

Flash Cards

to accompany

A First Course in Linear Algebra

by

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A **system of simultaneous linear equations** is a collection of m equations in the variable quantities $x_1, x_2, x_3, \dots, x_n$ of the form,

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

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

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

Given a system of simultaneous 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.

Suppose we apply one of the three equation operations of Definition EO to the system of simultaneous linear equations

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

Then the original system and the transformed system are equivalent systems.

An $m \times n$ **matrix** is a rectangular layout of numbers from \mathbb{C} having m rows and n columns.

Definition AM Augmented Matrix

Suppose we have a system of m equations in the n variables $x_1, x_2, x_3, \dots, x_n$ written as

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

then the **augmented matrix** of the system of equations is the $m \times (n + 1)$ matrix

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} & b_1 \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} & b_2 \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} & b_3 \\ \vdots & & & & & \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} & b_m \end{bmatrix}$$

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.

Two matrices, A and B , are **row-equivalent** if one can be obtained from the other by a sequence of row operations.

Suppose that A and B are row-equivalent augmented matrices. Then the systems of linear equations that they represent are equivalent systems.

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

1. A row where every entry is zero is below any row containing 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 $i < s$, then $j < t$.

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

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**.

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

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.

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

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 number of a column of B that contains the leading 1 for some row, and it is not the last column. Then the variable j is **dependent**. A variable that is not dependent is called **independent** or **free**.

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 .

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.

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.

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 zeros. Then the solution set can be described with $n - r$ free variables.

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

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

A system of linear equations is **homogeneous** if each equation has a 0 for its constant term. Such a system then has the form,

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

Suppose that a system of linear equations is homogeneous. Then the system is consistent.

Suppose a homogeneous system of linear equations has n variables. The solution $x_1 = 0, x_2 = 0, \dots, x_n = 0$ is called the **trivial solution**.

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

A **column vector** of **size** m is an ordered list of m numbers, which is written vertically, in order from top to bottom. At times, we will refer to a column vector as simply a **vector**.

The **zero vector** of size m is the column vector of size m where each entry is the number zero,

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

For a system of linear equations,

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

the **coefficient matrix** is the $m \times n$ matrix

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

For a system of linear equations,

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

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

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

For a system of linear equations,

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

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

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

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 $\mathcal{LS}(A, \mathbf{0})$.

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**.

Suppose A is a square matrix. And suppose the homogeneous linear system of equations $\mathcal{LS}(A, \mathbf{0})$ has *only* the trivial solution. Then we say that A is a **nonsingular** matrix. Otherwise we say A is a **singular** matrix.

The $m \times m$ **identity matrix**, $I_m = (a_{ij})$ has $a_{ij} = 1$ whenever $i = j$, and $a_{ij} = 0$ whenever $i \neq j$.

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.

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 trivial solution to the system $\mathcal{LS}(A, \mathbf{0})$, i.e. $\mathcal{N}(A) = \{\mathbf{0}\}$.

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

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 trivial solution, $\mathcal{N}(A) = \{\mathbf{0}\}$.
4. The linear system $\mathcal{LS}(A, \mathbf{b})$ has a unique solution for every possible choice of \mathbf{b} .

The vector space \mathbb{C}^m is the set of all column vectors (Definition CV) of size m with entries from the set of complex numbers, \mathbb{C} .

The vectors

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \qquad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}$$

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

Given the vectors

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \qquad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}$$

the **sum** of \mathbf{u} and \mathbf{v} is the vector

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

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 α is

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

Suppose that \mathbb{C}^m is the set of column vectors of size m (Definition VSCV) with addition and scalar multiplication as defined in Definition CVA and Definition CVSM. Then

- **ACC Additive Closure, Column Vectors** If $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$, then $\mathbf{u} + \mathbf{v} \in \mathbb{C}^m$.
- **SCC Scalar Closure, Column Vectors** If $\alpha \in \mathbb{C}$ and $\mathbf{u} \in \mathbb{C}^m$, then $\alpha \mathbf{u} \in \mathbb{C}^m$.
- **CC Commutativity, Column Vectors** If $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$, then $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$.
- **AAC Additive Associativity, Column Vectors** If $\mathbf{u}, \mathbf{v}, \mathbf{w} \in \mathbb{C}^m$, then $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$.
- **ZC Zero Vector, Column Vectors** There is a vector, $\mathbf{0}$, called the **zero vector**, such that $\mathbf{u} + \mathbf{0} = \mathbf{u}$ for all $\mathbf{u} \in \mathbb{C}^m$.
- **AIC Additive Inverses, Column Vectors** For each vector $\mathbf{u} \in \mathbb{C}^m$, there exists a vector $-\mathbf{u} \in \mathbb{C}^m$ so that $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$.
- **SMAC Scalar Multiplication Associativity, Column Vectors** If $\alpha, \beta \in \mathbb{C}$ and $\mathbf{u} \in \mathbb{C}^m$, then $\alpha(\beta \mathbf{u}) = (\alpha\beta)\mathbf{u}$.
- **DVAC Distributivity across Vector Addition, Column Vectors** If $\alpha \in \mathbb{C}$ and $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$, then $\alpha(\mathbf{u} + \mathbf{v}) = \alpha \mathbf{u} + \alpha \mathbf{v}$.
- **DSAC Distributivity across Scalar Addition, Column Vectors** If $\alpha, \beta \in \mathbb{C}$ and $\mathbf{u} \in \mathbb{C}^m$, then $(\alpha + \beta)\mathbf{u} = \alpha \mathbf{u} + \beta \mathbf{u}$.
- **OC One, Column Vectors** If $\mathbf{u} \in \mathbb{C}^m$, then $1\mathbf{u} = \mathbf{u}$.

Given n vectors $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n$ and n scalars $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n$, their **linear combination** is the vector

$$\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 + \cdots + \alpha_n\mathbf{u}_n.$$

Denote the columns of the $m \times n$ matrix A as the vectors $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n$. Then $\mathbf{x} =$

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha_n \end{bmatrix}$$

is a solution to the linear system of equations $\mathcal{LS}(A, \mathbf{b})$ if and only if

$$\alpha_1\mathbf{A}_1 + \alpha_2\mathbf{A}_2 + \alpha_3\mathbf{A}_3 + \cdots + \alpha_n\mathbf{A}_n = \mathbf{b}$$

Theorem VFSL Vector Form of Solutions to Linear Systems

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Suppose that $[A | \mathbf{b}]$ is the augmented matrix for a consistent linear system $\mathcal{LS}(A, \mathbf{b})$ of m equations in n variables. Denote the vector of variables as $\mathbf{x} = (x_i)$. Let $B = (b_{ij})$ 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 having indices $F = \{f_1, f_2, f_3, \dots, f_{n-r}, n+1\}$, and columns with leading 1's (pivot columns) having indices $D = \{d_1, d_2, d_3, \dots, d_r\}$. Define vectors $\mathbf{c} = (c_i)$, $\mathbf{u}_j = (u_{ij})$, $1 \leq j \leq n-r$ of size n by

$$c_i = \begin{cases} 0 & \text{if } i \in F \\ b_{k,n+1} & \text{if } i \in D, i = d_k \end{cases}$$
$$u_{ij} = \begin{cases} 1 & \text{if } i \in F, i = f_j \\ 0 & \text{if } i \in F, i \neq f_j \\ -b_{k,f_j} & \text{if } i \in D, i = d_k \end{cases}.$$

Then the set of solutions to the system of equations represented by the vector equation

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix} = \mathbf{c} + x_{f_1} \mathbf{u}_1 + x_{f_2} \mathbf{u}_2 + x_{f_3} \mathbf{u}_3 + \cdots + x_{f_{n-r}} \mathbf{u}_{n-r}$$

is equal to the set of solutions of $\mathcal{LS}(A, \mathbf{b})$.

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Theorem RREFU Reduced Row-Echelon Form is Unique

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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 $B = C$.

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Given a set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$, their **span**, $\mathcal{S}p(S)$, is the set of all possible linear combinations of $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t$. Symbolically,

$$\begin{aligned} \mathcal{S}p(S) &= \{\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 + \cdots + \alpha_t\mathbf{u}_t \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t\} \\ &= \left\{ \sum_{i=1}^t \alpha_i \mathbf{u}_i \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t \right\} \end{aligned}$$

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 $D = \{d_1, d_2, d_3, \dots, d_r\}$ and $F = \{f_1, f_2, f_3, \dots, f_{n-r}\}$ be the sets of column indices where B does and does not (respectively) have leading 1's. Construct the $n - r$ vectors $\mathbf{u}_j = (u_{ij})$, $1 \leq j \leq n - r$ of size n as

$$u_{ij} = \begin{cases} 1 & \text{if } i \in F, i = f_j \\ 0 & \text{if } i \in F, i \neq f_j \\ -b_{k,f_j} & \text{if } i \in D, i = d_k \end{cases}.$$

Then the null space of A is given by

$$\mathcal{N}(A) = \mathcal{S}p(\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_{n-r}\}).$$

Given a set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$, an equation of the form

$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_n \mathbf{u}_n = \mathbf{0}$$

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 .

The set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ 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.

Suppose that A is an $m \times n$ matrix and $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$ 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 $\mathcal{LS}(A, \mathbf{0})$ has a unique solution.

Suppose that A is an $m \times n$ matrix and $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$ 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 $n = r$.

Suppose that $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ is the set of vectors in \mathbb{C}^m , and that $n > m$. Then S is a linearly dependent set.

Suppose that $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ 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 $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_{t-1}, \mathbf{u}_{t+1}, \dots, \mathbf{u}_n$.

Suppose that A is a square matrix. Then A is nonsingular if and only if the columns of A form a linearly independent set.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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.

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 $D = \{d_1, d_2, d_3, \dots, d_r\}$ and $F = \{f_1, f_2, f_3, \dots, f_{n-r}\}$ 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 $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_{n-r}\}$. Then

1. $\mathcal{N}(A) = \mathcal{S}p(S)$.
2. S is a linearly independent set.

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

$$\bar{\mathbf{u}} = \begin{bmatrix} \bar{u}_1 \\ \bar{u}_2 \\ \bar{u}_3 \\ \vdots \\ \bar{u}_m \end{bmatrix}$$

Suppose \mathbf{x} and \mathbf{y} are two vectors from \mathbb{C}^m . Then

$$\overline{\mathbf{x} + \mathbf{y}} = \overline{\mathbf{x}} + \overline{\mathbf{y}}$$

Suppose \mathbf{x} is a vector from \mathbb{C}^m , and $\alpha \in \mathbb{C}$ is a scalar. Then

$$\overline{\alpha \mathbf{x}} = \overline{\alpha} \overline{\mathbf{x}}$$

Given the vectors

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{bmatrix} \qquad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_m \end{bmatrix}$$

the **inner product** of \mathbf{u} and \mathbf{v} is the scalar quantity in \mathbb{C} ,

$$\langle \mathbf{u}, \mathbf{v} \rangle = u_1 \overline{v_1} + u_2 \overline{v_2} + u_3 \overline{v_3} + \cdots + u_m \overline{v_m} = \sum_{i=1}^m u_i \overline{v_i}$$

Suppose $\mathbf{u}, \mathbf{v}, \mathbf{w} \in \mathbb{C}^m$. Then

1. $\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{w} \rangle + \langle \mathbf{v}, \mathbf{w} \rangle$
2. $\langle \mathbf{u}, \mathbf{v} + \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{v} \rangle + \langle \mathbf{u}, \mathbf{w} \rangle$

Suppose $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ and $\alpha \in \mathbb{C}$. Then

1. $\langle \alpha \mathbf{u}, \mathbf{v} \rangle = \alpha \langle \mathbf{u}, \mathbf{v} \rangle$
2. $\langle \mathbf{u}, \alpha \mathbf{v} \rangle = \bar{\alpha} \langle \mathbf{u}, \mathbf{v} \rangle$

Suppose that \mathbf{u} and \mathbf{v} are vectors in \mathbb{C}^m . Then $\langle \mathbf{u}, \mathbf{v} \rangle = \overline{\langle \mathbf{v}, \mathbf{u} \rangle}$.

The **norm** of the vector

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

is the scalar quantity in \mathbb{C}^m

$$\|\mathbf{u}\| = \sqrt{|u_1|^2 + |u_2|^2 + |u_3|^2 + \cdots + |u_m|^2} = \sqrt{\sum_{i=1}^m |u_i|^2}$$

Suppose that \mathbf{u} is a vector in \mathbb{C}^m . Then $\|\mathbf{u}\|^2 = \langle \mathbf{u}, \mathbf{u} \rangle$.

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 $\mathbf{u} = \mathbf{0}$.

A pair of vectors, \mathbf{u} and \mathbf{v} , from \mathbb{C}^m are **orthogonal** if their inner product is zero, that is, $\langle \mathbf{u}, \mathbf{v} \rangle = 0$.

Suppose that $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ 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 $\langle \mathbf{u}_i, \mathbf{u}_j \rangle = 0$ whenever $i \neq j$.

Suppose that $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ is an orthogonal set of nonzero vectors. Then S is linearly independent.

Suppose that $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_p\}$ is a linearly independent set of vectors in \mathbb{C}^m . Define the vectors \mathbf{u}_i , $1 \leq i \leq p$ by

$$\mathbf{u}_i = \mathbf{v}_i - \frac{\langle \mathbf{v}_i, \mathbf{u}_1 \rangle}{\langle \mathbf{u}_1, \mathbf{u}_1 \rangle} \mathbf{u}_1 - \frac{\langle \mathbf{v}_i, \mathbf{u}_2 \rangle}{\langle \mathbf{u}_2, \mathbf{u}_2 \rangle} \mathbf{u}_2 - \frac{\langle \mathbf{v}_i, \mathbf{u}_3 \rangle}{\langle \mathbf{u}_3, \mathbf{u}_3 \rangle} \mathbf{u}_3 - \dots - \frac{\langle \mathbf{v}_i, \mathbf{u}_{i-1} \rangle}{\langle \mathbf{u}_{i-1}, \mathbf{u}_{i-1} \rangle} \mathbf{u}_{i-1}$$

Then if $T = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_p\}$, then T is an orthogonal set of non-zero vectors, and $\mathcal{S}p(T) = \mathcal{S}p(S)$.

Suppose $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ is an orthogonal set of vectors such that $\|\mathbf{u}_i\| = 1$ for all $1 \leq i \leq n$. Then S is an **orthonormal** set of vectors.

The vector space M_{mn} is the set of all $m \times n$ matrices with entries from the set of complex numbers.

The $m \times n$ matrices

$$A = (a_{ij})$$

$$B = (b_{ij})$$

are **equal**, written $A = B$ provided $a_{ij} = b_{ij}$ for all $1 \leq i \leq m$, $1 \leq j \leq n$.

Given the $m \times n$ matrices

$$A = (a_{ij}) \qquad B = (b_{ij})$$

define the **sum** of A and B to be $A + B = C = (c_{ij})$, where

$$c_{ij} = a_{ij} + b_{ij}, \quad 1 \leq i \leq m, 1 \leq j \leq n.$$

Given the $m \times n$ matrix $A = (a_{ij})$ and the scalar $\alpha \in \mathbb{C}$, the **scalar multiple** of A by α is the matrix $\alpha A = C = (c_{ij})$, where

$$c_{ij} = \alpha a_{ij}, \quad 1 \leq i \leq m, 1 \leq j \leq n.$$

Suppose that M_{mn} is the set of all $m \times n$ matrices (Definition VSM) with addition and scalar multiplication as defined in Definition MA and Definition MSM. 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, \mathcal{O} , called the **zero matrix**, such that $A + \mathcal{O} = A$ for all $A \in M_{mn}$.
- **AIM Additive Inverses, Matrices** For each matrix $A \in M_{mn}$, there exists a matrix $-A \in M_{mn}$ so that $A + (-A) = \mathcal{O}$.
- **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 $1A = A$.

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Definition ZM Zero Matrix

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The $m \times n$ **zero matrix** is written as $\mathcal{O} = \mathcal{O}_{m \times n} = (z_{ij})$ and defined by $z_{ij} = 0$ for all $1 \leq i \leq m, 1 \leq j \leq n$. Or, equivalently, $[\mathcal{O}]_{ij} = 0$, for all $1 \leq i \leq m, 1 \leq j \leq n$.

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Given an $m \times n$ matrix A , its **transpose** is the $n \times m$ matrix A^t given by

$$[A^t]_{ij} = [A]_{ji}, \quad 1 \leq i \leq n, 1 \leq j \leq m.$$

The matrix A is **symmetric** if $A = A^t$.

Suppose that A is a symmetric matrix. Then A is square.

Suppose that A and B are $m \times n$ matrices. Then $(A + B)^t = A^t + B^t$.

Suppose that $\alpha \in \mathbb{C}$ and A is an $m \times n$ matrix. Then $(\alpha A)^t = \alpha A^t$.

Suppose that A is an $m \times n$ matrix. Then $(A^t)^t = A$.

Suppose A is an $m \times n$ matrix. Then the **conjugate** of A , written \overline{A} is an $m \times n$ matrix defined by

$$[A]_{ij} = \overline{[\overline{A}]_{ij}}$$

Suppose that A and B are $m \times n$ matrices. Then $\overline{A + B} = \overline{A} + \overline{B}$.

Suppose that $\alpha \in \mathbb{C}$ and A is an $m \times n$ matrix. Then $\overline{\alpha A} = \bar{\alpha} \bar{A}$.

Suppose that A is an $m \times n$ matrix with columns $\{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$. Then the **range** of A , written $\mathcal{R}(A)$, is the subset of \mathbb{C}^m containing all linear combinations of the columns of A ,

$$\mathcal{R}(A) = \mathcal{S}p(\{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\})$$

Suppose A is an $m \times n$ matrix and \mathbf{b} is a vector of size m . Then $\mathbf{b} \in \mathcal{R}(A)$ if and only if $\mathcal{LS}(A, \mathbf{b})$ is consistent.

Suppose that A is an $m \times n$ matrix with columns $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n$, and B is a row-equivalent matrix in reduced row-echelon form with r nonzero rows. Let $D = \{d_1, d_2, d_3, \dots, d_r\}$ be the set of column indices where B has leading 1's. Let $S = \{\mathbf{A}_{d_1}, \mathbf{A}_{d_2}, \mathbf{A}_{d_3}, \dots, \mathbf{A}_{d_r}\}$. Then

1. $\mathcal{R}(A) = \mathcal{Sp}(S)$.
2. S is a linearly independent set.

Suppose that A is an $m \times n$ matrix. Create the $m \times (n + m)$ matrix M by placing the $m \times m$ identity matrix I_m to the right of the matrix A . Symbolically, $M = [A \mid I_m]$. Let N be a matrix that is row-equivalent to M and in reduced row-echelon form. Suppose there are r leading 1's of N in the first n columns. If $r = m$, then $\mathcal{R}(A) = \mathbb{C}^m$. Otherwise, $r < m$ and let K be the $(m - r) \times m$ matrix formed from the entries of N in the last $m - r$ rows and last m columns. Then

1. K is in reduced row-echelon form.
2. K has no zero rows, or equivalently, K has $m - r$ leading 1's.
3. $\mathcal{R}(A) = \mathcal{N}(K)$.

Suppose A is a square matrix of size n . Then A is nonsingular if and only if $\mathcal{R}(A) = \mathbb{C}^n$.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.

Suppose A is an $m \times n$ matrix. Then the **row space** of A , $\mathcal{RS}(A)$, is the range of A^t , i.e. $\mathcal{RS}(A) = \mathcal{R}(A^t)$.

Suppose A and B are row-equivalent matrices. Then $\mathcal{RS}(A) = \mathcal{RS}(B)$.

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. $\mathcal{RS}(A) = \mathcal{Sp}(S)$.
2. S is a linearly independent set.

Suppose A is a matrix. Then $\mathcal{R}(A) = \mathcal{RS}(A^t)$.

Suppose A is an $m \times n$ matrix with columns $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n$ and \mathbf{u} is a vector of size n . Then the **matrix-vector product** of A with \mathbf{u} is

$$\mathbf{A}\mathbf{u} = [\mathbf{A}_1 | \mathbf{A}_2 | \mathbf{A}_3 | \dots | \mathbf{A}_n] \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_n \end{bmatrix} = u_1 \mathbf{A}_1 + u_2 \mathbf{A}_2 + u_3 \mathbf{A}_3 + \dots + u_n \mathbf{A}_n$$

Solutions to the linear system $\mathcal{LS}(A, \mathbf{b})$ are the solutions for \mathbf{x} in the vector equation $A\mathbf{x} = \mathbf{b}$.

Suppose A is an $m \times n$ matrix and B is an $n \times p$ matrix with columns $\mathbf{B}_1, \mathbf{B}_2, \mathbf{B}_3, \dots, \mathbf{B}_p$. Then the **matrix product** of A with B is the $m \times p$ matrix where column i is the matrix-vector product $A\mathbf{B}_i$. Symbolically,

$$AB = A[\mathbf{B}_1|\mathbf{B}_2|\mathbf{B}_3|\dots|\mathbf{B}_p] = [A\mathbf{B}_1|A\mathbf{B}_2|A\mathbf{B}_3|\dots|A\mathbf{B}_p].$$

Suppose $A = (a_{ij})$ is an $m \times n$ matrix and $B = (b_{ij})$ is an $n \times p$ matrix. Then the entries of $AB = C = (c_{ij})$ are given by

$$[C]_{ij} = c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + a_{i3}b_{3j} + \cdots + a_{in}b_{nj} = \sum_{k=1}^n a_{ik}b_{kj} = \sum_{k=1}^n [A]_{ik} [B]_{kj}$$

Suppose A is an $m \times n$ matrix. Then

1. $A\mathcal{O}_{n \times p} = \mathcal{O}_{m \times p}$
2. $\mathcal{O}_{p \times m}A = \mathcal{O}_{p \times n}$

Suppose A is an $m \times n$ matrix. Then

1. $AI_n = A$
2. $I_m A = A$

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. $(B + C)D = BD + CD$

Suppose A is an $m \times n$ matrix and B is an $n \times p$ matrix. Let α be a scalar. Then $\alpha(AB) = (\alpha A)B = A(\alpha B)$.

Suppose A is an $m \times n$ matrix, B is an $n \times p$ matrix and D is a $p \times s$ matrix. Then $A(BD) = (AB)D$.

If we consider the vectors $\mathbf{u}, \mathbf{v} \in \mathbb{C}^m$ as $m \times 1$ matrices then

$$\langle \mathbf{u}, \mathbf{v} \rangle = \mathbf{u}^t \bar{\mathbf{v}}$$

Suppose A is an $m \times n$ matrix and B is an $n \times p$ matrix. Then $\overline{AB} = \bar{A}\bar{B}$.

Suppose A is an $m \times n$ matrix and B is an $n \times p$ matrix. Then $(AB)^t = B^t A^t$.

Suppose that \mathbf{z} is one solution to the linear system of equations $\mathcal{LS}(A, b)$. Then \mathbf{y} is a solution to $\mathcal{LS}(A, b)$ if and only if $\mathbf{y} = \mathbf{z} + \mathbf{w}$ for some vector $\mathbf{w} \in N(A)$.

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 $B = A^{-1}$.

Let $\mathbf{e}_i \in \mathbb{C}^m$ denote the column vector that is column i of the $m \times m$ identity matrix I_m . Then the set

$$\{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \dots, \mathbf{e}_m\} = \{\mathbf{e}_i \mid 1 \leq i \leq m\}$$

is the set of **standard unit vectors** in \mathbb{C}^m .

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

$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}.$$

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 B be the matrix formed from the final n columns of N . Then $AB = I_n$.

Suppose the square matrix A has an inverse. Then A^{-1} is unique.

Suppose A and B are invertible matrices of size n . Then $(AB)^{-1} = B^{-1}A^{-1}$ and AB is an invertible matrix.

Suppose A is an invertible matrix. Then $(A^{-1})^{-1} = A$ and A^{-1} is invertible.

Suppose A is an invertible matrix. Then $(A^t)^{-1} = (A^{-1})^t$ and A^t is invertible.

Suppose A is an invertible matrix and α is a nonzero scalar. Then $(\alpha A)^{-1} = \frac{1}{\alpha}A^{-1}$ and αA is invertible.

Suppose that A or B are matrices of size n , and one, or both, is singular. Then their product, AB , is singular.

Suppose A and B are square matrices of size n such that $AB = I_n$. Then $BA = I_n$.

Suppose that A is a square matrix. Then A is nonsingular if and only if A is invertible.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.
7. A is invertible.

Suppose that A is nonsingular. Then the unique solution to $\mathcal{LS}(A, \mathbf{b})$ is $A^{-1}\mathbf{b}$.

Suppose that Q is a square matrix of size n such that $(\overline{Q})^t Q = I_n$. Then we say Q is **orthogonal**.

Suppose that Q is an orthogonal matrix of size n . Then Q is nonsingular, and $Q^{-1} = (\overline{Q})^t$.

Suppose that A is a square matrix of size n with columns $S = \{\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots, \mathbf{A}_n\}$. Then A is an orthogonal matrix if and only if S is an orthonormal set.

Suppose that Q is an orthogonal matrix of size n and \mathbf{u} and \mathbf{v} are two vectors from \mathbb{C}^n . Then

$$\langle Q\mathbf{u}, Q\mathbf{v} \rangle = \langle \mathbf{u}, \mathbf{v} \rangle \quad \text{and} \quad \|Q\mathbf{v}\| = \|\mathbf{v}\|$$

If A is a square matrix, then its **adjoint** is $A^H = (\overline{A})^t$.

The square matrix A is **Hermitian** (or **self-adjoint**) if $A = (\overline{A})^t$

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 $\mathbf{u}, \mathbf{v} \in V$, then $\mathbf{u} + \mathbf{v} \in V$.
2. **SC Scalar Closure** If $\alpha \in \mathbb{C}$ and $\mathbf{u} \in V$, then $\alpha\mathbf{u} \in V$.
3. **C Commutativity** If $\mathbf{u}, \mathbf{v} \in V$, then $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$.
4. **AA Additive Associativity** If $\mathbf{u}, \mathbf{v}, \mathbf{w} \in V$, then $\mathbf{u} + (\mathbf{v} + \mathbf{w}) = (\mathbf{u} + \mathbf{v}) + \mathbf{w}$.
5. **Z Zero Vector** There is a vector, $\mathbf{0}$, called the **zero vector**, such that $\mathbf{u} + \mathbf{0} = \mathbf{u}$ for all $\mathbf{u} \in V$.
6. **AI Additive Inverses** For each vector $\mathbf{u} \in V$, there exists a vector $-\mathbf{u} \in V$ so that $\mathbf{u} + (-\mathbf{u}) = \mathbf{0}$.
7. **SMA Scalar Multiplication Associativity** If $\alpha, \beta \in \mathbb{C}$ and $\mathbf{u} \in V$, then $\alpha(\beta\mathbf{u}) = (\alpha\beta)\mathbf{u}$.
8. **DVA Distributivity across Vector Addition** If $\alpha \in \mathbb{C}$ and $\mathbf{u}, \mathbf{v} \in V$, then $\alpha(\mathbf{u} + \mathbf{v}) = \alpha\mathbf{u} + \alpha\mathbf{v}$.
9. **DSA Distributivity across Scalar Addition** If $\alpha, \beta \in \mathbb{C}$ and $\mathbf{u} \in V$, then $(\alpha + \beta)\mathbf{u} = \alpha\mathbf{u} + \beta\mathbf{u}$.
10. **O One** If $\mathbf{u} \in V$, then $1\mathbf{u} = \mathbf{u}$.

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.

Suppose that V is a vector space. The zero vector, $\mathbf{0}$, is unique.

Suppose that V is a vector space. For each $\mathbf{u} \in V$, the additive inverse, $-\mathbf{u}$, is unique.

Suppose that V is a vector space and $\mathbf{u} \in V$. Then $0\mathbf{u} = \mathbf{0}$.

Suppose that V is a vector space and $\alpha \in \mathbb{C}$. Then $\alpha\mathbf{0} = \mathbf{0}$.

Suppose that V is a vector space and $\mathbf{u} \in V$. Then $-\mathbf{u} = (-1)\mathbf{u}$.

Suppose that V is a vector space and $\alpha \in \mathbb{C}$. Then if $\alpha \mathbf{u} = \mathbf{0}$, then either $\alpha = 0$ or $\mathbf{u} = \mathbf{0}$ (or both).

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 $\mathbf{u} = \mathbf{v}$.

Suppose V is a vector space, $\mathbf{u}, \mathbf{v} \in V$ and α is a nonzero scalar from \mathbb{C} . If $\alpha\mathbf{u} = \alpha\mathbf{v}$, then $\mathbf{u} = \mathbf{v}$.

Suppose V is a vector space, $\mathbf{u} \neq \mathbf{0}$ is a vector in V and $\alpha, \beta \in \mathbb{C}$. If $\alpha\mathbf{u} = \beta\mathbf{u}$, then $\alpha = \beta$.

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 .

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 $\mathbf{x} \in W$ and $\mathbf{y} \in W$, then $\mathbf{x} + \mathbf{y} \in W$.
3. Whenever $\alpha \in \mathbb{C}$ and $\mathbf{x} \in W$, then $\alpha\mathbf{x} \in W$.

Given the vector space V , the subspaces V and $\{\mathbf{0}\}$ are each called a **trivial 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 .

Suppose that V is a vector space. Given n vectors $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n$ and n scalars $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n$, their **linear combination** is the vector

$$\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 + \cdots + \alpha_n\mathbf{u}_n.$$

Suppose that V is a vector space. Given a set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$, their **span**, $\mathcal{S}p(S)$, is the set of all possible linear combinations of $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t$. Symbolically,

$$\begin{aligned}\mathcal{S}p(S) &= \{\alpha_1\mathbf{u}_1 + \alpha_2\mathbf{u}_2 + \alpha_3\mathbf{u}_3 + \cdots + \alpha_t\mathbf{u}_t \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t\} \\ &= \left\{ \sum_{i=1}^t \alpha_i \mathbf{u}_i \mid \alpha_i \in \mathbb{C}, 1 \leq i \leq t \right\}\end{aligned}$$

Suppose V is a vector space. Given a set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\} \subseteq V$, their span, $\mathcal{S}p(S)$, is a subspace.

Suppose that A is an $m \times n$ matrix. Then $\mathcal{R}(A)$ is a subspace of \mathbb{C}^m .

Suppose that A is an $m \times n$ matrix. Then $\mathcal{RS}(A)$ is a subspace of \mathbb{C}^n .

Suppose that V is a vector space. Given a set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$, an equation of the form

$$\alpha_1 \mathbf{u}_1 + \alpha_2 \mathbf{u}_2 + \alpha_3 \mathbf{u}_3 + \cdots + \alpha_n \mathbf{u}_n = \mathbf{0}$$

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 .

Suppose that V is a vector space. The set of vectors $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ 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.

Suppose V is a vector space and W is a subspace. A subset S of W is a **spanning set** for W if $\mathcal{S}p(S) = W$. In this case, we also say S **spans** W .

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 .

The set of standard unit vectors for \mathbb{C}^m , $B = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \dots, \mathbf{e}_m\} = \{\mathbf{e}_i \mid 1 \leq i \leq m\}$ is a basis for the vector space \mathbb{C}^m .

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.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.
7. A is invertible.
8. The columns of A are a basis for \mathbb{C}^n .

Suppose that V is a vector space with basis $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_m\}$ and that \mathbf{w} is a vector in V . Then there exist *unique* scalars $a_1, a_2, a_3, \dots, a_m$ such that

$$\mathbf{w} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + a_3\mathbf{v}_3 + \cdots + a_m\mathbf{v}_m.$$

Suppose that V is a vector space and $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_t\}$ 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.

Suppose that $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_t\}$ 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.

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.

The dimension of \mathbb{C}^m (Example VSCV) is m .

The dimension of P_n (Example VSP) is $n + 1$.

The dimension of M_{mn} (Example VSM) is mn .

Suppose that A is an $m \times n$ matrix. Then the **nullity** of A is the dimension of the null space of A , $n(A) = \dim(\mathcal{N}(A))$.

Suppose that A is an $m \times n$ matrix. Then the **rank** of A is the dimension of the range of A , $r(A) = \dim(\mathcal{R}(A))$.

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 $n(A) = n - r$.

Suppose that A is an $m \times n$ matrix. Then $r(A) + n(A) = n$.

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, $n(A) = 0$.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.
7. A is invertible.
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, $n(A) = 0$.

Suppose V is vector space and S is a linearly independent set of vectors from V . Suppose \mathbf{w} is a vector such that $\mathbf{w} \notin \mathcal{Sp}(S)$. Then the set $S' = S \cup \{\mathbf{w}\}$ is linearly independent.

Suppose that V is a vector space of dimension t . Let $S = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_m\}$ 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.

Suppose that U and V are subspaces of the vector space W , such that $U \subseteq V$ and $\dim(U) = \dim(V)$. Then $U = V$.

Suppose A is an $m \times n$ matrix. Then $r(A) = r(A^t)$.

Suppose that $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_p\}$ is an orthonormal basis of the subspace W of \mathbb{C}^m . For any $\mathbf{w} \in W$,

$$\mathbf{w} = \langle \mathbf{w}, \mathbf{v}_1 \rangle \mathbf{v}_1 + \langle \mathbf{w}, \mathbf{v}_2 \rangle \mathbf{v}_2 + \langle \mathbf{w}, \mathbf{v}_3 \rangle \mathbf{v}_3 + \cdots + \langle \mathbf{w}, \mathbf{v}_p \rangle \mathbf{v}_p$$

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 .

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 1×1 matrix, then $\det(A) = a$.

If $A = (a_{ij})$ is a matrix of size n with $n \geq 2$, then

$$\det(A) = a_{11} \det(A_{11}) - a_{12} \det(A_{12}) + a_{13} \det(A_{13}) - \cdots + (-1)^{n+1} a_{1n} \det(A_{1n})$$

Suppose that $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. Then $\det(A) = ad - bc$

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 ij is the determinant of the submatrix, $M_{A,ij} = \det(A_{ij})$.

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 ij is the signed determinant of the submatrix, $C_{A,ij} = (-1)^{i+j} \det(A_{ij})$.

Suppose that $A = (a_{ij})$ 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 .

Suppose that A is a square matrix. Then $\det(A^t) = \det(A)$.

Suppose that A and B are square matrices of size n . Then $\det(AB) = \det(A)\det(B)$.

Let A be a square matrix. Then A is singular if and only if $\det(A) = 0$.

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.
7. A is invertible.
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, $\det(A) \neq 0$.

Suppose that A is a square matrix of size n , $\mathbf{x} \neq \mathbf{0}$ is a vector from \mathbb{C}^n , and λ is a scalar from \mathbb{C} such that

$$A\mathbf{x} = \lambda\mathbf{x}$$

Then we say \mathbf{x} is an **eigenvector** of A with **eigenvalue** λ .

Suppose A is a square matrix. Then A has at least one eigenvalue.

Suppose that A is a square matrix of size n . Then the **characteristic polynomial** of A is the polynomial $p_A(x)$ defined by

$$p_A(x) = \det(A - xI_n)$$

Suppose A is a square matrix. Then λ is an eigenvalue of A if and only if $p_A(\lambda) = 0$.

Suppose that A is a square matrix and λ is an eigenvalue of A . Then the **eigenspace** of A for λ , $E_A(\lambda)$, is the set of all the eigenvectors of A for λ , with the addition of the zero vector.

Suppose A is a square matrix of size n and λ is an eigenvalue of A . Then the eigenspace $E_A(\lambda)$ is a subspace of the vector space \mathbb{C}^n .

Suppose A is a square matrix of size n and λ is an eigenvalue of A . Then

$$E_A(\lambda) = \mathcal{N}(A - \lambda I_n)$$

Suppose that A is a square matrix and λ is an eigenvalue of A . Then the **algebraic multiplicity** of λ , $\alpha_A(\lambda)$, is the highest power of $(x - \lambda)$ that divides the characteristic polynomial, $p_A(x)$.

Suppose that A is a square matrix and λ is an eigenvalue of A . Then the **geometric multiplicity** of λ , $\gamma_A(\lambda)$, is the dimension of the eigenspace $E_A(\lambda)$.

Suppose that A is a square matrix and $S = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_p\}$ is a set of eigenvectors with eigenvalues $\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_p$ such that $\lambda_i \neq \lambda_j$ whenever $i \neq j$. Then S is a linearly independent set.

Suppose A is a square matrix. Then A is singular if and only if $\lambda = 0$ is an eigenvalue of A .

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, $\mathcal{N}(A) = \{\mathbf{0}\}$.
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 are a linearly independent set.
6. The range of A is \mathbb{C}^n , $\mathcal{R}(A) = \mathbb{C}^n$.
7. A is invertible.
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 .

Suppose A is a square matrix and λ is an eigenvalue of A . Then $\alpha\lambda$ is an eigenvalue of αA .

Suppose A is a square matrix, λ is an eigenvalue of A , and $s \geq 0$ is an integer. Then λ^s is an eigenvalue of A^s .

Suppose A is a square matrix and λ is an eigenvalue of A . Let $q(x)$ be a polynomial in the variable x . Then $q(\lambda)$ is an eigenvalue of the matrix $q(A)$.

Suppose A is a square nonsingular matrix and λ is an eigenvalue of A . Then $\frac{1}{\lambda}$ is an eigenvalue of the matrix A^{-1} .

Suppose A is a square matrix and λ is an eigenvalue of A . Then λ is an eigenvalue of the matrix A^t .

Suppose A is a square matrix with real entries and $\underline{\mathbf{x}}$ is an eigenvector of A for the eigenvalue λ . Then $\overline{\underline{\mathbf{x}}}$ is an eigenvector of A for the eigenvalue $\overline{\lambda}$.

Suppose that A is a square matrix of size n . Then the characteristic polynomial of A , $p_A(x)$, has degree n .

Suppose that A is a square matrix of size n with distinct eigenvalues $\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_k$. Then

$$\sum_{i=1}^k \alpha_A(\lambda_i) = n$$

Suppose that A is a square matrix of size n and λ is an eigenvalue. Then

$$1 \leq \gamma_A(\lambda) \leq \alpha_A(\lambda) \leq n$$

Suppose that A is a square matrix of size n . Then A cannot have more than n distinct eigenvalues.

Suppose that A is a Hermitian matrix and λ is an eigenvalue of A . Then $\lambda \in \mathbb{R}$.

Suppose that A is a Hermitian matrix and \mathbf{x} and \mathbf{y} are two eigenvectors of A for different eigenvalues. Then \mathbf{x} and \mathbf{y} are orthogonal vectors.

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 $A = S^{-1}BS$.

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)

Suppose A and B are similar matrices. Then the characteristic polynomials of A and B are equal, that is $p_A(x) = p_B(x)$.

Suppose that $A = (a_{ij})$ is a square matrix. Then A is a **diagonal matrix** if $a_{ij} = 0$ whenever $i \neq j$.

Suppose A is a square matrix. Then A is **diagonalizable** if A is similar to a diagonal matrix.

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 .

Suppose A is a square matrix. Then A is diagonalizable if and only if $\gamma_A(\lambda) = \alpha_A(\lambda)$ for every eigenvalue λ of A .

Suppose A is a square matrix of size n with n distinct eigenvalues. Then A is diagonalizable.

Definition LT Linear Transformation

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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. $T(\mathbf{u}_1 + \mathbf{u}_2) = T(\mathbf{u}_1) + T(\mathbf{u}_2)$ for all $\mathbf{u}_1, \mathbf{u}_2 \in U$
2. $T(\alpha\mathbf{u}) = \alpha T(\mathbf{u})$ for all $\mathbf{u} \in U$ and all $\alpha \in \mathbb{C}$

Suppose $T: U \mapsto V$ is a linear transformation. Then $T(\mathbf{0}) = \mathbf{0}$.

Suppose that A is an $m \times n$ matrix. Define a function $T: \mathbb{C}^n \mapsto \mathbb{C}^m$ by $T(\mathbf{x}) = A\mathbf{x}$. Then T is a linear transformation.

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 $T(\mathbf{x}) = A\mathbf{x}$.

Suppose that $T: U \mapsto V$ is a linear transformation, $\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t$ are vectors from U and $a_1, a_2, a_3, \dots, a_t$ are scalars from \mathbb{C} . Then

$$T(a_1\mathbf{u}_1 + a_2\mathbf{u}_2 + a_3\mathbf{u}_3 + \cdots + a_t\mathbf{u}_t) = a_1T(\mathbf{u}_1) + a_2T(\mathbf{u}_2) + a_3T(\mathbf{u}_3) + \cdots + a_tT(\mathbf{u}_t)$$

Suppose that $T: U \mapsto V$ is a linear transformation, $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ is a basis for U and \mathbf{w} is a vector from U . Let $a_1, a_2, a_3, \dots, a_n$ be the scalars from \mathbb{C} such that

$$\mathbf{w} = a_1\mathbf{u}_1 + a_2\mathbf{u}_2 + a_3\mathbf{u}_3 + \cdots + a_n\mathbf{u}_n$$

Then

$$T(\mathbf{w}) = a_1T(\mathbf{u}_1) + a_2T(\mathbf{u}_2) + a_3T(\mathbf{u}_3) + \cdots + a_nT(\mathbf{u}_n)$$

Suppose that $T: U \mapsto V$ is a linear transformation. For each \mathbf{v} , define the **pre-image** of \mathbf{v} to be the subset of U given by

$$T^{-1}(\mathbf{v}) = \{\mathbf{u} \in U \mid T(\mathbf{u}) = \mathbf{v}\}$$

Suppose that $T: U \mapsto V$ and $S: U \mapsto V$ are two linear transformations with the same domain and codomain. Then their **sum** is the function $T + S: U \mapsto V$ whose outputs are defined by

$$(T + S)(\mathbf{u}) = T(\mathbf{u}) + S(\mathbf{u})$$

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.

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

$$(\alpha T)(\mathbf{u}) = \alpha T(\mathbf{u})$$

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.

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.

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

$$(S \circ T)(\mathbf{u}) = S(T(\mathbf{u}))$$

Theorem CLTLT Composition of Linear Transformations is a Linear Transformation **233**

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.

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Definition ILT Injective Linear Transformation

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Suppose $T: U \mapsto V$ is a linear transformation. Then T is **injective** if whenever $T(\mathbf{x}) = T(\mathbf{y})$, then $\mathbf{x} = \mathbf{y}$.

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Suppose $T: U \mapsto V$ is a linear transformation. Then the **null space** of T is the set $\mathcal{N}(T) = \{\mathbf{u} \in U \mid T(\mathbf{u}) = \mathbf{0}\}$

Suppose that $T: U \mapsto V$ is a linear transformation. Then the null space of T , $\mathcal{N}(T)$, is a subspace of U .

Suppose $T: U \mapsto V$ is a linear transformation and $\mathbf{v} \in V$. If the preimage $T^{-1}(\mathbf{v})$ is non-empty, and $\mathbf{u} \in T^{-1}(\mathbf{v})$ then

$$T^{-1}(\mathbf{v}) = \{\mathbf{u} + \mathbf{z} \mid \mathbf{z} \in \mathcal{N}(T)\} = \mathbf{u} + \mathcal{N}(T)$$

Suppose that $T: U \mapsto V$ is a linear transformation. Then T is injective if and only if the null space of T is trivial, $\mathcal{N}(T) = \{\mathbf{0}\}$.

Suppose that $T: U \mapsto V$ is an injective linear transformation and $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$ is a linearly independent subset of U . Then $R = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_t)\}$ is a linearly independent subset of V .

Suppose that $T: U \mapsto V$ is a linear transformation and $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_m\}$ is a basis of U . Then T is injective if and only if $C = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_m)\}$ is a linearly independent subset of V .

Suppose that $T: U \mapsto V$ is an injective linear transformation. Then $\dim(U) \leq \dim(V)$.

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are injective linear transformations. Then $(S \circ T): U \mapsto W$ is an injective linear transformation.

Suppose $T: U \mapsto V$ is a linear transformation. Then T is **surjective** if for every $\mathbf{v} \in V$ there exists a $\mathbf{u} \in U$ so that $T(\mathbf{u}) = \mathbf{v}$.

Suppose $T: U \mapsto V$ is a linear transformation. Then the **range** of T is the set

$$\mathcal{R}(T) = \{T(\mathbf{u}) \mid \mathbf{u} \in U\}$$

Suppose that $T: U \mapsto V$ is a linear transformation. Then the range of T , $\mathcal{R}(T)$, is a subspace of V .

Suppose that $T: U \mapsto V$ is a linear transformation. Then T is surjective if and only if the range of T equals the codomain, $\mathcal{R}(T) = V$.

Suppose that $T: U \mapsto V$ is a linear transformation and $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_t\}$ spans U . Then $R = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_t)\}$ spans $\mathcal{R}(T)$.

Suppose that $T: U \mapsto V$ is a linear transformation. Then

$$\mathbf{v} \in \mathcal{R}(T) \text{ if and only if } T^{-1}(\mathbf{v}) \neq \emptyset$$

Suppose that $T: U \mapsto V$ is a linear transformation and $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_m\}$ is a basis of U . Then T is surjective if and only if $C = \{T(\mathbf{u}_1), T(\mathbf{u}_2), T(\mathbf{u}_3), \dots, T(\mathbf{u}_m)\}$ is a spanning set for V .

Suppose that $T: U \mapsto V$ is a surjective linear transformation. Then $\dim(U) \geq \dim(V)$.

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.

The **identity linear transformation** on the vector space W is defined as

$$I_W: W \mapsto W, \quad I_W(\mathbf{w}) = \mathbf{w}$$

Suppose that $T: U \mapsto V$ is a linear transformation. If there is a function $S: V \mapsto U$ such that

$$S \circ T = I_U \qquad T \circ S = I_V$$

then T is **invertible**. In this case, we call S the **inverse** of T and write $S = T^{-1}$.

Suppose that $T: U \mapsto V$ is an invertible linear transformation. Then the function $T^{-1}: V \mapsto U$ is a linear transformation.

Suppose that $T: U \mapsto V$ is an invertible linear transformation. Then T^{-1} is an invertible linear transformation and $(T^{-1})^{-1} = T$.

Suppose $T: U \mapsto V$ is a linear transformation. Then T is invertible if and only if T is injective and surjective.

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are invertible linear transformations. Then the composition, $(S \circ T): U \mapsto W$ is an invertible linear transformation.

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are invertible linear transformations. Then $S \circ T$ is invertible and $(S \circ T)^{-1} = T^{-1} \circ S^{-1}$.

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 .

Suppose U and V are isomorphic vector spaces. Then $\dim(U) = \dim(V)$.

Suppose that $T: U \mapsto V$ is a linear transformation. Then the **rank** of T , $r(T)$, is the dimension of the range of T ,

$$r(T) = \dim(\mathcal{R}(T))$$

Suppose that $T: U \mapsto V$ is a linear transformation. Then the **nullity** of T , $n(T)$, is the dimension of the null space of T ,

$$n(T) = \dim(\mathcal{N}(T))$$

Suppose that $T: U \mapsto V$ 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.

Suppose that $T: U \mapsto V$ is an injective linear transformation. Then the nullity of T is zero, $n(T) = 0$, if and only if T is injective.

Suppose that $T: U \mapsto V$ is a linear transformation. Then

$$r(T) + n(T) = \dim(U)$$

Definition VR Vector Representation

Suppose that V is a vector space with a basis $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$. Define a function $\rho_B: V \mapsto \mathbb{C}^n$ as follows. For $\mathbf{w} \in V$, find scalars $a_1, a_2, a_3, \dots, a_n$ so that

$$\mathbf{w} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + a_3\mathbf{v}_3 + \cdots + a_n\mathbf{v}_n$$

then

$$\rho_B(\mathbf{w}) = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_n \end{bmatrix}$$

The function ρ_B (Definition VR) is a linear transformation.

The function ρ_B (Definition VR) is an injective linear transformation.

The function ρ_B (Definition VR) is a surjective linear transformation.

The function ρ_B (Definition VR) is an invertible linear transformation.

Suppose that V is a vector space with dimension n . Then V is isomorphic to \mathbb{C}^n .

Suppose U and V are both finite-dimensional vector spaces. Then U and V are isomorphic if and only if $\dim(U) = \dim(V)$.

Suppose that U is a vector space with a basis B of size n . Then $S = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_k\}$ is a linearly independent subset of U if and only if $R = \{\rho_B(\mathbf{u}_1), \rho_B(\mathbf{u}_2), \rho_B(\mathbf{u}_3), \dots, \rho_B(\mathbf{u}_k)\}$ is a linearly independent subset of \mathbb{C}^n .

Suppose that U is a vector space with a basis B of size n . Then $\mathbf{u} \in \mathcal{S}p(\{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_k\})$ if and only if $\rho_B(\mathbf{u}) \in \mathcal{S}p(\{\rho_B(\mathbf{u}_1), \rho_B(\mathbf{u}_2), \rho_B(\mathbf{u}_3), \dots, \rho_B(\mathbf{u}_k)\})$.

Suppose that $T: U \mapsto V$ is a linear transformation, $B = \{\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3, \dots, \mathbf{u}_n\}$ is a basis for U of size n , and C is a basis for V of size m . The the **matrix representation** of T relative to B and C is the $m \times n$ matrix,

$$M_{B,C}^T = [\rho_C(T(\mathbf{u}_1)) | \rho_C(T(\mathbf{u}_2)) | \rho_C(T(\mathbf{u}_3)) | \dots | \rho_C(T(\mathbf{u}_n))]$$

Suppose that $T: U \mapsto V$ 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 $\mathbf{u} \in U$,

$$\rho_C(T(\mathbf{u})) = M_{B,C}^T(\rho_B(\mathbf{u}))$$

or equivalently

$$T(\mathbf{u}) = \rho_C^{-1}(M_{B,C}^T(\rho_B(\mathbf{u})))$$

Suppose that $T: U \mapsto V$ and $S: U \mapsto V$ are linear transformations, B is a basis of U and C is a basis of V . Then

$$M_{B,C}^{T+S} = M_{B,C}^T + M_{B,C}^S$$

Suppose that $T: U \mapsto V$ is a linear transformation, $\alpha \in \mathbb{C}$, B is a basis of U and C is a basis of V . Then

$$M_{B,C}^{\alpha T} = \alpha M_{B,C}^T$$

Theorem MRCLT Matrix Representation of a Composition of Linear Transformations **279**

Suppose that $T: U \mapsto V$ and $S: V \mapsto W$ are linear transformations, B is a basis of U , C is a basis of V , and D is a basis of W . Then

$$M_{B,D}^{S \circ T} = M_{C,D}^S M_{B,C}^T$$

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Theorem INS Isomorphic Null Spaces

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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 null space of T is isomorphic to the null space of $M_{B,C}^T$,

$$\mathcal{N}(T) \cong \mathcal{N}(M_{B,C}^T)$$

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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 range of $M_{B,C}^T$,

$$\mathcal{R}(T) \cong \mathcal{R}(M_{B,C}^T)$$

Suppose that $T: U \mapsto V$ 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

$$M_{C,B}^{T^{-1}} = (M_{B,C}^T)^{-1}$$

Suppose that $T: V \mapsto V$ is a linear transformation. Then a nonzero vector $\mathbf{v} \in V$ is an **eigenvector** of T for the **eigenvalue** λ if $T(\mathbf{v}) = \lambda\mathbf{v}$.

Suppose that V is a vector space, and $I_V: V \mapsto V$ is the identity linear transformation on V . Let $B = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_n\}$ 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 ,

$$\begin{aligned} C_{B,C} &= M_{B,C}^{I_V} \\ &= [\rho_C(I_V(\mathbf{v}_1)) \mid \rho_C(I_V(\mathbf{v}_2)) \mid \rho_C(I_V(\mathbf{v}_3)) \mid \dots \mid \rho_C(I_V(\mathbf{v}_n))] \\ &= [\rho_C(\mathbf{u}_1) \mid \rho_C(\mathbf{u}_2) \mid \rho_C(\mathbf{u}_3) \mid \dots \mid \rho_C(\mathbf{u}_n)] \end{aligned}$$

Suppose that \mathbf{u} is a vector in the vector space V and B and C are bases of V . Then

$$C_{B,C}\rho_B(\mathbf{v}) = \rho_C(\mathbf{v})$$

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

$$C_{B,C}^{-1} = C_{C,B}$$

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

$$M_{B,D}^T = C_{E,D} M_{C,E}^T C_{B,C}$$

Suppose that $T: V \mapsto V$ is a linear transformation and B and C are bases of V . Then

$$M_{B,B}^T = C_{B,C}^{-1} M_{C,C}^T C_{B,C}$$

Suppose that $T: V \mapsto V$ is a linear transformation and B is a basis of V . Then $\mathbf{v} \in V$ is an eigenvector of T for the eigenvalue λ if and only if $\rho_B(\mathbf{v})$ is an eigenvector of $M_{B,B}^T$ for the eigenvalue λ .