

MA1522 Linear Algebra for Computing
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Notes

Sim Ray En Ryan

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Contents

1 Linear Equations	4
1.1 Linear Equation	4
2 Matrix Algebra	4
2.1 Linear Systems / Matrices	4
2.1.1 Consistency of Linear Systems	4
2.1.2 Augmented Matrix	4
2.1.3 Matrix Naming and Size	4
2.2 Row Operations and Echelon Forms	4
2.2.1 Fundamental Row Operations	4
2.2.2 Echelon Forms	5
2.3 Vectors and Span	5
2.3.1 Vectors	5
2.3.2 Span	5
2.4 Matrix and Vector Equations	5
2.4.1 Matrix Equation	5
2.4.2 Homogeneous Systems	6
2.4.3 Parametric Forms	6
2.5 Matrix Operations	6
2.5.1 Matrix Equality	6
2.5.2 Basic Operations	6
2.5.3 Matrix Multiplication	6
2.5.4 Matrix Powers	6
2.5.5 Transpose	7
3 Determinants and Inverses	7
3.1 Matrix Inverse	7
3.1.1 Definition and Calculation	7
3.1.2 Elementary Matrices	7
3.1.3 Adjoint Matrix	7
3.2 Determinant	8
3.2.1 Calculation	8
3.2.2 Determinant Algebra	8
3.2.3 Cramer's Rule	8
3.3 LU Factorization	8
4 Vector Spaces and Subspaces	9
4.1 Subspaces	9
4.2 Linear Independence and Basis	9
4.2.1 Linear Independence	9
4.2.2 Basis	9

4.3	Fundamental Subspaces	9
4.3.1	Column Space	9
4.3.2	Row Space	10
4.3.3	Nullspace	10
4.4	Rank and Nullity	10
4.4.1	Consistency and Rank	10
4.4.2	Full Rank (Invertibility Conditions)	10
5	Orthogonal Projection and Least Squares	11
5.1	Dot Product, Norm, and Angle	11
5.2	Orthogonality	11
5.3	Orthogonal Projection	12
5.4	Gram-Schmidt Process	12
5.5	QR Factorization	12
5.6	Least Squares Approximation	13
6	Diagonalization and Eigenspaces	13
6.1	Eigenvalues and Eigenvectors	13
6.2	Characteristic Polynomial and Eigenspace	13
6.3	Multiplicities	13
6.4	Diagonalization	14
6.5	Orthogonal Diagonalization	14
7	Linear Transformations	14
7.1	Definition and Standard Matrix	14
7.2	Range and Kernel	15
7.3	Injective, Surjective, and Bijective	15
7.4	Invertible Transformations	15
8	Invertible Matrix Theorem (Summary)	15

1 Linear Equations

1.1 Linear Equation

A **linear equation** is an equation of the form $ax_1 + bx_2 + cx_3 + \dots + zx_z = n(x_0)$.

- a, b, c, \dots are the **coefficients**.
- x_1, x_2, x_3, \dots are the **variables**.

2 Matrix Algebra

2.1 Linear Systems / Matrices

A system of linear equations can be represented by a matrix.

2.1.1 Consistency of Linear Systems

- **Inconsistent:** No solution.
- **Consistent:** Has at least one solution.
 - **One solution.**
 - **Infinite solutions** (e.g., the equations describe the same line).

2.1.2 Augmented Matrix

An **Augmented Matrix** is a matrix that contains the constants from the right-hand side of the linear equations, separated from the coefficient matrix by a vertical line.

2.1.3 Matrix Naming and Size

- A matrix is referred to as $m \times n$ (read as “ m by n ”), where m is the number of **rows** and n is the number of **columns**.
- A **Square matrix** of order n has n rows and n columns.

2.2 Row Operations and Echelon Forms

2.2.1 Fundamental Row Operations

- **Replacement:** Adding or subtracting a multiple of one row to another row (e.g., $R_i + cR_j \rightarrow R_i$).
- **Interchange:** Swapping two rows ($R_i \leftrightarrow R_j$).
- **Scaling:** Multiplying a row by a non-zero scalar (e.g., $cR_x \rightarrow R_x$).

2.2.2 Echelon Forms

- **Echelon form:**
 - Any row of all zeros is at the bottom of the matrix.
 - The leading non-zero entry (pivot) of each non-zero row is in a column to the right of the leading entry of the row above it (staircase pattern).
- **Reduced Row Echelon Form (RREF):** An echelon form matrix where:
 - Each leading entry is 1 (a **leading 1**).
 - Each leading 1 is the only non-zero entry in its column.
- **Pivot Columns:** Columns that contain a leading 1.
 - Variables corresponding to pivot columns are **Basic Variables**.
 - Other variables are **Free Variables**.

2.3 Vectors and Span

2.3.1 Vectors

- A **vector** is an $n \times 1$ matrix. The set of all $n \times 1$ matrices is denoted R^n .
- A vector represents a line segment from the origin to a point in n -dimensional space.
- The **zero vector (0)** or **null vector** is a vector where all entries are zero.

2.3.2 Span

- $\text{Span}\{\mathbf{v}\}$ is the set of all scalar multiples of \mathbf{v} (points on the line that passes through $\mathbf{0}$ and \mathbf{v}).
- $\text{Span}\{\mathbf{u}, \mathbf{v}\}$ will describe a plane in R^n space, provided \mathbf{u} is not a scalar multiple of \mathbf{v} .
- $\text{Span}\{\mathbf{v}_1, \mathbf{v}_2, \dots\}$ is the set of all possible linear combinations $a\mathbf{v}_1 + b\mathbf{v}_2 + \dots$

2.4 Matrix and Vector Equations

2.4.1 Matrix Equation

A **matrix equation** is written as $A\mathbf{x} = \mathbf{b}$, where:

- A is an $m \times n$ matrix.
- \mathbf{x} is an $n \times 1$ vector (A must have as many columns as \mathbf{x} has rows).
- \mathbf{b} is an $m \times 1$ vector.

2.4.2 Homogeneous Systems

- A system is **homogeneous** if $A\mathbf{x} = \mathbf{0}$.
- A homogeneous system always has the **trivial solution** ($\mathbf{x} = \mathbf{0}$).
- If a homogeneous system has a free variable, it has infinite solutions.
- The solution set of a homogeneous system is a **subspace** called the **nullspace** ($\text{Null}(A)$).

2.4.3 Parametric Forms

The solution set of a linear system can be expressed in **parametric forms**:

- **Line:** $\mathbf{x} = s\mathbf{u}$.
- **Plane:** $\mathbf{x} = s\mathbf{u} + t\mathbf{v}$.

2.5 Matrix Operations

2.5.1 Matrix Equality

Two matrices are equal if they have the same size (rows and columns) and their corresponding entries are equal.

2.5.2 Basic Operations

- **Addition:** Only possible if the matrices have the same size.
- **Scalar Multiplication:** Multiplying every entry in a matrix by a scalar.

2.5.3 Matrix Multiplication

- AB is only possible if the number of columns of A equals the number of rows of B .
- The entry in row i and column j of the product AB is given by $(AB)_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \dots$
- **Right multiplying** B to A means AB .
- **Left multiplying** B to A means BA .

2.5.4 Matrix Powers

- **Power:** Multiplying a square matrix by itself ($A^m = A \cdot A \cdot \dots \cdot A$).
- **Power 0:** $A^0 = I$, where I is the **Identity Matrix** (a square matrix with 1s on the main diagonal and 0s elsewhere).

2.5.5 Transpose

- **Transpose (A^T):** Rows become columns, and columns become rows.
- **Property:** $(AB)^T = B^T A^T$.

3 Determinants and Inverses

3.1 Matrix Inverse

3.1.1 Definition and Calculation

- **Inverse (A^{-1}):** For a square matrix A , C is the inverse if $AC = I$ and $CA = I$ (written $C = A^{-1}$).
- A is **invertible** if and only if $\det(A) \neq 0$.

- **For a 2×2 matrix $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$:**

$$A^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix} = \frac{1}{\det(A)} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

- **Solution to $Ax = b$:** If A is invertible, the unique solution is $x = A^{-1}b$.
- **Inverse of a Product:** $(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$.

3.1.2 Elementary Matrices

- An **Elementary Matrix (E)** is a matrix obtained by performing a single row operation on the identity matrix I .
- If $A \sim E_1 A \sim E_2 E_1 A = I$, then $A^{-1} = E_k \dots E_2 E_1$.
- **Finding A^{-1} :** The inverse can be found by row reducing the augmented matrix $(A|I)$ to $(I|A^{-1})$.

3.1.3 Adjoint Matrix

- **Adjoint ($\text{adj}(A)$):** The transpose of the matrix of cofactors.
- **Inverse Formula:** $A^{-1} = \frac{1}{\det(A)} \cdot \text{adj}(A)$.

3.2 Determinant

3.2.1 Calculation

- **Cofactor:** $C_{ij} = (-1)^{i+j} \det(A_{ij})$, where A_{ij} is the submatrix obtained by removing row i and column j .
- **Cofactor Expansion (Theorem 3.1):** The determinant of A can be calculated by cofactor expansion along any row i or column j :

$$\det(A) = a_{i1}C_{i1} + a_{i2}C_{i2} + \dots$$

- **Strategy:** Choose the row or column with the most zeros.
- **Triangular Matrix:** The determinant is the product of the diagonal entries.

3.2.2 Determinant Algebra

- **Row Replacement** ($R_i + cR_j \rightarrow R_i$): The determinant remains unchanged.
- **Row Interchange** ($R_i \leftrightarrow R_j$): The determinant changes sign (becomes negative).
- **Row Scaling** ($cR_i \rightarrow R_i$): The new determinant is $c \cdot \det(A)$.
- **Transpose** (A^T): $\det(A^T) = \det(A)$.
- **Product Rule:** $\det(AB) = \det(A) \det(B)$.
- **Inverse Rule:** $\det(A^{-1}) = (\det(A))^{-1}$.

3.2.3 Cramer's Rule

Cramer's Rule provides a formula for the unique solution $\mathbf{x} = (x_1, \dots, x_n)$ of $A\mathbf{x} = \mathbf{b}$ when $\det(A) \neq 0$:

$$x_i = \frac{\det(A_i(\mathbf{b}))}{\det(A)}$$

where $A_i(\mathbf{b})$ is the matrix formed by replacing the i -th column of A with the vector \mathbf{b} .

3.3 LU Factorization

- **Factorization:** $A = LU$, where L is a **lower triangular matrix** (1s on the diagonal and non-zero entries only below) and U is an **upper triangular matrix** (the Echelon form of A using only row replacements).
- **Solving $A\mathbf{x} = \mathbf{b}$:** This is solved in two steps:
 1. Solve $L\mathbf{y} = \mathbf{b}$ for \mathbf{y} (using forward substitution or RREF of $(L|\mathbf{b})$).
 2. Solve $U\mathbf{x} = \mathbf{y}$ for \mathbf{x} (using backward substitution or RREF of $(U|\mathbf{y})$).

4 Vector Spaces and Subspaces

4.1 Subspaces

A subset V of R^n is a **subspace** if it is a linear span of a set of vectors and satisfies:

1. V contains the origin ($\mathbf{0} \in V$).
 2. V is closed under addition (if $\mathbf{u}, \mathbf{v} \in V$, then $\mathbf{u} + \mathbf{v} \in V$).
 3. V is closed under scalar multiplication (if $\mathbf{u} \in V$ and $a \in R$, then $a\mathbf{u} \in V$).
- **Spans as Subspaces:** $\text{Span}\{\mathbf{v}_1, \mathbf{v}_2, \dots\}$ is always a subspace.

4.2 Linear Independence and Basis

4.2.1 Linear Independence

- A set of vectors is **linearly independent** if the only solution to the linear combination $c_1\mathbf{v}_1 + c_2\mathbf{v}_2 + \dots = \mathbf{0}$ is the trivial solution $c_1 = c_2 = \dots = 0$.
- A set is linearly independent if the RREF of the matrix formed by the vectors as columns has **no non-pivot columns**.
- A set of more than n vectors in R^n space is always **linearly dependent**.
- The zero vector $\mathbf{0}$ always makes a set linearly dependent.

4.2.2 Basis

A set S is a **basis** for a vector space V if:

1. $\text{Span}(S) = V$.
2. S is **linearly independent**.

4.3 Fundamental Subspaces

Let A be an $m \times n$ matrix.

4.3.1 Column Space

- **Column Space ($\text{Col}(A)$):** The span of the columns of A . $\text{Col}(A) \subseteq R^m$.
- $\text{Col}(A) = \{\mathbf{v} \in R^m \mid A\mathbf{x} = \mathbf{v} \text{ is consistent}\}$.
- **Basis of $\text{Col}(A)$:** The pivot columns of the original matrix A (not $\text{RREF}(A)$).
- **Note:** $\text{Col}(A) \neq \text{Col}(\text{RREF}(A))$, as row operations do not preserve the column space.

4.3.2 Row Space

- **Row Space ($\text{Row}(A)$):** The span of the rows of A . $\text{Row}(A) \subseteq R^n$.
- $\text{Row}(A) = \text{Row}(\text{RREF}(A))$.
- **Basis of $\text{Row}(A)$:** The non-zero rows of $\text{RREF}(A)$.

4.3.3 Nullspace

- **Nullspace ($\text{Null}(A)$) or Kernel ($\text{Ker}(T)$):** The solution space to the homogeneous system $A\mathbf{x} = \mathbf{0}$.
- $\text{Null}(A) = \{\mathbf{v} \in R^n \mid A\mathbf{v} = \mathbf{0}\}$.

4.4 Rank and Nullity

- **Rank ($\text{rank}(A)$):** $\dim(\text{Col}(A))$. It equals the number of pivot columns in $\text{RREF}(A)$ and the number of non-zero rows in $\text{RREF}(A)$ ($\dim(\text{Row}(A))$).
- **Nullity ($\text{nullity}(A)$):** $\dim(\text{Null}(A))$. It equals the number of non-pivot columns (free variables) in $\text{RREF}(A)$.
- **Rank-Nullity Theorem:** $\text{rank}(A) + \text{nullity}(A) = \text{number of columns of } A$.

4.4.1 Consistency and Rank

The system $A\mathbf{x} = \mathbf{b}$ is **consistent** if and only if $\text{rank}(A) = \text{rank}([Ab])$. If inconsistent, $\text{rank}(A) < \text{rank}([Ab])$.

4.4.2 Full Rank (Invertibility Conditions)

- **If A is $n \times n$ (square):** A is invertible $\iff \text{rank}(A) = n$ ($\iff \text{RREF}(A) = I_n$).
- **If A is $m \times n$ and $\text{rank}(A) = n$ (full column rank, $m \geq n$):**
 - * $\text{Col}(A)$ is R^m .
 - * Columns of A are linearly independent.
 - * $\text{Null}(A) = \{\mathbf{0}\}$ ($\text{nullity}(A) = 0$).
 - * $A\mathbf{x} = \mathbf{0}$ has only the trivial solution.
 - * $A^T A$ is an invertible matrix of order n .
 - * A has a **left inverse** B such that $BA = I_n$.
- **If A is $m \times n$ and $\text{rank}(A) = m$ (full row rank, $m \leq n$):**

- * $\text{Col}(A) = R^m$.
- * $A\mathbf{x} = \mathbf{b}$ is consistent for every \mathbf{b} in R^m .
- * Rows of A are linearly independent.
- * $\text{RREF}(A)$ has no zero rows.
- * AA^T is an invertible matrix of order m .
- * A has a **right inverse** B such that $AB = I_m$.

5 Orthogonal Projection and Least Squares

5.1 Dot Product, Norm, and Angle

- **Inner Product (Dot Product):** For vectors \mathbf{u}, \mathbf{v} , the inner product is $\mathbf{u}^T \mathbf{v}$, which results in a 1×1 matrix (a scalar value).
- **Outer Product:** $\mathbf{u}\mathbf{v}^T$, which results in an $n \times n$ matrix.
- **Length / Norm ($\|\mathbf{u}\|$):** The distance of \mathbf{u} from the origin. Calculated as $\|\mathbf{u}\| = \sqrt{\mathbf{u} \cdot \mathbf{u}}$.
- **Unit Vector:** A vector \mathbf{u} such that $\|\mathbf{u}\| = 1$. Found by $\mathbf{u} = \mathbf{v}/\|\mathbf{v}\|$.
- **Angle between \mathbf{u} and \mathbf{v} :**

$$\theta = \cos^{-1} \left(\frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \cdot \|\mathbf{v}\|} \right)$$

5.2 Orthogonality

- **Orthogonal Vectors:** \mathbf{u} and \mathbf{v} are **orthogonal** if their dot product is zero ($\mathbf{u} \cdot \mathbf{v} = 0$). The zero vector is orthogonal to every vector.
- **Orthogonal Set (Basis S):** A set of non-zero vectors where every pair of distinct vectors is orthogonal.
- **Orthonormal Set (Basis S):** An orthogonal set where every vector is a unit vector.
- **Orthogonal Matrix (A):** A square matrix whose columns are an orthonormal basis for R^n . This implies $A^T A = I = AA^T$ and $A^T = A^{-1}$.

5.3 Orthogonal Projection

- **Coordinates relative to an Orthogonal Basis** $B = \{\mathbf{u}_1, \dots, \mathbf{u}_n\}$: If $\mathbf{v} = c_1\mathbf{u}_1 + \dots + c_n\mathbf{u}_n$, the coordinate c_i is found by:

$$c_i = \frac{\mathbf{u}_i \cdot \mathbf{v}}{\|\mathbf{u}_i\|^2} = \frac{\mathbf{u}_i \cdot \mathbf{v}}{\mathbf{u}_i \cdot \mathbf{u}_i}$$

- **Coordinates relative to an Orthonormal Basis**: If the basis is orthonormal, $c_i = \mathbf{u}_i \cdot \mathbf{v}$.
- **Projection of \mathbf{w} onto Subspace** $V = \text{Span}\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$: If B is an orthogonal basis for V , the projection \mathbf{w}_p is:

$$\mathbf{w}_p = \sum_{i=1}^k \frac{\mathbf{u}_i \cdot \mathbf{w}}{\|\mathbf{u}_i\|^2} \mathbf{u}_i$$

- **Decomposition**: Any vector \mathbf{w} can be decomposed as $\mathbf{w} = \mathbf{w}_p + \mathbf{w}_n$, where \mathbf{w}_p is the projection of \mathbf{w} onto the subspace (in the subspace) and \mathbf{w}_n is the component normal (orthogonal) to the subspace.

5.4 Gram-Schmidt Process

The **Gram-Schmidt Process** converts a basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ for a subspace into an orthogonal basis $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$.

- $\mathbf{v}_1 = \mathbf{u}_1$.
- $\mathbf{v}_2 = \mathbf{u}_2 - \text{proj}_{\mathbf{v}_1} \mathbf{u}_2 = \mathbf{u}_2 - \frac{\mathbf{u}_2 \cdot \mathbf{v}_1}{\|\mathbf{v}_1\|^2} \mathbf{v}_1$.
- $\mathbf{v}_3 = \mathbf{u}_3 - \text{proj}_{\mathbf{v}_1} \mathbf{u}_3 - \text{proj}_{\mathbf{v}_2} \mathbf{u}_3$.
- If any resulting $\mathbf{v}_i = \mathbf{0}$, the original set was linearly dependent.

5.5 QR Factorization

- **Factorization**: $A = QR$, where A must have linearly independent columns.
- Q is an orthogonal matrix obtained by performing the Gram-Schmidt process on the columns of A . $Q^T Q = I$.
- R is an upper triangular matrix with positive diagonal entries, calculated as $R = Q^T A$.

5.6 Least Squares Approximation

- **Least-Squares Solution ($\hat{\mathbf{x}}$)**: A vector $\hat{\mathbf{x}}$ is a least-squares solution to $A\mathbf{x} = \mathbf{b}$ if $\|A\hat{\mathbf{x}} - \mathbf{b}\| \leq \|A\mathbf{v} - \mathbf{b}\|$ for all \mathbf{v} .
- $A\hat{\mathbf{x}}$ is the vector in $\text{Col}(A)$ that is **closest to \mathbf{b}** , i.e., $A\hat{\mathbf{x}} = \text{proj}_{\text{Col}(A)}\mathbf{b}$.
- **Normal Equations**: The least-squares solutions are the solutions $\hat{\mathbf{x}}$ to the system:

$$A^T A \mathbf{x} = A^T \mathbf{b}$$

- **Unique Solution**: The least-squares solution $\hat{\mathbf{x}}$ is unique if $A^T A$ is invertible. In this case, $\hat{\mathbf{x}} = (A^T A)^{-1} A^T \mathbf{b}$.

6 Diagonalization and Eigenspaces

6.1 Eigenvalues and Eigenvectors

- **Eigenvalue (λ)**: A scalar λ is an eigenvalue of an $n \times n$ matrix A if there is a non-zero vector \mathbf{v} such that $A\mathbf{v} = \lambda\mathbf{v}$.
- **Eigenvector (\mathbf{v})**: The non-zero vector \mathbf{v} is the eigenvector corresponding to the eigenvalue λ .

6.2 Characteristic Polynomial and Eigenspace

- **Characteristic Polynomial ($\text{char}(A)$)**: $\det(A - \lambda I)$ or $\det(\lambda I - A)$.
- **Finding Eigenvalues**: The eigenvalues are the roots λ of the characteristic equation $\det(A - \lambda I) = 0$.
- **Eigenspace (E_λ)**: The set of all vectors \mathbf{v} such that $A\mathbf{v} = \lambda\mathbf{v}$. It is the $\text{Null}(A - \lambda I)$ (the solution space to the homogeneous system $(A - \lambda I)\mathbf{x} = \mathbf{0}$).

6.3 Multiplicities

- **Algebraic Multiplicity (AM)**: The number of times λ appears as a root of the characteristic polynomial.
- **Geometric Multiplicity (GM)**: $\dim(E_\lambda) = \text{nullity}(A - \lambda I)$ (the number of free variables when solving for the eigenspace).
- **Relationship**: $1 \leq \text{Geometric Multiplicity} \leq \text{Algebraic Multiplicity}$. If $\text{AM} = 1$, then $\text{GM} = 1$.

6.4 Diagonalization

- **Diagonalizable:** A is **diagonalizable** if it is similar to a diagonal matrix D , meaning $A = PDP^{-1}$ or $P^{-1}AP = D$.
- D is the diagonal matrix made up of the eigenvalues of A .
- P is the matrix whose columns are the corresponding eigenvectors of A .
- **Condition for Diagonalization:** A is diagonalizable if and only if the sum of the geometric multiplicities of all eigenvalues equals n , or if A has n distinct eigenvalues.
- **Application:** Calculating powers of A : $A^m = PD^mP^{-1}$, where D^m is easy to calculate.

6.5 Orthogonal Diagonalization

- **Orthogonally Diagonalizable:** A is **orthogonally diagonalizable** if $A = PDP^T$ (where $P^T = P^{-1}$).
- **Condition:** A must be a **symmetric matrix** ($A^T = A$).
- **Property:** Eigenvectors from different eigenspaces are orthogonal to each other if A is symmetric.
- **Process:** Use Gram-Schmidt to find an orthonormal basis for each eigenspace.

7 Linear Transformations

7.1 Definition and Standard Matrix

- **Linear Transformation (T):** A function $T : R^n \rightarrow R^m$ that satisfies:
 1. $T(\mathbf{u} + \mathbf{v}) = T(\mathbf{u}) + T(\mathbf{v})$
 2. $T(c\mathbf{u}) = cT(\mathbf{u})$This is equivalent to $T(c\mathbf{u} + d\mathbf{v}) = cT(\mathbf{u}) + dT(\mathbf{v})$.
- **Standard Matrix (A):** Every linear transformation T can be represented by an $m \times n$ matrix A such that $T(\mathbf{x}) = A\mathbf{x}$.
- **Domain and Codomain:** R^n is the **domain**, and R^m is the **codomain**.
- **Image:** $T(\mathbf{x})$ is the image of \mathbf{x} in R^m .

7.2 Range and Kernel

- **Range ($R(T)$):** The set of all images $T(\mathbf{x})$. $R(T) = \text{Col}(A)$. The range is a subspace of the codomain R^m .
- **Kernel ($\text{Ker}(T)$):** The set of vectors \mathbf{u} in the domain R^n that are sent to $\mathbf{0}$ in the codomain. $\text{Ker}(T) = \text{Null}(A)$. The kernel is a subspace of the domain R^n .
- **Rank-Nullity Theorem for Transformations:** $\dim(\text{Range}(T)) + \dim(\text{Ker}(T)) = n$ (dimension of the domain).

7.3 Injective, Surjective, and Bijective

- **Surjective (Onto):** T is surjective if each \mathbf{b} in R^m is the image of at least one \mathbf{a} in R^n .
 - * $\iff \text{Range}(T) = R^m$
 - * $\iff \text{rank}(T) = m$.
- **Injective (One-to-One):** T is injective if each \mathbf{b} in R^m is the image of at most one \mathbf{a} in R^n .
 - * $\iff T(\mathbf{x}) = \mathbf{0}$ only has the trivial solution $\mathbf{x} = \mathbf{0}$.
 - * $\iff \text{Ker}(T) = \{\mathbf{0}\}$.
 - * $\iff \text{nullity}(T) = 0$.
- **Bijective:** T is bijective if it is both injective and surjective.

7.4 Invertible Transformations

- A linear transformation $T : R^n \rightarrow R^n$ (square) is **invertible** if and only if its standard matrix A is invertible.
- **Area/Volume Scaling:** If S is a set in R^n , the volume of $T(S)$ is $|\det(A)| \times$ volume of S .

8 Invertible Matrix Theorem (Summary)

Let A be a square matrix of order n . The following statements are equivalent to A being invertible:

- **Definition / Inverse:**
 - * A is invertible.
 - * There exists an $n \times n$ matrix C such that $CA = I_n$ (Left Inverse).

- * There exists an $n \times n$ matrix D such that $AD = I_n$ (Right Inverse).
- * A^T is invertible.

– **Linear Systems:**

- * $A\mathbf{x} = \mathbf{0}$ has only the trivial solution $\mathbf{x} = \mathbf{0}$.
- * $A\mathbf{x} = \mathbf{b}$ has a unique solution $\mathbf{x} = A^{-1}\mathbf{b}$ for every \mathbf{b} .

– **Row Operations / Echelon Form:**

- * $\text{RREF}(A) = I_n$.
- * A is a product of elementary matrices.
- * A has n pivot positions.

– **Determinants / Eigenspaces:**

- * $\det(A) \neq 0$.
- * 0 is not an eigenvalue of A .

– **Vector Spaces / Rank:**

- * The columns of A form a linearly independent set.
- * The rows of A form a linearly independent set.
- * The columns (or rows) of A form a basis for R^n .
- * $\text{rank}(A) = n$.
- * $\text{nullity}(A) = 0$.
- * A has no non-pivot columns.

– **Linear Transformations:**

- * The linear transformation $T(\mathbf{x}) = A\mathbf{x}$ is **bijective** (one-to-one and onto).
- * $T(\mathbf{x}) = A\mathbf{x}$ maps R^n **onto** R^n (surjective).