (Definition EELT 549, Theorem EER 552):

\[
\lambda = -1 \quad E_T(-1) = S_p \begin{bmatrix} 0 \\ 2 \\ 3 \\ 3 \\ 1 \end{bmatrix}
\]

\[
\lambda = 0 \quad E_T(0) = S_p \begin{bmatrix} 3 \\ 4 \\ 1 \\ 3 \\ 3 \end{bmatrix}
\]

\[
\lambda = 1 \quad E_T(1) = S_p \begin{bmatrix} 5, -3 \\ 3, 1 \\ 0, 0 \\ 0, 2 \\ 2, 0 \end{bmatrix}
\]

Evaluate the linear transformation with each of these eigenvectors.

A diagonal matrix representation relative to a basis of eigenvectors:
Basis:

\[ B = \begin{Bmatrix}
\begin{bmatrix} 0 \\ 2 \\ 3 \\ 3 \\ 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 1 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 5 \\ 0 \\ 3 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} -3 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 0 \\ 0 \\ 0 \end{bmatrix}
\end{Bmatrix} \]

Representation:

\[ T : \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T(x) = \rho_B^{-1}(D \rho_B(x)) \]

\[ D = \begin{bmatrix}
-1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix} \]
Archetype R

Summary
Linear transformation with equal-sized domain and codomain. Injective, surjective, invertible, diagonalizable, the works.

A linear transformation: \( \text{Definition LT} \) \[429\]

\[
T : \mathbb{C}^5 \rightarrow \mathbb{C}^5, \quad T \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} -65x_1 + 128x_2 + 10x_3 - 262x_4 + 40x_5 \\ 36x_1 - 73x_2 - x_3 + 151x_4 - 16x_5 \\ -44x_1 + 88x_2 + 5x_3 - 180x_4 + 24x_5 \\ 34x_1 - 68x_2 - 3x_3 + 140x_4 - 18x_5 \\ 12x_1 - 24x_2 - x_3 + 49x_4 - 5x_5 \end{pmatrix}
\]

A basis for the null space of the linear transformation: \( \text{Definition KLT} \) \[457\]

\[
\{ \} 
\]

Injective: Yes. \( \text{Definition ILT} \) \[453\]

Since the kernel is trivial \( \text{Theorem KILT} \) \[460\] tells us that the linear transformation is injective.

A basis for the range of the linear transformation: \( \text{Definition RLT} \) \[473\]

Evaluate the linear transformation on a standard basis to get a spanning set for the range \( \text{Theorem SSRLT} \) \[478\]:

\[
\begin{pmatrix} -65 \\ 36 \\ -44 \\ 34 \\ 12 \end{pmatrix}, \begin{pmatrix} 128 \\ -73 \\ 88 \\ -68 \\ -24 \end{pmatrix}, \begin{pmatrix} 10 \\ -1 \\ 5 \\ -3 \\ -1 \end{pmatrix}, \begin{pmatrix} -262 \\ 151 \\ -180 \\ 140 \\ 49 \end{pmatrix}, \begin{pmatrix} 40 \\ -16 \\ 24 \\ -18 \\ -5 \end{pmatrix}
\]

If the linear transformation is injective, then the set above is guaranteed to be linearly independent \( \text{Theorem ILTLI} \) \[461\]. This spanning set may be converted to a “nice” basis, by making the column vectors the rows of a matrix, row-reducing, and retaining the nonzero rows \( \text{Theorem BRS} \) \[245\]. A basis for the range is:

\[
\begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}
\]
Surjective: Yes/No. (Definition SLT [469])
A basis for the range is the standard basis of $\mathbb{C}^5$, so $R(T) = \mathbb{C}^5$ and Theorem RSLT [476] tells us $T$ is surjective. Or, the dimension of the range is 5, and the codomain ($\mathbb{C}^5$) has dimension 5. So the transformation is surjective.

Subspace dimensions associated with the linear transformation. Examine parallels with earlier results for matrices. Verify Theorem RPNDD [496].

Domain dimension: 5  
Rank: 5  
Nullity: 0

Invertible: Yes.
Both injective and surjective. Notice that since the domain and codomain have the same dimension, either the transformation is both injective and surjective (making it invertible, as in this case) or else it is both not injective and not surjective.

Matrix representation (Theorem MLTCV [437]):

$T: \mathbb{C}^5 \rightarrow \mathbb{C}^5$,  $T(x) = Ax$,  $A = \begin{bmatrix}-65 & 128 & 10 & -262 & 40 \\ 36 & -73 & -1 & 151 & -16 \\ -44 & 88 & 5 & -180 & 24 \\ 34 & -68 & -3 & 140 & -18 \\ 12 & -24 & -1 & 49 & -5\end{bmatrix}$

The inverse linear transformation (Definition IVLT [487]):

$T^{-1}: \mathbb{C}^5 \rightarrow \mathbb{C}^5$,  $T^{-1} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix}-47x_1 + 92x_2 + x_3 - 181x_4 - 14x_5 \\ 27x_1 - 55x_2 + \frac{7}{2}x_3 + \frac{221}{2}x_4 + 11x_5 \\ -32x_1 + 64x_2 - x_3 - 126x_4 - 12x_5 \\ 25x_1 - 50x_2 + \frac{3}{2}x_3 + \frac{169}{2}x_4 + 9x_5 \\ 9x_1 - 18x_2 + \frac{1}{2}x_3 + \frac{7}{2}x_4 + 4x_5 \end{bmatrix}$

Verify that $T(T^{-1}(x)) = x$ and $T(T^{-1}(x)) = x$, and notice that the representations of the transformation and its inverse are matrix inverses (Theorem IMR [540], Definition MI [208]).

Eigenvalues and eigenvectors (Definition EELT [549], Theorem EER [552]):
\[ \lambda = -1 \quad E_T(-1) = Sp \left\{ \begin{pmatrix} -57 \\ 0 \\ -18 \\ 14 \\ 5 \end{pmatrix}, \begin{pmatrix} 2 \\ 1 \end{pmatrix} \right\} \]

\[ \lambda = 1 \quad E_T(1) = Sp \left\{ \begin{pmatrix} -10 \\ -5 \\ -6 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 3 \end{pmatrix} \right\} \]

\[ \lambda = 2 \quad E_T(2) = Sp \left\{ \begin{pmatrix} -6 \\ 3 \\ -4 \\ 3 \\ 1 \end{pmatrix} \right\} \]

Evaluate the linear transformation with each of these eigenvectors.

A diagonal matrix representation relative to a basis of eigenvectors:

Basis:

\[ B = \left\{ \begin{pmatrix} -57 \\ 0 \\ -18 \\ 14 \\ 5 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -10 \\ -5 \\ -6 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 3 \end{pmatrix}, \begin{pmatrix} -6 \\ 3 \\ -4 \\ 3 \\ 1 \end{pmatrix} \right\} \]

Representation:

\[ T : \mathbb{C}^5 \to \mathbb{C}^5, \quad T(x) = \rho_B^{-1}(D \rho_B(x)) \]

\[ D = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 2 \end{bmatrix} \]
Archetype S

Summary  Domain is column vectors, codomain is matrices. Domain is dimension 3 and codomain is dimension 4. Not injective, not surjective.

- A linear transformation:  
  \[ T: \mathbb{C}^3 \mapsto M_{22}, \quad T\left( \begin{bmatrix} a \\ b \\ c \end{bmatrix} \right) = \begin{bmatrix} a - b & 2a + 2b + c \\ 3a + b + c & -2a - 6b - 2c \end{bmatrix} \]

Archetype T

Summary  Domain and codomain are polynomials. Domain has dimension 5, while codomain has dimension 6. Is injective, can’t be surjective.

- A linear transformation:  
  \[ T: P_4 \mapsto P_5, \quad T\left( p(x) \right) = (x - 2)p(x) \]

Archetype U

Summary  Domain is matrices, codomain is column vectors. Domain has dimension 6, while codomain has dimension 4. Can’t be injective, is surjective.

- A linear transformation:  
  \[ T: M_{23} \mapsto \mathbb{C}^4, \quad T\left( \begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix} \right) = \begin{bmatrix} a + 2b + 12c - 3d + e + 6f \\ 2a - b - c + d - 11f \\ a + b + 7c + 2d + e - 3f \\ a + 2b + 12c + 5e - 5f \end{bmatrix} \]

Archetype V

Summary  Domain is polynomials, codomain is matrices. Domain and codomain both have dimension 4. Injective, surjective, invertible, (eigenvalues, diagonalizable???)

- A linear transformation:  
  \[ T: P_3 \mapsto M_{22}, \quad T\left( a + bx + cx^2 + dx^3 \right) = \begin{bmatrix} a + b & a - 2c \\ d & b - d \end{bmatrix} \]
When invertible, the inverse linear transformation. (Definition IVLT [487])

\[ T^{-1}: M_{22} \rightarrow P_3, \quad T^{-1}\left(\begin{bmatrix} a & b \\ c & d \end{bmatrix}\right) = (a - c - d) + (c + d)x + \frac{1}{2}(a - b - c - d)x^2 + cx^3 \]

**Archetype W**

**Summary**  Domain is polynomials, codomain is polynomials. Domain and codomain both have dimension 3. Injective, surjective, invertible, (eigenvalues, diagonalizable??).
Part T
Topics
In this section we review the basics of working with complex numbers.

**Subsection CNA**
**Arithmetic with complex numbers**

A complex number is a linear combination of 1 and $i = \sqrt{-1}$, typically written in the form $a + bi$. Complex numbers can be added, subtracted, multiplied and divided, just like we are used to doing with real numbers, including the restriction on division by zero. We will not define these operations carefully, but instead illustrate with examples.

**Example ACN**
**Arithmetic of complex numbers**

\[
(2 + 5i) + (6 - 4i) = (2 + 6) + (5 + (-4))i = 8 + i \\
(2 + 5i) - (6 - 4i) = (2 - 6) + (5 - (-4))i = -4 + 9i \\
(2 + 5i)(6 - 4i) = (2)(6) + (5i)(6) + (2)(-4i) + (5i)(-4i) = 12 + 30i - 8i - 20i^2 \\
= 12 + 22i - 20(-1) = 32 + 22i
\]

Division takes just a bit more care. We multiply the denominator by a complex number chosen to produce a real number and then we can produce a complex number as a result.

\[
\frac{2 + 5i}{6 - 4i} = \frac{2 + 5i}{6 - 4i} \cdot \frac{6 + 4i}{6 + 4i} = \frac{-8 + 38i}{52} = -\frac{8}{52} + \frac{38}{52}i = -\frac{2}{13} + \frac{19}{26}i
\]

In this example, we used $6 + 4i$ to convert the denominator in the fraction to a real number. This number is known as the conjugate, which we now define.
Subsection CCN
Conjugates of Complex Numbers

Definition CCN
Conjugate of a Complex Number
The conjugate of the complex number $c = a + bi \in \mathbb{C}$ is the complex number $\overline{c} = a - bi$. △

Example CSCN
Conjugate of some complex numbers

\[
2 + 3i = 2 - 3i \\
5 - 4i = 5 + 4i \\
-3 + 0i = -3 + 0i \\
0 + 0i = 0 + 0i
\]

Notice how the conjugate of a real number leaves the number unchanged. The conjugate enjoys some basic properties that are useful when we work with linear expressions involving addition and multiplication.

Theorem CCRA
Complex Conjugation Respects Addition
Suppose that $c$ and $d$ are complex numbers. Then $c + d = \overline{c} + \overline{d}$. □

Proof Let $c = a + bi$ and $d = r + si$. Then
\[
\overline{c + d} = (a + r) + (b + s)i = (a + r) - (b + s)i = (a - bi) + (r - si) = \overline{c} + \overline{d}
\]

Theorem CCRM
Complex Conjugation Respects Multiplication
Suppose that $c$ and $d$ are complex numbers. Then $\overline{cd} = \overline{c} \overline{d}$. □

Proof Let $c = a + bi$ and $d = r + si$. Then
\[
\overline{cd} = (ar - bs) + (as + br)i = (ar - bs) - (as + br)i = (ar - (-b)(-s)) + (a(-s) + (-b)r)i = (a - bi)(r - si) = \overline{c} \overline{d}
\]

Theorem CCT
Complex Conjugation Twice
Suppose that $c$ is a complex number. Then $\overline{\overline{c}} = c$. □

Proof Let $c = a + bi$. Then
\[
\overline{\overline{c}} = \overline{a - bi} = a - (-bi) = a + bi = c
\]

Version 0.52
Subsection MCN
Modulus of a Complex Number

We define one more operation with complex numbers that may be new to you.

Definition MCN
Modulus of a Complex Number
The modulus of the complex number $c = a + bi \in \mathbb{C}$, is the nonnegative real number

$$|c| = \sqrt{c \overline{c}} = \sqrt{a^2 + b^2}. \quad \triangle$$

Example MSCN
Modulus of some complex numbers

$$|2 + 3i| = \sqrt{13} \quad |5 - 4i| = \sqrt{41} \quad |-3 + 0i| = 3 \quad |0 + 0i| = 0 \quad \odot$$

The modulus can be interpreted as a version of the absolute value for complex numbers, as is suggested by the notation employed. You can see this in how $|-3| = |-3 + 0i| = 3$. Notice too how the modulus of the complex zero, $0 + 0i$, has value 0.
Part A
Applications
Index

A
  (archetype), 563
  A (chapter), 559
  A (definition), 229
  A (part), 645
  A (subsection of WILA), 4
  AA (Property), 276
  AAC (Property), 92
  AALC (example), 102
  AAM (Property), 181
  ABLC (example), 101
  AC (Property), 275
  ACC (Property), 92
  ACM (Property), 181
  ACN (example), 639
  additive associativity
    column vectors
      Property AAC, 92
    matrices
      Property AAM, 181
    vectors
      Property AA, 276
  additive inverse
    from scalar multiplication
      theorem AISM, 283
  additive inverses
    column vectors
      Property AIC, 92
    matrices
      Property AIM, 181
    unique
      theorem AIU, 282
    vectors
      Property AI, 276
  additive closure
    column vectors
      Property ACC, 92
    matrices
      Property ACM, 181
    vectors
      Property AC, 275
  adjoint
    definition A, 229
    AHSAC (example), 63
    AI (Property), 276
    AIC (Property), 92
    AIM (Property), 181
    AISM (theorem), 283
    AIU (theorem), 282
    AIVLT (example), 487
    ALT (example), 430
    ALTMM (example), 527
    AM (definition), 31
    AM (example), 29
    AMAA (example), 31
    AME (definition), 384
    AMN (notation), 68
    ANILT (example), 488
    AOS (example), 171
  Archetype A
    column space, 240
    definition, 563
    linearly dependent columns, 139
    singular matrix, 76
    solving homogeneous system, 64
    system as linear combination, 102
  archetype A
    augmented matrix
      example AMAA, 31
    archetype A:solutions
      example SAA, 38
  Archetype B
    column space, 241
    definition, 568
    inverse
      example CMIAB, 214
    linearly independent columns, 139
    nonsingular matrix, 76
    not invertible
      example MWIAA, 208
    solutions via inverse
      example SABMI, 207
INDEX 647

solving homogeneous system, 64
system as linear combination, 101
vector equality, 88
archetype B
solutions
example SAB, 37
Archetype C
definition, 573
homogeneous system, 63
Archetype D
definition, 577
range, original columns, 239
solving homogeneous system, 65
vector form of solutions, 104
Archetype E
definition, 581
archetype E: solutions
example SAE, 39
Archetype F
definition, 585
Archetype G
definition, 590
Archetype H
definition, 594
Archetype I
column space from row operations, 246
definition, 599
null space, 69
row space, 242
vector form of solutions, 108
Archetype I: casting out vectors, 154
Archetype J
definition, 604
Archetype K
definition, 609
inverse
example CMIAK, 211
example MIAK, 209
Archetype L
definition, 613
null space span, linearly independent, 141
vector form of solutions, 110
Archetype M
definition, 617
Archetype N
definition, 620
Archetype O
definition, 622
Archetype P
definition, 625
Archetype Q
definition, 627
Archetype R
definition, 631
Archetype S
definition, 634
Archetype T
definition, 634
Archetype U
definition, 634
Archetype V
definition, 634
Archetype W
definition, 635
ASC (example), 513
augmented matrix
notation AMN, 68
AVR (example), 324
B
(archetype), 568
B (definition), 517
B (section), 509
B (subsection of B), 517
basis
columns nonsingular matrix
example CABAK, 323
common size
theorem BIS, 335
definition B, 317
matrices
example BM, 319
example BSM22, 320
polynomials
example BP, 318
example BPR, 349
example BSP4, 319
example SVP4, 350
subspace of matrices
example BDM22, 349
BCSOC (theorem), 238
BDE (example), 402
BDM22 (example), 349
best cities
theorem CSRST, 246
basis of original columns
  theorem BCSOC, 238
consistent system
  theorem CSCS, 236
consistent systems
  example CSMCS, 235
isomorphic to range, 538
matrix. 235
nonsingular matrix
  theorem CSNSM, 241
row operations, Archetype I
  example CSROI, 246
testing membership
  example MCSM, 237
two computations
  example CSTW, 238
commutativity
column vectors
  Property CC, 92
  Property CM, 181
  Property C, 275
complex m-space
  example VSCV, 277
complex arithmetic
  example ACN, 639
complex number
  conjugate
    example CScN, 640
    modulus
      example MSCN, 641
  complex conjugate
    definition CCN, 640
    modulus
      definition MCN, 641
complex vector space
dimension
  theorem DCM, 336
composition
injective linear transformations
  theorem CILTI, 463
surjective linear transformations
  theorem CSLTS, 481
computation

LS.MMA, 57
ME.MMA, 30
ME.TI83, 30
ME.TI86, 30
ML.MMA, 214
MM.MMA, 192
RR.MMA, 40
RR.TI83, 40
RR.TI86, 40
TM.MMA, 185
TM.TI86, 185
VLC.MMA, 91
VLC.TI83, 92
VLC.TI86, 91
conjugate
  addition
    theorem CCRA, 640
  column vector
    definition CCCV, 165
  matrix
    definition CCM, 185
  multiplication
    theorem CCRM, 640
  scalar multiplication
    theorem CRSM, 166
twice
  theorem CCT, 640
  vector addition
    theorem CRVA, 165
conjugation
  matrix addition
    theorem CRMA, 185
  matrix scalar multiplication
    theorem CRMSM, 186
consistent linear system, 53
consistent linear systems
  theorem CSRN, 54
consistent system
  definition CS, 49
constructive proofs
  technique C, 35
contrapositive
  technique CP, 53
converse
  technique CV, 55
coordinates
orthonormal basis
  theorem COB, 353
coordinatization
  linear combination of matrices
  example CM32, 515
  linear independence
  theorem CLI, 514
  orthonormal basis
  example CROB3, 355
  example CROB4, 354
  spanning sets
  theorem CSS, 514
coordinatization principle, 515
coordinatizing
polynomials
  example CP2, 515
COV (example), 154
COV (subsection of LDS), 153
CP (definition), 381
CP (subsection of VR), 513
CP (technique), 53
CP2 (example), 515
CPMS3 (example), 381
crazy vector space
  example CVSR, 513
  properties
  example PCVS, 284
CRMA (theorem), 185
CRMSM (theorem), 186
CRN (theorem), 339
CROB3 (example), 355
CROB4 (example), 354
CRS (section), 235
CRS (subsection of FS), 255
CRSM (theorem), 166
CRVA (theorem), 165
CS (definition), 49
CSAA (example), 240
CSAB (example), 241
CSANS (example), 256
CSCN (example), 640
CSCS (theorem), 236
CSIP (example), 167
CSLT (subsection of SLT), 481
CSLTS (theorem), 481
CSM (definition), 235
CSMCS (example), 235
CSNSM (subsection of CRS), 240
CSNSM (theorem), 241
CSRN (theorem), 54
CSROI (example), 246
CSRST (theorem), 246
CSS (theorem), 514
CSSE (subsection of CRS), 235
CSSM (theorem), 285
CSSOC (subsection of CRS), 237
CSTW (example), 238
CTLT (example), 447
CV (definition), 66
CV (technique), 55
CVA (definition), 80
CVE (definition), 88
CVS (example), 280
CVS (subsection of VR), 512
CVSM (definition), 90
CVSM (example), 90
CVSM (theorem), 286
CVSR (example), 513
D
  (archetype), 577
D (chapter), 361
D (definition), 331
D (section), 331
D (subsection of D), 331
D (subsection of SD), 415
D (technique), 13
D33M (example), 362
DAB (example), 415
decomposition
  technique DC, 101
DED (theorem), 120
definition
  A, 229
  AM, 31
  AME, 384
  B, 317
  CBM, 549
  CCCV, 165
  CCM, 185
  CCN, 640
  CIM, 363
  CM, 56
  CP, 381
<table>
<thead>
<tr>
<th>Definition</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS, 49</td>
<td></td>
</tr>
<tr>
<td>CSM, 235</td>
<td></td>
</tr>
<tr>
<td>CV, 66</td>
<td></td>
</tr>
<tr>
<td>CVA, 89</td>
<td></td>
</tr>
<tr>
<td>CVE, 88</td>
<td></td>
</tr>
<tr>
<td>CVSM, 90</td>
<td></td>
</tr>
<tr>
<td>D, 331</td>
<td></td>
</tr>
<tr>
<td>DIM, 415</td>
<td></td>
</tr>
<tr>
<td>DM, 361</td>
<td></td>
</tr>
<tr>
<td>DZM, 415</td>
<td></td>
</tr>
<tr>
<td>EEF, 259</td>
<td></td>
</tr>
<tr>
<td>EELT, 549</td>
<td></td>
</tr>
<tr>
<td>EEM, 373</td>
<td></td>
</tr>
<tr>
<td>EM, 382</td>
<td></td>
</tr>
<tr>
<td>EO, 16</td>
<td></td>
</tr>
<tr>
<td>ES, 16</td>
<td></td>
</tr>
<tr>
<td>GME, 384</td>
<td></td>
</tr>
<tr>
<td>HM, 229</td>
<td></td>
</tr>
<tr>
<td>HS, 63</td>
<td></td>
</tr>
<tr>
<td>IDLT, 487</td>
<td></td>
</tr>
<tr>
<td>IDV, 52</td>
<td></td>
</tr>
<tr>
<td>ILT, 453</td>
<td></td>
</tr>
<tr>
<td>IM, 76</td>
<td></td>
</tr>
<tr>
<td>IP, 106</td>
<td></td>
</tr>
<tr>
<td>IVLT, 487</td>
<td></td>
</tr>
<tr>
<td>IVS, 393</td>
<td></td>
</tr>
<tr>
<td>KLT, 457</td>
<td></td>
</tr>
<tr>
<td>LC, 297</td>
<td></td>
</tr>
<tr>
<td>LCCV, 99</td>
<td></td>
</tr>
<tr>
<td>LI, 309</td>
<td></td>
</tr>
<tr>
<td>LICV, 133</td>
<td></td>
</tr>
<tr>
<td>LNS, 255</td>
<td></td>
</tr>
<tr>
<td>LO, 34</td>
<td></td>
</tr>
<tr>
<td>LT, 429</td>
<td></td>
</tr>
<tr>
<td>LTA, 444</td>
<td></td>
</tr>
<tr>
<td>LTC, 446</td>
<td></td>
</tr>
<tr>
<td>LTSM, 445</td>
<td></td>
</tr>
<tr>
<td>M, 29</td>
<td></td>
</tr>
<tr>
<td>MA, 180</td>
<td></td>
</tr>
<tr>
<td>MCN, 641</td>
<td></td>
</tr>
<tr>
<td>ME, 179</td>
<td></td>
</tr>
<tr>
<td>MI, 208</td>
<td></td>
</tr>
<tr>
<td>MIM, 363</td>
<td></td>
</tr>
<tr>
<td>MM, 191</td>
<td></td>
</tr>
<tr>
<td>MN, 29</td>
<td></td>
</tr>
<tr>
<td>MR, 923</td>
<td></td>
</tr>
<tr>
<td>MSM, 180</td>
<td></td>
</tr>
<tr>
<td>MVP, 187</td>
<td></td>
</tr>
<tr>
<td>N, 75</td>
<td></td>
</tr>
<tr>
<td>NOLT, 495</td>
<td></td>
</tr>
<tr>
<td>NOM, 338</td>
<td></td>
</tr>
<tr>
<td>NSM, 68</td>
<td></td>
</tr>
<tr>
<td>NV, 169</td>
<td></td>
</tr>
<tr>
<td>OM, 226</td>
<td></td>
</tr>
<tr>
<td>ONS, 175</td>
<td></td>
</tr>
<tr>
<td>OSV, 171</td>
<td></td>
</tr>
<tr>
<td>OV, 171</td>
<td></td>
</tr>
<tr>
<td>PC, 34</td>
<td></td>
</tr>
<tr>
<td>PI, 442</td>
<td></td>
</tr>
<tr>
<td>REM, 32</td>
<td></td>
</tr>
<tr>
<td>RLD, 309</td>
<td></td>
</tr>
<tr>
<td>RLDCV, 133</td>
<td></td>
</tr>
<tr>
<td>RLT, 473</td>
<td></td>
</tr>
<tr>
<td>RO, 32</td>
<td></td>
</tr>
<tr>
<td>ROLT, 495</td>
<td></td>
</tr>
<tr>
<td>ROM, 338</td>
<td></td>
</tr>
<tr>
<td>RREF, 34</td>
<td></td>
</tr>
<tr>
<td>RSM, 242</td>
<td></td>
</tr>
<tr>
<td>S, 291</td>
<td></td>
</tr>
<tr>
<td>SIM, 411</td>
<td></td>
</tr>
<tr>
<td>SLE, 14</td>
<td></td>
</tr>
<tr>
<td>SLT, 469</td>
<td></td>
</tr>
<tr>
<td>SM, 361</td>
<td></td>
</tr>
<tr>
<td>SQM, 75</td>
<td></td>
</tr>
<tr>
<td>SS, 298</td>
<td></td>
</tr>
<tr>
<td>SSCV, 119</td>
<td></td>
</tr>
<tr>
<td>SUV, 210</td>
<td></td>
</tr>
<tr>
<td>SV, 67</td>
<td></td>
</tr>
<tr>
<td>SYM, 183</td>
<td></td>
</tr>
<tr>
<td>TM, 182</td>
<td></td>
</tr>
<tr>
<td>TS, 295</td>
<td></td>
</tr>
<tr>
<td>TSHSE, 64</td>
<td></td>
</tr>
<tr>
<td>TSS, 313</td>
<td></td>
</tr>
<tr>
<td>VOC, 67</td>
<td></td>
</tr>
<tr>
<td>VR, 505</td>
<td></td>
</tr>
<tr>
<td>VS, 275</td>
<td></td>
</tr>
<tr>
<td>VSCV, 87</td>
<td></td>
</tr>
<tr>
<td>VSM, 179</td>
<td></td>
</tr>
<tr>
<td>ZM, 182</td>
<td></td>
</tr>
<tr>
<td>ZRM, 34</td>
<td></td>
</tr>
<tr>
<td>ZV, 66</td>
<td></td>
</tr>
</tbody>
</table>

Definitions

- technique D, 13
- DEHD (example), 420
- DEMS5 (example), 390
- DERC (theorem), 364
determinant
computed two ways
example TCSD, 364
definition DM, 364
expansion
theorem DERC, 364
matrix multiplication
theorem DRMM, 366
nonsingular matrix
size 2 matrix
theorem DMST, 362
size 3 matrix
example D33M, 362
transpose
theorem DT, 365
zero
theorem SMZD, 366
zero versus nonzero
example ZNDAB, 366
determinant, upper triangular matrix
example DUTM, 365
diagonal matrix
definition DIM, 415
diagonalizable
definition DZM, 415
distinct eigenvalues
example DEHD, 420
theorem DED, 420
large eigenspaces
theorem DMLE, 418
not
example NDMS4, 420
diagonalizable matrix
high power
example HPDM, 421
diagonalization
Archetype B
example DAB, 415
criteria
theorem DC, 415
example DMS3, 417
DIM (definition), 415
dimension
definition D, 331
polynomial subspace
example DSP4, 337
subspace
example DSM22, 336
distributivity, matrix addition
matrices
Property DMAM, 181
distributivity, scalar addition
column vectors
Property DSAC, 93
matrices
Property DSAM, 181
vectors
Property DSA, 276
distributivity, vector addition
column vectors
Property DVAC, 92
vectors
Property DVA, 276
DLDS (theorem), 151
DM (definition), 364
DM (section), 364
DM (theorem), 336
DMAM (Property), 181
DMLE (theorem), 418
DMS3 (example), 417
DMST (theorem), 362
DP (theorem), 336
DRMM (theorem), 366
DSA (Property), 276
DSAC (Property), 93
DSAM (Property), 181
DSM22 (example), 336
DSP4 (example), 337
DT (theorem), 365
DUTM (example), 365
DVA (Property), 276
DVAC (Property), 92
DVS (subsection of D), 336
DZM (definition), 415

E
(archetype), 581
E (chapter), 373
E (technique), 52
ECREE (subsection of EE), 384
EDELI (theorem), 399
EDYES (theorem), 350
EE (section), 373
EEE (subsection of EE), 377
EEF (definition), 259
EEF (subsection of FS), 259
EELT (definition), 549
EELT (subsection of CB), 549
EEM (definition), 373
EEM (subsection of EE), 373
EENS (example), 414
EER (theorem), 552
EHM (subsection of PEE), 408
eigenspace
  as null space  
    theorem EMNS, 383
    definition EM, 382
  subspace  
    theorem EMS, 382
eigenvalue
  algebraic multiplicity  
    definition AME, 384
  complex  
    example CEMS6, 387
    definition EEM, 373
  existence  
    example CAEHW, 378
    theorem EMHE, 377
  geometric multiplicity  
    definition GME, 384
  linear transformation  
    definition EELT, 549
  multiplicities  
    example EMMS4, 384
  power  
    theorem EOMP, 401
  root of characteristic polynomial  
    theorem EMRCP, 381
  scalar multiple  
    theorem ESMM, 401
  symmetric matrix  
    example ESMS4, 385
  zero  
    theorem SMZE, 400
eigenvalues
  building desired  
    example BDE, 402
  conjugate pairs  
    theorem ERMCP, 404
  distinct  
    example DEMS5, 390
  example SEE, 373
  Hermitian matrices  
    theorem HMRE, 408
  inverse  
    theorem EIM, 403
  maximum number  
    theorem MNEM, 408
  multiplicities  
    example HMEM5, 386
    theorem ME, 406
  number  
    theorem NEM, 406
  of a polynomial  
    theorem EPM, 402
  size 3 matrix  
    example EMS3, 382
    example ESMS3, 383
  transpose  
    theorem ETM, 404
  eigenvalues, eigenvectors  
    vector, matrix representations  
      theorem EER, 552
  eigenvector, 373
  linear transformation, 349
eigenvectors, 374
  conjugate pairs, 404
  Hermitian matrices  
    theorem HMOE, 409
  linearly independent  
    theorem EDELI, 399
EILT (subsection of ILT), 453
EIM (theorem), 403
ELIS (theorem), 347
EM (definition), 382
EMHE (theorem), 377
EMMS4 (example), 384
EMMVP (theorem), 190
EMS (theorem), 383
EMP (theorem), 193
EMRCP (theorem), 381
EMS (theorem), 382
EMS3 (example), 382
EO (definition), 16
EOMP (theorem), 401
EOPSS (theorem), 17
EPM (theorem), 402
equal matrices  
  via equal matrix-vector products  
    theorem EMMVP, 190
equation operations  
  definition EO, 16
### INDEX

<table>
<thead>
<tr>
<th>Term</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>theorem EOPSS</td>
<td>17</td>
</tr>
<tr>
<td>equivalence technique E</td>
<td>52</td>
</tr>
<tr>
<td>equivalent systems definition ES</td>
<td>16</td>
</tr>
<tr>
<td>ERMCP (theorem)</td>
<td>404</td>
</tr>
<tr>
<td>ES (definition)</td>
<td>16</td>
</tr>
<tr>
<td>ESEO (subsection of SSLE)</td>
<td>16</td>
</tr>
<tr>
<td>ESLT (subsection of SLT)</td>
<td>469</td>
</tr>
<tr>
<td>ESMM (theorem)</td>
<td>401</td>
</tr>
<tr>
<td>ESMS3 (example)</td>
<td>383</td>
</tr>
<tr>
<td>ESMS4 (example)</td>
<td>385</td>
</tr>
<tr>
<td>ETM (theorem)</td>
<td>404</td>
</tr>
<tr>
<td>EVS (subsection of VS)</td>
<td>277</td>
</tr>
<tr>
<td>example AALC</td>
<td>102</td>
</tr>
<tr>
<td>ABLC</td>
<td>101</td>
</tr>
<tr>
<td>ACN</td>
<td>639</td>
</tr>
<tr>
<td>AHSAC</td>
<td>63</td>
</tr>
<tr>
<td>AIVLT</td>
<td>487</td>
</tr>
<tr>
<td>ALT</td>
<td>430</td>
</tr>
<tr>
<td>ALTMM</td>
<td>527</td>
</tr>
<tr>
<td>AM</td>
<td>29</td>
</tr>
<tr>
<td>AMAA</td>
<td>31</td>
</tr>
<tr>
<td>ANILT</td>
<td>488</td>
</tr>
<tr>
<td>AOS</td>
<td>171</td>
</tr>
<tr>
<td>ASC</td>
<td>513</td>
</tr>
<tr>
<td>AVR</td>
<td>324</td>
</tr>
<tr>
<td>BDE</td>
<td>402</td>
</tr>
<tr>
<td>BDM2</td>
<td>349</td>
</tr>
<tr>
<td>BM</td>
<td>319</td>
</tr>
<tr>
<td>BP</td>
<td>318</td>
</tr>
<tr>
<td>BPR</td>
<td>349</td>
</tr>
<tr>
<td>BRLT</td>
<td>479</td>
</tr>
<tr>
<td>BSM2</td>
<td>320</td>
</tr>
<tr>
<td>BSP4</td>
<td>319</td>
</tr>
<tr>
<td>CABAK</td>
<td>323</td>
</tr>
<tr>
<td>CAEHW</td>
<td>378</td>
</tr>
<tr>
<td>CCM</td>
<td>185</td>
</tr>
<tr>
<td>CEMS6</td>
<td>387</td>
</tr>
<tr>
<td>CFV</td>
<td>55</td>
</tr>
<tr>
<td>CM32</td>
<td>515</td>
</tr>
<tr>
<td>CMIAB</td>
<td>214</td>
</tr>
<tr>
<td>CMIAK</td>
<td>211</td>
</tr>
<tr>
<td>CNS1</td>
<td>69</td>
</tr>
<tr>
<td>CNS2</td>
<td>70</td>
</tr>
<tr>
<td>CNSV</td>
<td>169</td>
</tr>
<tr>
<td>COV</td>
<td>154</td>
</tr>
<tr>
<td>CP2</td>
<td>515</td>
</tr>
<tr>
<td>CPMS3</td>
<td>381</td>
</tr>
<tr>
<td>CROB</td>
<td>355</td>
</tr>
<tr>
<td>CROB4</td>
<td>354</td>
</tr>
<tr>
<td>CSAA</td>
<td>240</td>
</tr>
<tr>
<td>CSAB</td>
<td>241</td>
</tr>
<tr>
<td>CSANS</td>
<td>256</td>
</tr>
<tr>
<td>CSCN</td>
<td>640</td>
</tr>
<tr>
<td>CSIP</td>
<td>167</td>
</tr>
<tr>
<td>CSMCS</td>
<td>235</td>
</tr>
<tr>
<td>CSROI</td>
<td>246</td>
</tr>
<tr>
<td>CSTW</td>
<td>238</td>
</tr>
<tr>
<td>CTLT</td>
<td>447</td>
</tr>
<tr>
<td>CVS</td>
<td>280</td>
</tr>
<tr>
<td>CVSM</td>
<td>90</td>
</tr>
<tr>
<td>CVSR</td>
<td>513</td>
</tr>
<tr>
<td>D33M</td>
<td>362</td>
</tr>
<tr>
<td>DAB</td>
<td>415</td>
</tr>
<tr>
<td>DEHD</td>
<td>120</td>
</tr>
<tr>
<td>DEMS5</td>
<td>390</td>
</tr>
<tr>
<td>DMS3</td>
<td>417</td>
</tr>
<tr>
<td>DSM2</td>
<td>336</td>
</tr>
<tr>
<td>DSP4</td>
<td>337</td>
</tr>
<tr>
<td>DUTM</td>
<td>365</td>
</tr>
<tr>
<td>EENS</td>
<td>414</td>
</tr>
<tr>
<td>EMMS4</td>
<td>384</td>
</tr>
<tr>
<td>EMS3</td>
<td>382</td>
</tr>
<tr>
<td>ESMS3</td>
<td>383</td>
</tr>
<tr>
<td>ESMS4</td>
<td>385</td>
</tr>
<tr>
<td>FRAN</td>
<td>475</td>
</tr>
<tr>
<td>FS1</td>
<td>263</td>
</tr>
<tr>
<td>FS2</td>
<td>263</td>
</tr>
<tr>
<td>FSAG</td>
<td>265</td>
</tr>
<tr>
<td>GSTV</td>
<td>174</td>
</tr>
<tr>
<td>HISAA</td>
<td>64</td>
</tr>
<tr>
<td>HISAD</td>
<td>65</td>
</tr>
<tr>
<td>HMEM5</td>
<td>386</td>
</tr>
<tr>
<td>HPDM</td>
<td>121</td>
</tr>
<tr>
<td>HUSAB</td>
<td>64</td>
</tr>
<tr>
<td>IAP</td>
<td>461</td>
</tr>
<tr>
<td>IAR</td>
<td>454</td>
</tr>
<tr>
<td>IAS</td>
<td>245</td>
</tr>
<tr>
<td>IAV</td>
<td>455</td>
</tr>
<tr>
<td>ILTVR</td>
<td>541</td>
</tr>
<tr>
<td>IM</td>
<td>76</td>
</tr>
<tr>
<td>IS</td>
<td>21</td>
</tr>
<tr>
<td>ISSI</td>
<td>50</td>
</tr>
<tr>
<td>IVSAV</td>
<td>494</td>
</tr>
<tr>
<td>INDEX 655</td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td></td>
</tr>
<tr>
<td>KVMR, 536</td>
<td></td>
</tr>
<tr>
<td>LCM, 297</td>
<td></td>
</tr>
<tr>
<td>LDCAA, 139</td>
<td></td>
</tr>
<tr>
<td>LDHS, 136</td>
<td></td>
</tr>
<tr>
<td>LDP4, 335</td>
<td></td>
</tr>
<tr>
<td>LDRN, 138</td>
<td></td>
</tr>
<tr>
<td>LDS, 133</td>
<td></td>
</tr>
<tr>
<td>LICAB, 139</td>
<td></td>
</tr>
<tr>
<td>LIHS, 136</td>
<td></td>
</tr>
<tr>
<td>LIM32, 311</td>
<td></td>
</tr>
<tr>
<td>LIP4, 309</td>
<td></td>
</tr>
<tr>
<td>LIS, 134</td>
<td></td>
</tr>
<tr>
<td>LLDS, 138</td>
<td></td>
</tr>
<tr>
<td>LTDB1, 440</td>
<td></td>
</tr>
<tr>
<td>LTDB2, 440</td>
<td></td>
</tr>
<tr>
<td>LTDB3, 441</td>
<td></td>
</tr>
<tr>
<td>LTM, 434</td>
<td></td>
</tr>
<tr>
<td>LTPM, 432</td>
<td></td>
</tr>
<tr>
<td>LTPP, 433</td>
<td></td>
</tr>
<tr>
<td>MA, 180</td>
<td></td>
</tr>
<tr>
<td>MBC, 189</td>
<td></td>
</tr>
<tr>
<td>MC, 363</td>
<td></td>
</tr>
<tr>
<td>MCSM, 237</td>
<td></td>
</tr>
<tr>
<td>MFLT, 436</td>
<td></td>
</tr>
<tr>
<td>MIAK, 209</td>
<td></td>
</tr>
<tr>
<td>MIVS, 513</td>
<td></td>
</tr>
<tr>
<td>MMNC, 192</td>
<td></td>
</tr>
<tr>
<td>MNSLE, 188</td>
<td></td>
</tr>
<tr>
<td>MOLT, 438</td>
<td></td>
</tr>
<tr>
<td>MPMR, 532</td>
<td></td>
</tr>
<tr>
<td>MSCN, 641</td>
<td></td>
</tr>
<tr>
<td>MSM, 180</td>
<td></td>
</tr>
<tr>
<td>MTV, 187</td>
<td></td>
</tr>
<tr>
<td>MWIAA, 208</td>
<td></td>
</tr>
<tr>
<td>NDMS4, 120</td>
<td></td>
</tr>
<tr>
<td>NIAO, 461</td>
<td></td>
</tr>
<tr>
<td>NIAQ, 453</td>
<td></td>
</tr>
<tr>
<td>NIAQR, 460</td>
<td></td>
</tr>
<tr>
<td>NIDAU, 463</td>
<td></td>
</tr>
<tr>
<td>NKAQ, 457</td>
<td></td>
</tr>
<tr>
<td>NLT, 451</td>
<td></td>
</tr>
<tr>
<td>NRREF, 35</td>
<td></td>
</tr>
<tr>
<td>NS, 76</td>
<td></td>
</tr>
<tr>
<td>NSAQ, 477</td>
<td></td>
</tr>
<tr>
<td>NSAQR, 477</td>
<td></td>
</tr>
<tr>
<td>NSC2A, 295</td>
<td></td>
</tr>
<tr>
<td>NSC2S, 295</td>
<td></td>
</tr>
<tr>
<td>NSC2Z, 294</td>
<td></td>
</tr>
<tr>
<td>NSDAT, 481</td>
<td></td>
</tr>
<tr>
<td>NSE, 14</td>
<td></td>
</tr>
<tr>
<td>NSEAII, 69</td>
<td></td>
</tr>
<tr>
<td>NSLE, 68</td>
<td></td>
</tr>
<tr>
<td>NSLIL, 141</td>
<td></td>
</tr>
<tr>
<td>NSNS, 78</td>
<td></td>
</tr>
<tr>
<td>NSSR, 77</td>
<td></td>
</tr>
<tr>
<td>NSS, 78</td>
<td></td>
</tr>
<tr>
<td>OLTTR, 523</td>
<td></td>
</tr>
<tr>
<td>OM3, 226</td>
<td></td>
</tr>
<tr>
<td>ONFV, 176</td>
<td></td>
</tr>
<tr>
<td>ONTV, 175</td>
<td></td>
</tr>
<tr>
<td>OPM, 226</td>
<td></td>
</tr>
<tr>
<td>OSGMD, 57</td>
<td></td>
</tr>
<tr>
<td>OSMC, 228</td>
<td></td>
</tr>
<tr>
<td>PCVS, 284</td>
<td></td>
</tr>
<tr>
<td>PM, 375</td>
<td></td>
</tr>
<tr>
<td>PSNS, 200</td>
<td></td>
</tr>
<tr>
<td>PTM, 191</td>
<td></td>
</tr>
<tr>
<td>PTMEE, 193</td>
<td></td>
</tr>
<tr>
<td>RAO, 473</td>
<td></td>
</tr>
<tr>
<td>RES, 159</td>
<td></td>
</tr>
<tr>
<td>RNM, 338</td>
<td></td>
</tr>
<tr>
<td>RNSM, 339</td>
<td></td>
</tr>
<tr>
<td>ROCD, 239</td>
<td></td>
</tr>
<tr>
<td>RREF, 34</td>
<td></td>
</tr>
<tr>
<td>RREFN, 49</td>
<td></td>
</tr>
<tr>
<td>RRTI, 352</td>
<td></td>
</tr>
<tr>
<td>RS, 322</td>
<td></td>
</tr>
<tr>
<td>RSAII, 242</td>
<td></td>
</tr>
<tr>
<td>RSB, 321</td>
<td></td>
</tr>
<tr>
<td>RSC5, 152</td>
<td></td>
</tr>
<tr>
<td>RSNS, 296</td>
<td></td>
</tr>
<tr>
<td>RSREM, 244</td>
<td></td>
</tr>
<tr>
<td>RSSC4, 158</td>
<td></td>
</tr>
<tr>
<td>RVMR, 530</td>
<td></td>
</tr>
<tr>
<td>S, 76</td>
<td></td>
</tr>
<tr>
<td>SAA, 38</td>
<td></td>
</tr>
<tr>
<td>SAB, 37</td>
<td></td>
</tr>
<tr>
<td>SABMI, 207</td>
<td></td>
</tr>
<tr>
<td>SAE, 39</td>
<td></td>
</tr>
<tr>
<td>SAN, 478</td>
<td></td>
</tr>
<tr>
<td>SAR, 470</td>
<td></td>
</tr>
<tr>
<td>SAV, 471</td>
<td></td>
</tr>
<tr>
<td>SC3, 291</td>
<td></td>
</tr>
<tr>
<td>SCAA, 119</td>
<td></td>
</tr>
<tr>
<td>SCAB, 121</td>
<td></td>
</tr>
</tbody>
</table>

Version 0.52
SCAD, 124
SEE, 373
SEEF, 259
SM32, 300
SMLT, 446
SMS4, 412
SMS5, 411
SP4, 294
SPIAS, 442
SRR, 77
SS, 361
SSM22, 315
SSNS, 123
SSP, 299
SSP4, 313
STLT, 444
STNE, 13
SUVOS, 171
SVP4, 350
SYM, 183
TCSD, 364
TIVS, 513
TKAP, 458
TLC, 99
TM, 182
TMP, 4
TOV, 171
TREM, 32
TTS, 15
US, 20
USR, 33
VA, 89
VESE, 88
VFSAD, 104
VFSAI, 108
VFSAL, 110
VRC4, 507
VRP2, 509
VSCV, 277
VSF, 279
VSI5, 278
VSM, 277
VSP, 277
VSPUD, 337
VSS, 279
ZNDAB, 366
EXC (subsection of B), 327
EXC (subsection of CB), 555
EXC (subsection of CRS), 249
EXC (subsection of D), 343
EXC (subsection of DM), 369
EXC (subsection of EE), 393
EXC (subsection of FS), 269
EXC (subsection of HSE), 71
EXC (subsection of I LT), 465
EXC (subsection of IVLT), 501
EXC (subsection of LC), 115
EXC (subsection of LDS), 161
EXC (subsection of LI), 143
EXC (subsection of LT), 449
EXC (subsection of MISM), 231
EXC (subsection of MISLE), 219
EXC (subsection of MR), 454
EXC (subsection of NSM), 88
EXC (subsection of O), 177
EXC (subsection of PD), 357
EXC (subsection of RREF), 43
EXC (subsection of S), 305
EXC (subsection of SD), 425
EXC (subsection of SLT), 483
EXC (subsection of SS), 127
EXC (subsection of SSLE), 25
EXC (subsection of TSS), 59
EXC (subsection of V O), 95
EXC (subsection of VR), 519
EXC (subsection of VS), 289
EXC (subsection of WILA), 9
extended echelon form
submatrices
example SEEF, 259
extended reduced row-echelon form
properties
theorem PEEF, 260
F
(archetype), 585
four subsets
example FS1, 263
example FS2, 263
FRAN (example), 475
free variables
example CFV, 55
free variables, number
theorem FVCS, 55
FS (section), 255
example IAR, 434
not
example NIAO, 461
example NIAQ, 453
example NIAQR, 460
not, by dimension
example NIDAU, 463
polynomials to matrices
example IAV, 455
injective linear transformation
bases
theorem ILTB, 462
injective linear transformations
dimension
theorem ILTD, 462
inner product
anti-commutative
theorem IPAC, 168
example CSIP, 167
norm
theorem IPN, 170
positive
theorem PIP, 170
scalar multiplication
theorem IPSM, 168
vector addition
theorem IPVA, 167
inverse
composition of linear transformations
theorem ICLT, 492
invertible linear transformations
composition
theorem CIVLT, 492
IP (definition), 166
IP (subsection of O), 166
IPAC (theorem), 168
IPN (theorem), 170
IPSM (theorem), 168
IPVA (theorem), 167
IS (example), 21
isomorphic
multiple vector spaces
example MIVS, 513
vector spaces
example IVSAV, 494
isomorphic vector spaces
dimension
theorem IVSED, 495
example TIVS, 513
ISSI (example), 50
IV (subsection of IVLT), 491
IVLT (definition), 487
IVLT (section), 487
IVLT (subsection of IVLT), 487
IVLT (subsection of MR), 540
IVS (definition), 493
IVSAV (example), 494
IVSED (theorem), 495
J
(archetype), 604
K
(archetype), 609
kernel
injective linear transformation
theorem KILT, 460
isomorphic to null space
theorem KNSI, 535
linear transformation
example NKAO, 457
of a linear transformation
definition KLT, 457
pre-image, 459
subspace
theorem KLTS, 458
trivial
example TKAP, 458
via matrix representation
example KVMR, 536
KILT (theorem), 460
KLT (definition), 457
KLT (subsection of ILT), 456
KLTS (theorem), 458
KNSI (theorem), 535
KPI (theorem), 459
KVMR (example), 536
L
(archetype), 613
L (technique), 22
LA (subsection of WILA), 3
language
technique L, 22
LC (definition), 297
LC (section), 99
LC (subsection of LC), 99
INDEX

659

LCCV (definition), 99
LCM (example), 297
LDCAA (example), 139
LDHS (example), 136
LDP4 (example), 335
LDRN (example), 138
LDS (example), 133
LDS (section), 151
LDSS (subsection of LDS), 151
leading ones
definition LO, 34
left null space
as row space, 262
definition LNS, 255
LI (definition), 309
LI (section), 133
LI (subsection of B), 309
LICAB (example), 139
LICV (definition), 133
LIHS (example), 136
LIM32 (example), 311
linear combination
system of equations
definition ABLC, 101
definition LC, 297
definition LCCV, 99
example TLC, 99
linear transformation, 439
matrices
definition LCM, 297
system of equations
example AALC, 102
linear combinations
solutions to linear systems
theorem SLSLC, 103
linear dependence
more vectors than size
theorem MVSLD, 139
linear independence
definition LI, 309
definition LICV, 133
homogeneous systems
theorem LIVHS, 135
injective linear transformation
theorem ILTLT, 447
matrices
definition LIM32, 311
orthogonal, 172
r and n
definition LIVRN, 137
linear solve
mathematica, 57
linear system
consistent
theorem RCLS, 53
notation LSN, 68
linear systems
notation
definition MNSLE, 188
definition NSLE, 68
linear transformation
polynomials to polynomials
definition LTPP, 333
addition
definition LTA, 444
definition MLTLT, 445
theorem SLTLT, 444
as matrix multiplication
definition ALTMM, 527
basis of range
example BRLT, 479
checking
definition ALT, 430
composition
definition LTC, 446
theorem CLTLT, 447
defined by a matrix
definition LTM, 434
defined on a basis
example LTDB1, 440
example LTDB2, 440
example LTDB3, 441
theorem LTDB, 439
definition LT, 429
identity
definition IDLT, 487
injection
definition ILT, 453
inverse
definition IILT, 490
inverse of inverse
theorem ILTLT, 490
invertible
definition IVLT, 487
example AIVLT, 487
invertible, injective and surjective
linear combination

matrix of, 437
example MFLT, 436
equivalent MOLT, 438
not
equivalent NLT, 431
not invertible
example ANILT, 488
polynomials to matrices
equivalent LTPM, 432
rank plus nullity
theorem RPNDD, 496
scalar multiple
example SMLT, 446
scalar multiplication
definition LTSM, 445
spanning range
theorem SSRLT, 478
sum
equivalent STLT, 444
surjection
definition SLT, 469
vector space of, 446
zero vector
theorem LTTZZ, 433
linear transformation inverse
via matrix representation
equivalent ILTNR, 541
linear transformations
compositions
equivalent CTLT, 447
from matrices
theorem MBLT, 435
linearly dependent
$r < n$
equivalent LDRN, 138
via homogeneous system
equivalent LDHS, 136
linearly dependent columns
Archetype A
equivalent LDCAA, 139
linearly dependent set
equivalent LDS, 133
linear combinations within
theorem DLDS, 151
polynomials
example LDP4, 335
linearly independent
extending sets
theorem ELIS, 347
polynomials
equivalent LIP4, 309
via homogeneous system
equivalent LIHS, 136
linearly independent columns
Archetype B
equivalent LICAB, 139
linearly independent set
equivalent LIS, 134
example LLDS, 138
LINS (subsection of LI), 139
LIP4 (example), 309
LIS (example), 134
LIV (subsection of LI), 133
LIVHS (theorem), 135
LIVRN (theorem), 137
LLDS (example), 138
LNS (definition), 255
LNS (subsection of FS), 255
LO (definition), 34
LS.MMA (computation), 37
LSN (notation), 68
LT (chapter), 429
LT (definition), 429
LT (section), 429
LT (subsection of LT), 429
LTA (definition), 444
LTC (definition), 446
LTDB (theorem), 439
LTDB1 (example), 440
LTDB2 (example), 440
LTDB3 (example), 441
LTLC (subsection of LT), 439
LTLC (theorem), 439
LTM (example), 434
LTPM (example), 432
LTPP (example), 433
LTSM (definition), 445
LTTZZ (theorem), 433

M
archetype, 617
M (chapter), 179
M (definition), 29
MA (definition), 180
MA (example), 180
mathematica
  linear solve
    computation LS.MMA, 57
  matrix entry
    computation ME.MMA, 30
  matrix inverses
    computation MI.MMA, 214
  matrix multiplication
    computation MM.MMA, 192
  row reduce
    computation RR.MMA, 40
  transpose of a matrix
    computation TM.MMA, 185
  vector linear combinations
    computation VLC.MMA, 91

matrix
  addition
    definition MA, 180
  augmented
    definition AM, 31
  cofactor
    definition CIM, 363
  complex conjugate
    example CCM, 185
  definition M, 29
  equality
    definition ME, 179
  example AM, 29
  identity
    definition IM, 76
  minor
    definition MIM, 363
  minors, cofactors
    example MC, 363
  nonsingular
    definition NM, 75
  of a linear transformation
    theorem MLTCV, 437
  orthogonal
    definition OM, 226
  orthogonal is invertible
    theorem OMI, 227
  product
    example PTM, 191
    example PTMEE, 193
  rectangular, 75
  scalar multiplication
    definition MSM, 180
  singular, 75
  square
    definition SQM, 75
  submatrices
    example SS, 361
  submatrix
    definition SM, 361
  symmetric
    definition SYM, 183
  transpose
    definition TM, 182
  zero
    definition ZM, 182
  zero row
    definition ZRM, 34

matrix inverse
  Archetype B, 214
  Archetype K, 209, 211
  computation
    theorem CINSM, 213
  nonsingular matrix
    theorem NSI, 225
  of a matrix inverse
    theorem MIMI, 216
  one-sided
    theorem OSIS, 224
  product
    theorem SS, 214
  scalar multiple
    theorem MISM, 216
  size 2 matrices
    theorem TTMI, 210
  transpose
    theorem MIT, 216
  uniqueness
    theorem MIU, 214

matrix inverses
  mathematica, 214
matrix multiplication
  associativity
    theorem MMA, 196
  complex conjugation
    theorem MMCC, 197
  distributivity
    theorem MMDAA, 195
  entry-by-entry
    theorem EMP, 193
  identity matrix
    theorem MMIM, 195
  inner product
    theorem MMIP, 197
  mathematica, 192
  noncommutative
    example MMNC, 192
  scalar matrix multiplication
    theorem MMSMM, 196
  systems of linear equations
    theorem SLEMM, 188
  transposes
    theorem MMT, 198
  zero matrix
    theorem MMZM, 194
matrix notation
  definition MN, 29
matrix product
  as composition of linear transformations
    example MPMR, 532
  composition of linear transformations
    theorem MRCLLT, 531
  definition MR, 523
  invertible
    theorem IMR, 540
  multiple of a linear transformation
    theorem MRMLT, 530
  sum of linear transformations
    theorem MRSLT, 530
    theorem FTMR, 526
matrix representations
  example OLTTR, 523
matrix scalar multiplication
  example MSM, 180
matrix vector space
  dimension
    theorem DM, 336
matrix-vector product
  example MTV, 187
  matrix:column space
    definition CSM, 235
  matrix:inverse
    definition MI, 208
  matrix:multiplication
    definition MM, 191
  matrix:product with vector
    definition MVP, 187
  matrix:row space
    definition RSM, 242
MBC (example), 189
MBLT (theorem), 435
MC (example), 363
MCC (subsection of MO), 185
MCN (definition), 641
MCN (subsection of CNO), 641
MCSM (example), 237
ME (definition), 179
ME (notation), 29
ME (subsection of PEE), 405
ME (technique), 81
ME (theorem), 406
ME.MMA (computation), 30
ME.TI83 (computation), 30
ME.TI86 (computation), 30
MEASM (subsection of MO), 179
MFLT (example), 436
MI (definition), 208
MLMMA (computation), 214
MIAK (example), 209
MIM (definition), 363
MIMI (theorem), 216
MINSM (section), 223
MISLE (section), 207
MISM (theorem), 216
MIT (theorem), 216
MIU (theorem), 214
MIVS (example), 513
MLT (subsection of LT), 434
MLTCV (theorem), 437
MLTLT (theorem), 445
MM (definition), 191
MM (section), 187
MM (subsection of MM), 191
MM.MMA (computation), 192
MMA (theorem), 196
notation for a linear system
  
  example NSE, 14
  
  NRFO (subsection of MR), 530
  
  NRREF (example), 35
  
  NS (example), 76
  
  NSAO (example), 477
  
  NSAQ (example), 469
  
  NSAQR (example), 477
  
  NSC2A (example), 295
  
  NSC2S (example), 295
  
  NSC2Z (example), 294
  
  NSDAT (example), 481
  
  NSE (example), 14
  
  NSEAI (example), 69
  
  NSI (theorem), 225
  
  NSLE (example), 68
  
  NSLIC (theorem), 139
  
  NSLIL (example), 141
  
  NSM (definition), 68
  
  NSM (section), 75
  
  NSM (subsection of HSE), 68
  
  NSM (subsection of NSM), 75
  
  NSME1 (theorem), 82
  
  NSME2 (theorem), 140
  
  NSME3 (theorem), 225
  
  NSME4 (theorem), 241
  
  NSME5 (theorem), 323
  
  NSME6 (theorem), 341
  
  NSME7 (theorem), 366
  
  NSME8 (theorem), 400
  
  NSMI (subsection of MINSM), 223
  
  NSMS (theorem), 296
  
  NSMUS (theorem), 79
  
  NSNS (example), 78
  
  NSRR (example), 77
  
  NSRRI (theorem), 77
  
  NSS (example), 78
  
  NSSLI (subsection of LI), 140
  
  NSTNS (theorem), 78

null space
  
  Archetype I
    
    example NSEAI, 69

basis
  
  theorem BNS, 141

computation
  
  example CNS1, 69
  
  example CNS2, 70

isomorphic to kernel, 535

nullity

null space span, linearly independent
  
  Archetype L
    
    example NSLIL, 141

matrix
  
  definition NSM, 68
  
  nonsingular matrix, 78
  
  singular matrix, 78

spanning set
  
  example SSNS, 123

theorem SSNS, 122

subspace
  
  theorem NSMS, 296

null space span, linearly independent

nullity
  
  computing, 339

injective linear transformation
  
  theorem NOILT, 496

linear transformation
  
  definition NOLT, 495

matrix, 338
  
  definition NOM, 338

square matrix, 340

NV (definition), 169

O
  
  (archetype), 622

O (Property), 276

O (section), 165

OBC (subsection of PD), 353

OC (Property), 93

OD (subsection of SD), 423

OLTTR (example), 523

OM (definition), 226

OM (Property), 181

OM (subsection of MINSM), 226

OM3 (example), 226

OMI (theorem), 227

OMPIP (theorem), 228

one

column vectors
  
  Property OC, 93

matrices
  
  Property OM, 181

vectors
  
  Property O, 276

ONFV (example), 176

ONS (definition), 175

ONTV (example), 175

OPM (example), 226
orthogonal
linear independence
  theorem OSLI, 172
permutation matrix
  example OPM, 226
set
  example AOS, 171
  set of vectors
  definition OSV, 171
  size 3
  example OM3, 226
vector pairs
  definition OV, 171
orthogonal matrices
  columns
  theorem COMOS, 227
orthogonal matrix
  inner product
  theorem OMPIP, 228
orthogonal vectors
  example TOV, 171
orthonormal
  definition ONS, 175
  matrix columns
  example OSMC, 228
orthonormal set
  four vectors
  example ONFV, 176
  three vectors
  example ONTV, 175
OSGMD (example), 57
OSIS (theorem), 224
OSLI (theorem), 172
OSMC (example), 228
OSV (definition), 171
OV (definition), 171
OV (subsection of O), 170

P
  (archetype), 625
P (chapter), 639
P (technique), 183
particular solutions
  example PSNS, 200
PC (definition), 34
PCVS (example), 284
PD (section), 347
PD (subsection of DM), 365
PEE (section), 399
PEEF (theorem), 260
PI (definition), 442
PI (subsection of LT), 441
PI (technique), 93
PIP (theorem), 170
pivot column
  definition PC, 34
PM (example), 375
PM (subsection of EE), 375
PMI (subsection of MISLE), 214
PMM (subsection of MM), 194
PMR (subsection of MR), 535
polynomial
  of a matrix
  example PM, 375
polynomial vector space
  dimension
  theorem DP, 336
practice
  technique P, 183
pre-image
  definition PI, 442
  kernel
  theorem KPI, 459
pre-images
  example SPIAS, 442
Property
  AA, 276
  AAC, 92
  AAM, 181
  AC, 275
  ACC, 92
  ACM, 181
  AI, 276
  AIC, 92
  AIM, 181
  C, 275
  CC, 92
  CM, 181
  DMAM, 181
  DVA, 276
  DVAC, 92
  O, 276
  OC, 93
OM, 181
SC, 275
SCC, 92
SCM, 181
SMA, 276
SMAC, 92
SMAM, 181
Z, 276
ZC, 92
ZM, 181

PSHS (subsection of MM), 199
PSM (subsection of SD), 412
PSNS (example), 200
PSPHS (theorem), 199
PSS (subsection of SSLE), 15
PSSLS (theorem), 56
PTM (example), 191
PTMEE (example), 193
PWSMS (theorem), 223

Q
(archetype), 627

R
(archetype), 631
R (chapter), 505
range
full
example FRAN, 475
isomorphic to column space
theorem RCSI, 538
linear transformation
example RAO, 473
of a linear transformation
definition RLT, 473
original columns, Archetype D
example ROCD, 239
pre-image
definition RPI, 479
subspace
theorem RLTS, 475
theorem RMS, 302
surjective linear transformation
theorem RSLT, 476
via matrix representation
example RVMR, 539
rank
computing
definition CRN, 339
linear transformation
definition ROLT, 495
matrix
definition ROM, 338
example RNM, 338
of transpose
example RRTI, 352
square matrix
example RNSM, 339
surjective linear transformation
theorem ROSLT, 495
transpose
definition RMRT, 351
rank+nullity
theorem RPN, 339
RAO (example), 473
RCLS (theorem), 53
RCSI (theorem), 538
RD (subsection of VS), 286
READ (subsection of B), 325
READ (subsection of CB), 553
READ (subsection of CRS), 248
READ (subsection of D), 341
READ (subsection of DM), 367
READ (subsection of EE), 391
READ (subsection of FS), 267
READ (subsection of HSE), 70
READ (subsection of ILT), 464
READ (subsection of IVLT), 500
READ (subsection of LC), 114
READ (subsection of LDS), 160
READ (subsection of LI), 142
READ (subsection of LT), 448
READ (subsection of MINSM), 229
READ (subsection of MISLE), 217
READ (subsection of MM), 202
READ (subsection of MO), 186
READ (subsection of MR), 543
READ (subsection of NSM), 82
READ (subsection of O), 176
READ (subsection of PD), 356
READ (subsection of PEE), 410
READ (subsection of REF), 41
READ (subsection of S), 303
READ (subsection of SD), 423
READ (subsection of SLT), 481
READ (subsection of SS), 126
READ (subsection of SSLE), 24
INDEX  667

READ (subsection of TSS),  58
READ (subsection of VO),  94
READ (subsection of VR),  516
READ (subsection of VS),  287
READ (subsection of WILA),  8
reduced row-echelon form
  analysis
    notation RREFA,  49
    definition RREF,  34
    example NRREF,  35
    example RREF,  34
  extended
    definition EEF,  259
    example RREFN,  49
    unique
    theorem RREFU,  112
reducing a span
  example RSC5,  152
relation of linear dependence
  definition RLD,  309
  definition RLDCV,  133
REM (definition),  32
REMEF (theorem),  35
REMES (theorem),  32
REMRS (theorem),  243
RES (example),  159
RLD (definition),  309
RLDCV (definition),  133
RLT (definition),  473
RLT (subsection of SLT),  473
RLTS (theorem),  475
RMRT (theorem),  351
RMS (theorem),  302
RNLT (subsection of IVLT),  495
RNM (example),  338
RNM (subsection of D),  338
RNNSM (subsection of D),  339
RNNSM (theorem),  340
RNSM (example),  339
RO (definition),  32
ROCD (example),  239
ROLT (definition),  495
ROM (definition),  338
ROS LT (theorem),  495
row operations
  definition RO,  32
row reduce
  mathematica,  40
  ti83,  40
  ti86,  40
row space
  Archetype I
    example RSAI,  242
  as column space,  246
  basis
    example RSB,  321
    theorem BRS,  245
  matrix,  242
  row-equivalent matrices
    theorem REMRS,  243
subspace
  theorem RSMS,  303
row-equivalent matrices
  definition REM,  32
  example TREM,  32
  row space,  243
  row spaces
    example RSREM,  244
    theorem REMES,  32
row-reduced matrices
  theorem REMEF,  35
RPI (theorem),  479
RPNC (theorem),  339
RPNDD (theorem),  496
RR.MMA (computation),  40
RR.TI83 (computation),  40
RR.TI86 (computation),  40
RREF (definition),  34
RREF (example),  34
RREF (section),  29
RREFA (notation),  49
RREFN (example),  49
RREFU (theorem),  112
RS (example),  322
RSAI (example),  242
RSB (example),  321
RSC5 (example),  152
RSLT (theorem),  476
RSM (definition),  242
RSM (subsection of CRS),  242
RSMS (theorem),  303
RSNS (example),  296
RSREM (example),  244
RSS (theorem),  157
<table>
<thead>
<tr>
<th>Term</th>
<th>Page(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSSC4 (example)</td>
<td>158</td>
</tr>
<tr>
<td>RT (subsection of PD)</td>
<td>351</td>
</tr>
<tr>
<td>RVMR (example)</td>
<td>539</td>
</tr>
<tr>
<td>S</td>
<td>634</td>
</tr>
<tr>
<td>(archetype)</td>
<td>291</td>
</tr>
<tr>
<td>S (definition)</td>
<td>291</td>
</tr>
<tr>
<td>(example)</td>
<td>76</td>
</tr>
<tr>
<td>S (section)</td>
<td>291</td>
</tr>
<tr>
<td>SAA (example)</td>
<td>38</td>
</tr>
<tr>
<td>SAB (example)</td>
<td>37</td>
</tr>
<tr>
<td>SABMI (example)</td>
<td>207</td>
</tr>
<tr>
<td>SAE (example)</td>
<td>39</td>
</tr>
<tr>
<td>SAN (example)</td>
<td>478</td>
</tr>
<tr>
<td>SAR (example)</td>
<td>470</td>
</tr>
<tr>
<td>SAV (example)</td>
<td>471</td>
</tr>
<tr>
<td>SC (Property)</td>
<td>275</td>
</tr>
<tr>
<td>SC (subsection of S)</td>
<td>302</td>
</tr>
<tr>
<td>SC3 (example)</td>
<td>291</td>
</tr>
<tr>
<td>SCAA (example)</td>
<td>119</td>
</tr>
<tr>
<td>SCAB (example)</td>
<td>121</td>
</tr>
<tr>
<td>SCAD (example)</td>
<td>124</td>
</tr>
<tr>
<td>scalar closure</td>
<td></td>
</tr>
<tr>
<td>column vectors</td>
<td></td>
</tr>
<tr>
<td>Property SCC</td>
<td>92</td>
</tr>
<tr>
<td>matrices</td>
<td></td>
</tr>
<tr>
<td>Property SCM</td>
<td>181</td>
</tr>
<tr>
<td>vectors</td>
<td></td>
</tr>
<tr>
<td>Property SC</td>
<td>275</td>
</tr>
<tr>
<td>scalar multiple</td>
<td></td>
</tr>
<tr>
<td>matrix inverse</td>
<td>216</td>
</tr>
<tr>
<td>scalar multiplication</td>
<td></td>
</tr>
<tr>
<td>canceling scalars</td>
<td></td>
</tr>
<tr>
<td>theorem CSSM</td>
<td>285</td>
</tr>
<tr>
<td>canceling vectors</td>
<td></td>
</tr>
<tr>
<td>theorem CVSM</td>
<td>286</td>
</tr>
<tr>
<td>zero scalar</td>
<td></td>
</tr>
<tr>
<td>theorem ZSSM</td>
<td>283</td>
</tr>
<tr>
<td>zero vector</td>
<td></td>
</tr>
<tr>
<td>theorem ZVSM</td>
<td>283</td>
</tr>
<tr>
<td>zero vector result</td>
<td></td>
</tr>
<tr>
<td>theorem SMEZV</td>
<td>284</td>
</tr>
<tr>
<td>scalar multiplication associativity</td>
<td></td>
</tr>
<tr>
<td>column vectors</td>
<td></td>
</tr>
<tr>
<td>Property SMAC</td>
<td>92</td>
</tr>
<tr>
<td>matrices</td>
<td></td>
</tr>
<tr>
<td>Property SMAM</td>
<td>181</td>
</tr>
<tr>
<td>vectors</td>
<td></td>
</tr>
<tr>
<td>Property SMA</td>
<td>276</td>
</tr>
<tr>
<td>SCB (theorem)</td>
<td>551</td>
</tr>
<tr>
<td>SCC (Property)</td>
<td>92</td>
</tr>
<tr>
<td>SCM (Property)</td>
<td>181</td>
</tr>
<tr>
<td>SD (section)</td>
<td>411</td>
</tr>
<tr>
<td>SE (technique)</td>
<td>17</td>
</tr>
<tr>
<td>SEE (example)</td>
<td>373</td>
</tr>
<tr>
<td>SEEF (example)</td>
<td>259</td>
</tr>
<tr>
<td>SER (theorem)</td>
<td>413</td>
</tr>
<tr>
<td>set equality</td>
<td></td>
</tr>
<tr>
<td>technique SE</td>
<td>17</td>
</tr>
<tr>
<td>set notation</td>
<td></td>
</tr>
<tr>
<td>technique SN</td>
<td>51</td>
</tr>
<tr>
<td>shoes</td>
<td>215</td>
</tr>
<tr>
<td>SHS (subsection of HSE)</td>
<td>63</td>
</tr>
<tr>
<td>SI (subsection of IVLT)</td>
<td>493</td>
</tr>
<tr>
<td>SIM (definition)</td>
<td>411</td>
</tr>
<tr>
<td>similar matrices</td>
<td></td>
</tr>
<tr>
<td>equal eigenvalues</td>
<td></td>
</tr>
<tr>
<td>example EENS</td>
<td>414</td>
</tr>
<tr>
<td>equal eigenvalues</td>
<td></td>
</tr>
<tr>
<td>theorem SMEE</td>
<td>414</td>
</tr>
<tr>
<td>example SMS4</td>
<td>412</td>
</tr>
<tr>
<td>example SMS5</td>
<td>411</td>
</tr>
<tr>
<td>similarity</td>
<td></td>
</tr>
<tr>
<td>definition SIM</td>
<td>411</td>
</tr>
<tr>
<td>equivalence relation</td>
<td></td>
</tr>
<tr>
<td>theorem SER</td>
<td>413</td>
</tr>
<tr>
<td>singular matrix</td>
<td></td>
</tr>
<tr>
<td>Archetype A</td>
<td></td>
</tr>
<tr>
<td>example S</td>
<td>76</td>
</tr>
<tr>
<td>null space</td>
<td></td>
</tr>
<tr>
<td>example NSS</td>
<td>78</td>
</tr>
<tr>
<td>product with</td>
<td></td>
</tr>
<tr>
<td>theorem PWSMS</td>
<td>223</td>
</tr>
<tr>
<td>singular matrix, row-reduced</td>
<td></td>
</tr>
<tr>
<td>example SRR</td>
<td>77</td>
</tr>
<tr>
<td>SLE (chapter)</td>
<td>3</td>
</tr>
<tr>
<td>SLE (definition)</td>
<td>14</td>
</tr>
<tr>
<td>SLELT (subsection of IVLT)</td>
<td>498</td>
</tr>
<tr>
<td>SLEMM (theorem)</td>
<td>188</td>
</tr>
<tr>
<td>SLSLC (theorem)</td>
<td>103</td>
</tr>
<tr>
<td>SLT (definition)</td>
<td>469</td>
</tr>
<tr>
<td>SLT (section)</td>
<td>469</td>
</tr>
<tr>
<td>SLTB (theorem)</td>
<td>480</td>
</tr>
<tr>
<td>SLTD (subsection of SLT)</td>
<td>480</td>
</tr>
<tr>
<td>SLTD (theorem)</td>
<td>480</td>
</tr>
<tr>
<td>SLTLT (theorem)</td>
<td>444</td>
</tr>
</tbody>
</table>
INDEX 669

SM (definition), 361
SM (subsection of SD), 411
SM32 (example), 300
SMA (Property), 276
SMAC (Property), 92
SMAM (Property), 181
SMEE (theorem), 414
SMEZV (theorem), 284
SMLT (example), 446
SMS (theorem), 183
SMS4 (example), 412
SMS5 (example), 411
SMZD (theorem), 366
SMZE (theorem), 400
SN (technique), 51
SNSCM (theorem), 225
socks, 215
SOL (subsection of B), 329
SOL (subsection of CB), 557
SOL (subsection of CRS), 253
SOL (subsection of D), 345
SOL (subsection of DM), 371
SOL (subsection of EE), 395
SOL (subsection of FS), 271
SOL (subsection of HSE), 73
SOL (subsection of ILT), 467
SOL (subsection of IVLT), 503
SOL (subsection of LC), 117
SOL (subsection of LDS), 163
SOL (subsection of LI), 147
SOL (subsection of LT), 451
SOL (subsection of MINSM), 233
SOL (subsection of MISLE), 221
SOL (subsection of MM), 205
SOL (subsection of MR), 547
SOL (subsection of NSM), 85
SOL (subsection of PD), 359
SOL (subsection of RREF), 45
SOL (subsection of S), 307
SOL (subsection of SD), 427
SOL (subsection of SLT), 485
SOL (subsection of SS), 129
SOL (subsection of SSLE), 27
SOL (subsection of TSS), 61
SOL (subsection of VO), 97
SOL (subsection of VR), 521
SOL (subsection of WILA), 11

solution set theorem PSPHS, 199
solution sets possibilities theorem PSSLS, 56
solution vector definition SV, 67
solving homogeneous system Archetype A example HISAA, 64
Archetype B example HUSAB, 64
Archetype D example HISAD, 65
solving nonlinear equations example STNE, 13
SP4 (example), 294
span definition SS, 298
improved example IAS, 245
reducing example RSSC4, 158
reduction example RS, 322
removing vectors example COV, 154
reworking elements example RES, 159
set of polynomials example SSP, 299
subspace theorem SSS, 298
span of columns Archetype A example SCAA, 119
Archetype B example SCAB, 121
Archetype D example SCAD, 124
span: definition definition SSCV, 119
spanning set definition TSS, 313
matrices example SSM22, 315
more vectors theorem SSLD, 331
polynomials
INDEX 671

D, 13
DC, 101
E, 52
GS, 23
L, 22
ME, 81
P, 183
PI, 93
SE, 17
SN, 51
T, 17
U, 78

Theorem

AISM, 283
AIU, 282
BCSOC, 238
BIS, 335
BNS, 141
BRS, 245
CB, 550
CCRA, 640
CCRM, 640
CCT, 640
CFDV5, 512
CILT, 463
CINSM, 213
CIVLT, 492
CLI, 514
CLTLT, 447
CMVEI, 56
CNSMB, 323
COB, 353
COMOS, 227
CRMA, 185
CRNSM, 186
CRN, 339
CRSM, 166
CRVA, 165
CSCS, 236
CSLTS, 481
CSNSM, 241
CSRN, 54
CSRST, 246
CSS, 514
CSSM, 285
CVSM, 286
DC, 415
DCM, 336
DCP, 405
DED, 420
DERC, 364
DLDS, 151
DM, 336
DMLE, 418
DMST, 362
DP, 336
DRMM, 366
DT, 365
EDELI, 399
EDYES, 350
EER, 552
EIM, 403
ELIS, 347
EMHE, 377
EMMVP, 190
EMNS, 383
EMP, 193
EMRCP, 381
EMS, 382
EOMP, 401
EOPSS, 17
EPM, 402
ERM, 404
ETM, 404
FS, 262
FTMR, 526
FVCS, 55
G, 348
GSPCV, 173
HMOE, 409
HMRE, 408
HMVEI, 65
HSC, 64
ICBM, 550
ICLT, 492
ICRN, 54
IFDVS, 513
II, 490
II, 402
ILTB, 462
ILTD, 462
ILTIS, 491
ILTL, 461
ILTLD, 490
IMR, 540
IPAC, 168

Version 0.52
<table>
<thead>
<tr>
<th>Term</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPN</td>
<td>170</td>
</tr>
<tr>
<td>IPSM</td>
<td>168</td>
</tr>
<tr>
<td>IPVA</td>
<td>167</td>
</tr>
<tr>
<td>IVSED</td>
<td>495</td>
</tr>
<tr>
<td>KILT</td>
<td>460</td>
</tr>
<tr>
<td>KLTS</td>
<td>458</td>
</tr>
<tr>
<td>KNSI</td>
<td>535</td>
</tr>
<tr>
<td>KPI</td>
<td>459</td>
</tr>
<tr>
<td>LIVHS</td>
<td>135</td>
</tr>
<tr>
<td>LIVRN</td>
<td>137</td>
</tr>
<tr>
<td>LTDB</td>
<td>439</td>
</tr>
<tr>
<td>LTLC</td>
<td>439</td>
</tr>
<tr>
<td>LTTZZ</td>
<td>433</td>
</tr>
<tr>
<td>MBLT</td>
<td>435</td>
</tr>
<tr>
<td>ME</td>
<td>406</td>
</tr>
<tr>
<td>MIMI</td>
<td>216</td>
</tr>
<tr>
<td>MISM</td>
<td>216</td>
</tr>
<tr>
<td>MIT</td>
<td>216</td>
</tr>
<tr>
<td>MIU</td>
<td>214</td>
</tr>
<tr>
<td>MLTCV</td>
<td>437</td>
</tr>
<tr>
<td>MLTLT</td>
<td>445</td>
</tr>
<tr>
<td>MMA</td>
<td>196</td>
</tr>
<tr>
<td>MMCC</td>
<td>197</td>
</tr>
<tr>
<td>MMDAA</td>
<td>195</td>
</tr>
<tr>
<td>MMIM</td>
<td>195</td>
</tr>
<tr>
<td>MMIP</td>
<td>197</td>
</tr>
<tr>
<td>MMSMM</td>
<td>196</td>
</tr>
<tr>
<td>MMT</td>
<td>198</td>
</tr>
<tr>
<td>MMZM</td>
<td>194</td>
</tr>
<tr>
<td>MNEM</td>
<td>408</td>
</tr>
<tr>
<td>MRCB</td>
<td>551</td>
</tr>
<tr>
<td>MRCLT</td>
<td>531</td>
</tr>
<tr>
<td>MRMLT</td>
<td>530</td>
</tr>
<tr>
<td>MRSLT</td>
<td>530</td>
</tr>
<tr>
<td>MVSLD</td>
<td>139</td>
</tr>
<tr>
<td>NEM</td>
<td>406</td>
</tr>
<tr>
<td>NOILT</td>
<td>496</td>
</tr>
<tr>
<td>NSI</td>
<td>225</td>
</tr>
<tr>
<td>NSLIC</td>
<td>139</td>
</tr>
<tr>
<td>NSME1</td>
<td>82</td>
</tr>
<tr>
<td>NSME2</td>
<td>140</td>
</tr>
<tr>
<td>NSME3</td>
<td>225</td>
</tr>
<tr>
<td>NSME4</td>
<td>241</td>
</tr>
<tr>
<td>NSME5</td>
<td>323</td>
</tr>
<tr>
<td>NSME6</td>
<td>341</td>
</tr>
<tr>
<td>NSME7</td>
<td>360</td>
</tr>
<tr>
<td>NSME8</td>
<td>400</td>
</tr>
<tr>
<td>NSMS</td>
<td>296</td>
</tr>
<tr>
<td>NSMUS</td>
<td>79</td>
</tr>
<tr>
<td>NSRRI</td>
<td>77</td>
</tr>
<tr>
<td>NSTNS</td>
<td>78</td>
</tr>
<tr>
<td>OMI</td>
<td>227</td>
</tr>
<tr>
<td>OMPIP</td>
<td>228</td>
</tr>
<tr>
<td>OSIS</td>
<td>224</td>
</tr>
<tr>
<td>OSLI</td>
<td>172</td>
</tr>
<tr>
<td>PEEF</td>
<td>260</td>
</tr>
<tr>
<td>PIP</td>
<td>170</td>
</tr>
<tr>
<td>PSPHS</td>
<td>199</td>
</tr>
<tr>
<td>PSSLS</td>
<td>56</td>
</tr>
<tr>
<td>PWSMS</td>
<td>223</td>
</tr>
<tr>
<td>RCLS</td>
<td>53</td>
</tr>
<tr>
<td>RCSI</td>
<td>538</td>
</tr>
<tr>
<td>REMEF</td>
<td>55</td>
</tr>
<tr>
<td>REMES</td>
<td>32</td>
</tr>
<tr>
<td>REMRS</td>
<td>243</td>
</tr>
<tr>
<td>RLTS</td>
<td>475</td>
</tr>
<tr>
<td>RMRT</td>
<td>351</td>
</tr>
<tr>
<td>RMS</td>
<td>302</td>
</tr>
<tr>
<td>RNNSM</td>
<td>340</td>
</tr>
<tr>
<td>ROSLT</td>
<td>495</td>
</tr>
<tr>
<td>RPI</td>
<td>479</td>
</tr>
<tr>
<td>RPNC</td>
<td>339</td>
</tr>
<tr>
<td>RPNDL</td>
<td>496</td>
</tr>
<tr>
<td>RREFU</td>
<td>112</td>
</tr>
<tr>
<td>RSLT</td>
<td>476</td>
</tr>
<tr>
<td>RSLS</td>
<td>476</td>
</tr>
<tr>
<td>RSMS</td>
<td>303</td>
</tr>
<tr>
<td>RSS</td>
<td>137</td>
</tr>
<tr>
<td>SCB</td>
<td>551</td>
</tr>
<tr>
<td>SER</td>
<td>413</td>
</tr>
<tr>
<td>SLEMM</td>
<td>138</td>
</tr>
<tr>
<td>SLSLC</td>
<td>103</td>
</tr>
<tr>
<td>SLTB</td>
<td>480</td>
</tr>
<tr>
<td>SLTD</td>
<td>480</td>
</tr>
<tr>
<td>SLTLT</td>
<td>144</td>
</tr>
<tr>
<td>SMEE</td>
<td>414</td>
</tr>
<tr>
<td>SMEVZ</td>
<td>284</td>
</tr>
<tr>
<td>SMS</td>
<td>183</td>
</tr>
<tr>
<td>SMZD</td>
<td>366</td>
</tr>
<tr>
<td>SMZE</td>
<td>100</td>
</tr>
<tr>
<td>SNCSM</td>
<td>225</td>
</tr>
<tr>
<td>SS</td>
<td>215</td>
</tr>
<tr>
<td>SSLD</td>
<td>331</td>
</tr>
<tr>
<td>SSNS</td>
<td>122</td>
</tr>
<tr>
<td>SSRLT</td>
<td>178</td>
</tr>
<tr>
<td>SSS</td>
<td>298</td>
</tr>
<tr>
<td>SUVB</td>
<td>318</td>
</tr>
</tbody>
</table>
TMA, 184
TMSM, 184
TSS, 293
TT, 184
TTMI, 210
VAC, 285
VFSLS, 106
VRI, 511
VRILT, 512
VRLT, 505
VRRB, 324
VRS, 511
VSLT, 146
VSPCV, 92
VSPM, 181
ZSSM, 283
ZVSM, 283
ZVU, 282

theorems

- technique T, 17
- theorem TMSM, 184
- theorem TMA, 184
- theorem TT, 184
- theorem TTMI, 210
- theorem TTML, 40
- theorem VLC.TI83, 92

- matrix entry computation ME.TI83, 30
- row reduce computation RR.TI83, 40
- vector linear combinations computation VLC.TI83, 92

- matrix entry computation ME.TI86, 30
- row reduce computation RR.TI86, 40
- transpose of a matrix computation TM.TI86, 185
- vector linear combinations computation VLC.TI86, 91

- TIVS (example), 513
- TKAP (example), 458
- TLC (example), 99
- TM (definition), 182
- TM (example), 182
- TM.MMA (computation), 185
- TM.TI86 (computation), 185
- TMA (theorem), 184
- TMP (example), 4
- TMSM (theorem), 184
- TOV (example), 171

trail mix

- example TMP, 4
- transpose matrix scalar multiplication

- theorem TMSM, 184
- example TM, 182
- matrix addition theorem TMA, 184
- matrix inverse, 216
- scalar multiplication, 184
- transpose of a matrix mathematica, 185
- ti86, 185
- transpose of a transpose theorem TT, 184
- TREM (example), 32
- trivial solution system of equations
definition TSHSE, 64
- TS (definition), 295
- TS (subsection of S), 292
- TSHSE (definition), 64
- TSM (subsection of MO), 182
- TSS (definition), 313
- TSS (section), 49
- TSS (subsection of S), 297
- TSS (theorem), 293
- TT (theorem), 184
- TTMI (theorem), 210
- TTS (example), 15
- typical systems, 2 × 2
  - example TTS, 15

U

- (archetype), 634
- (technique), 78
- unique solution, 3 × 3
  - example US, 20
  - example USR, 33
- uniqueness
  - technique U, 78
- unit vectors
  - basis theorem SUVB, 318
  - definition SUI, 210
  - orthogonal
    - example SUVOS, 171
    - URREF (subsection of LC), 111
    - US (example), 20
USR (example), 33

V
  (archetype), 634
V (chapter), 87
VA (example), 89
VAC (theorem), 285
VEASM (subsection of VO), 88
vector
  addition
    definition CVA, 89
  column
    definition CV, 66
  equality
    definition CVE, 88
  inner product
    definition IP, 166
  norm
    definition NV, 169
  notation VN, 66
  of constants
    definition VOC, 67
  product with matrix
    187, 191
  scalar multiplication
    definition CVSM, 90
vector addition
  example VA, 89
vector form of solutions
  Archetype D
    example VFSAD, 104
  Archetype I
    example VFSAI, 108
  Archetype L
    example VFSAL, 110
  theorem VFSLS, 106
vector linear combinations
  mathematica, 91
ti83, 92
ti86, 91
vector representation
  example AVR, 324
  example VRC4, 507
injective
  theorem VRI, 511
invertible
  theorem VRILT, 512
linear transformation
  definition VR, 505
  theorem VRLT, 505
  surjective
    theorem VRS, 515
    theorem VRRB, 324
vector representations
  polynomials
    example VRP2, 509
vector scalar multiplication
  example CVSM, 90
vector space
  characterization
    theorem CFDVS, 512
  definition VS, 275
  infinite dimension
    example VSPUD, 337
  linear transformations
    theorem VSLT, 446
vector space of functions
  example VSF, 279
vector space of infinite sequences
  example VSIS, 278
vector space of matrices
  example VSM, 277
vector space of matrices:definition
  definition VSM, 179
vector space of polynomials
  example VSP, 277
vector space properties
  column vectors
    theorem VSPCV, 92
  matrices
    theorem VSPM, 181
vector space, crazy
  example CVS, 280
vector space, singleton
  example VSS, 279
vector space:definition
  definition VSCV, 87
vector spaces
  isomorphic
    definition IVS, 493
    theorem IFDVS, 513
VESE (example), 88
VFSAD (example), 104
VFSAI (example), 108
VFSAL (example), 110
VFSLS (theorem), 106
VFSS (subsection of LC), 104
<table>
<thead>
<tr>
<th>Index Term</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>VLC.MMA (computation)</td>
<td>91</td>
</tr>
<tr>
<td>VLC.TI83 (computation)</td>
<td>92</td>
</tr>
<tr>
<td>VLC.TI86 (computation)</td>
<td>91</td>
</tr>
<tr>
<td>VN (notation)</td>
<td>66</td>
</tr>
<tr>
<td>VO (section)</td>
<td>87</td>
</tr>
<tr>
<td>VOC (definition)</td>
<td>67</td>
</tr>
<tr>
<td>VR (definition)</td>
<td>505</td>
</tr>
<tr>
<td>VR (section)</td>
<td>505</td>
</tr>
<tr>
<td>VR (subsection of B)</td>
<td>324</td>
</tr>
<tr>
<td>VRC4 (example)</td>
<td>507</td>
</tr>
<tr>
<td>VRI (theorem)</td>
<td>511</td>
</tr>
<tr>
<td>VRILT (theorem)</td>
<td>512</td>
</tr>
<tr>
<td>VRLT (theorem)</td>
<td>505</td>
</tr>
<tr>
<td>VRP2 (example)</td>
<td>509</td>
</tr>
<tr>
<td>VRRB (theorem)</td>
<td>324</td>
</tr>
<tr>
<td>VRS (theorem)</td>
<td>511</td>
</tr>
<tr>
<td>VS (chapter)</td>
<td>275</td>
</tr>
<tr>
<td>VS (definition)</td>
<td>275</td>
</tr>
<tr>
<td>VS (section)</td>
<td>275</td>
</tr>
<tr>
<td>VS (subsection of VS)</td>
<td>275</td>
</tr>
<tr>
<td>VSCV (definition)</td>
<td>87</td>
</tr>
<tr>
<td>VSCV (example)</td>
<td>277</td>
</tr>
<tr>
<td>VSF (example)</td>
<td>279</td>
</tr>
<tr>
<td>VSIS (example)</td>
<td>278</td>
</tr>
<tr>
<td>VSLT (theorem)</td>
<td>446</td>
</tr>
<tr>
<td>VSM (definition)</td>
<td>179</td>
</tr>
<tr>
<td>VSM (example)</td>
<td>277</td>
</tr>
<tr>
<td>VSP (example)</td>
<td>277</td>
</tr>
<tr>
<td>VSP (subsection of MO)</td>
<td>181</td>
</tr>
<tr>
<td>VSP (subsection of VO)</td>
<td>92</td>
</tr>
<tr>
<td>VSP (subsection of VS)</td>
<td>282</td>
</tr>
<tr>
<td>VSPCV (theorem)</td>
<td>92</td>
</tr>
<tr>
<td>VSPM (theorem)</td>
<td>181</td>
</tr>
<tr>
<td>VSPU (example)</td>
<td>337</td>
</tr>
<tr>
<td>VSS (example)</td>
<td>279</td>
</tr>
<tr>
<td>W (archetype)</td>
<td>635</td>
</tr>
<tr>
<td>WILA (section)</td>
<td>3</td>
</tr>
<tr>
<td>Z (Property)</td>
<td>276</td>
</tr>
<tr>
<td>ZC (Property)</td>
<td>92</td>
</tr>
<tr>
<td>zero vector column vectors</td>
<td>unique theorem ZVU</td>
</tr>
<tr>
<td>Property ZV</td>
<td>66</td>
</tr>
<tr>
<td>Property ZC</td>
<td>92</td>
</tr>
<tr>
<td>Property ZM</td>
<td>182</td>
</tr>
<tr>
<td>Property ZM (definition)</td>
<td>182</td>
</tr>
<tr>
<td>Property ZM (Property)</td>
<td>181</td>
</tr>
<tr>
<td>ZNDAB (example)</td>
<td>366</td>
</tr>
<tr>
<td>ZRM (definition)</td>
<td>34</td>
</tr>
<tr>
<td>ZSSM (theorem)</td>
<td>283</td>
</tr>
<tr>
<td>ZV (definition)</td>
<td>66</td>
</tr>
<tr>
<td>ZV (notation)</td>
<td>66</td>
</tr>
<tr>
<td>ZVSM (theorem)</td>
<td>283</td>
</tr>
<tr>
<td>ZVU (theorem)</td>
<td>282</td>
</tr>
</tbody>
</table>