

Chapter 2 Vector Spaces and Matrices

1. Vector and Matrix
2. Rank of Matrix
3. Linear Equations
4. Inner Product and Norm



Notation

- **set**: If \mathcal{X} is a set and x is an element of \mathcal{X} , we write $x \in \mathcal{X}$.
- **max/min**: maximum/minimum point of \mathcal{X} .
- **sup/inf**: supremum/infimum of \mathcal{X} . e.g., $\inf_x \exp(x) = 0$, $\sup_x \arctan(x) = \frac{\pi}{2}$
- For $x = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$, we use x_i as its i th coordinate.
Note: Throughout the text we adopt the convention that the term vector (without the qualifier row or column) refers to a **column vector**.
- **subspace**: $\emptyset \neq \mathcal{V} \subset \mathbb{R}^n$ is called subspace if $ax + by \in \mathcal{V}$, $\forall x, y \in \mathcal{V}$.
- **affine set**: A set $\mathcal{X} = \bar{x} + \mathcal{V}$, where $\bar{x} \in \mathbb{R}^n$ and $\mathcal{V} \subseteq \mathbb{R}^n$ is a subspace.

Definition (linear dependent)

A set of vectors a_1, \dots, a_k are said to be linearly independent if the equality

$$\alpha_1 a_1 + \alpha_2 a_2 + \dots + \alpha_k a_k = 0$$

implies that all coefficients α_i ($i = 1, \dots, k$), are equal to zero. A set of the vectors a_1, \dots, a_k are linearly dependent if it is not linearly independent.

★ The set composed of the single vector 0 is always linearly dependent.

Definition (linear combination)

A vector \mathbf{a} is said to be a linear combination of vectors $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k$ if there are scalars $\alpha_1, \alpha_2, \dots, \alpha_k \in \mathbb{R}$ such that

$$\mathbf{a} = \alpha_1 \mathbf{a}_1 + \alpha_2 \mathbf{a}_2 + \cdots \alpha_k \mathbf{a}_k.$$

Proposition (property of linear dependent)

A set of vectors $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k$ are linearly dependent if and only if one of the vectors from the set is a linear combination of the remaining vectors.

Definition (span subspace)

Let $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k$ be vectors in \mathbb{R}^n . The set of all their linear combinations is called the span of $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k$ and is denoted

$$\text{span}[\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k] = \left\{ \sum_{i=1}^k \alpha_i \mathbf{a}_i \mid \alpha_1, \dots, \alpha_k \in \mathbb{R} \right\}.$$

Definition (basis of the subspace)

Given a subspace \mathcal{V} , any set of linearly independent vectors $\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k\} \subset \mathcal{V}$ such that $\mathcal{V} = \text{span}[\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k]$ is referred to as a basis of the subspace \mathcal{V} .

★ All the bases of a subspace \mathcal{V} contain the same number of vectors. This number is called the dimension of \mathcal{V} , denoted by $\dim \mathcal{V}$.

Proposition (property of linear dependent)

If $\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k\}$ is a basis of \mathcal{V} , then any vector $\mathbf{a} \in \mathcal{V}$ can be represented uniquely as

$$\mathbf{a} = \alpha_1 \mathbf{a}_1 + \alpha_2 \mathbf{a}_2 + \cdots \alpha_k \mathbf{a}_k,$$

where the coefficients $\alpha_i \in \mathbb{R}$, $i = 1, 2, \dots, k$. The α_i , $i = 1, 2, \dots, k$, are called the coordinates of \mathbf{a} with respect to the basis $\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k\}$.

Definition (natural basis)

The natural (or canonical) basis of \mathbb{R}^n is the column vectors of $n \times n$ identity.

Matrix

Matrices are rectangular array of numbers. A matrix with m rows and n columns is called an $m \times n$ matrix, and we write

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}, \quad \mathbf{A}^\top = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{m1} \\ a_{12} & a_{22} & \cdots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{mn} \end{bmatrix} \text{ is its transpose.}$$

Definition (range and null of $\mathbf{A} \in \mathbb{R}^{m \times n}$)

- **Range of \mathbf{A} :** $\mathcal{R}(\mathbf{A}) = \{\mathbf{y} \in \mathbb{R}^m \mid \mathbf{y} = \mathbf{A}\mathbf{x}, \forall \mathbf{x} \in \mathbb{R}^n\}$.
- **Null of \mathbf{A} :** $\mathcal{N}(\mathbf{A}) = \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{A}\mathbf{x} = \mathbf{0}\}$.

Definition (trace of square matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$): $\text{tr}(\mathbf{A}) = \sum_{i=1}^n a_{ii}$

properties of trace:

- $\text{tr}(\alpha\mathbf{A} + \beta\mathbf{B}) = \alpha\text{tr}(\mathbf{A}) + \beta\text{tr}(\mathbf{B})$; $\text{tr}(\mathbf{A}^T) = \text{tr}(\mathbf{A})$; $\text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA})$;
- $\text{tr}(\mathbf{A}) = \sum_{i=1}^n \lambda_i$ the eigenvalues of \mathbf{A} are denoted by $\lambda_1, \dots, \lambda_n$.

Definition (rank of matrix)

The maximal number of linearly independent columns of \mathbf{A} is called the rank of the matrix \mathbf{A} , denoted $\text{rank}\mathbf{A}$.

★ $\text{rank}\mathbf{A} = \text{dimension of } \text{span}[\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n] = \text{span}[\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_m]$.

preserving rank, i.e., $\text{rank}\mathbf{A}$ is invariant under some operations

- ① Multiplication of the columns of \mathbf{A} by nonzero scalars.
- ② Interchange of the columns.
- ③ Addition to a given column a linear combination of other columns.
- ④ Multiplied by invertible matrix.
- ⑤ Rigid transform (e.g., transform, rotation, flip, reflective, \dots)
- ⑥

★ $\text{rank}\mathbf{A}$ is invariant when operation is applied to rows.



Definition (determinant)

For any square matrix, e.g., $\mathbf{A} \in \mathbb{R}^{n \times n}$, a scalar called the determinant of \mathbf{A} , denoted $\det \mathbf{A}$ or $|\mathbf{A}|$.

★ Properties and calculations of determinant (cf. linear algebra textbook).

Proposition

If matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ ($m > n$) has a nonzero n th-order minor, then the columns of \mathbf{A} are linearly independent; i.e., $\text{rank} \mathbf{A} = n$.

Definition

A nonsingular matrix is a square matrix satisfying $\det \mathbf{A} \neq 0$. Suppose that $\mathbf{A} \in \mathbb{R}^{n \times n}$. Then, \mathbf{A} is nonsingular if and only if there is a $\mathbf{B} \in \mathbb{R}^{n \times n}$ such that $\mathbf{AB} = \mathbf{BA} = \mathbf{I}_n$. The matrix \mathbf{B} is called inverse of \mathbf{A} .

Linear Equations

Definition (linear equations)

$$\mathbf{A}\mathbf{x} = \mathbf{b} \quad \text{or} \quad x_1\mathbf{a}_1 + x_2\mathbf{a}_2 + \cdots + x_n\mathbf{a}_n = \mathbf{b}.$$

Theorem (existence, uniqueness of solution)

The linear equations $\mathbf{A}\mathbf{x} = \mathbf{b}$ with $\mathbf{A} \in \mathbb{R}^{m \times n}$, it has

- solution $\iff \text{rank}\mathbf{A} = \text{rank}[\mathbf{A}, \mathbf{b}]$.
- unique solution $\iff \text{rank}\mathbf{A} = \text{rank}[\mathbf{A}, \mathbf{b}] = n$.
- infinite solutions $\iff \text{rank}\mathbf{A} = \text{rank}[\mathbf{A}, \mathbf{b}] < n$.

Theorem

The linear equations $\mathbf{A}\mathbf{x} = \mathbf{b}$ with $\mathbf{A} \in \mathbb{R}^{m \times n}$. The solution set of $\mathbf{A}\mathbf{x} = \mathbf{b}$ can be formulated by

- $\mathbf{x} = \mathbf{x}^0 + k_1\boldsymbol{\xi}_1 + k_2\boldsymbol{\xi}_2 + \cdots + k_{n-r}\boldsymbol{\xi}_{n-r};$
- $\mathbf{x} = \mathbf{x}^0 + \mathcal{N}(\mathbf{A});$
- $\mathbf{x} = \mathbf{A}^\dagger \mathbf{b}; \dots$

Inner Products and Norms

Definition (Euclidean inner product)

For $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, the Euclidean inner product is $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n x_i y_i = \mathbf{x}^\top \mathbf{y}$.

Definition (inner product)

The inner product is a real-valued function $\langle \cdot, \cdot \rangle : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ with the following properties:

- 1 Nonnegativity: $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$, and $\langle \mathbf{x}, \mathbf{x} \rangle = 0 \iff \mathbf{x} = \mathbf{0}$.
- 2 Symmetry: $\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{y}, \mathbf{x} \rangle$.
- 3 Additivity: $\langle \mathbf{x} + \mathbf{y}, \mathbf{z} \rangle = \langle \mathbf{x}, \mathbf{z} \rangle + \langle \mathbf{y}, \mathbf{z} \rangle$.
- 4 Homogeneity: $\langle r\mathbf{x}, \mathbf{y} \rangle = r\langle \mathbf{x}, \mathbf{y} \rangle$ for every $r \in \mathbb{R}$.

Definition (orthogonal)

The vectors \mathbf{x} and \mathbf{y} are said to be orthogonal if $\langle \mathbf{x}, \mathbf{y} \rangle = 0$.

Inner Products and Norms

Definition (Euclidean norm)

The Euclidean norm of an $\mathbf{x} \in \mathbb{R}^n$ is defined as $\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle} = \sqrt{\mathbf{x}^\top \mathbf{x}}$.

Theorem (Cauchy-Schwarz inequality)

For any \mathbf{x} and \mathbf{y} in \mathbb{R}^n , the Cauchy-Schwarz inequality $|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\| \|\mathbf{y}\|$ holds. Furthermore, “=” holds if and only if $\mathbf{x} = \alpha \mathbf{y}$ for some $\alpha \in \mathbb{R}$.

★ variation of Cauchy-Schwarz inequality (e.g., p -norm, Q -norm, \dots)

Definition (norm)

The Euclidean norm of a vector $\|\mathbf{x}\|$ has the following properties:

- 1 Nonnegativity: $\|\mathbf{x}\| \geq 0$, and $\|\mathbf{x}\| = 0 \iff \mathbf{x} = \mathbf{0}$.
- 2 Homogeneity: $\|r\mathbf{x}\| = |r| \|\mathbf{x}\|$ for every $r \in \mathbb{R}$.
- 3 Triangle inequality: $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$.

Inner Products and Norms

Theorem (Pythagorean theorem)

If \mathbf{x} and \mathbf{y} are orthogonal, i.e. $\langle \mathbf{x}, \mathbf{y} \rangle = 0$, then $\|\mathbf{x} + \mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2$.

General norms

$$\|\mathbf{x}\|_p = \begin{cases} (|x_1|^p + |x_2|^p + \cdots + |x_n|^p)^{1/p}, & \text{if } 1 \leq p < \infty, \\ \max\{|x_1|, |x_2|, \cdots, |x_n|\}, & \text{if } p = \infty, \end{cases}$$

Definition (equivalent of norm)

Let $\|\cdot\|_*$, $\|\cdot\|_{\dagger}$ be two norms in \mathbb{R}^n . For any $\mathbf{x} \in \mathbb{R}^n$, there exist $c_1 > 0$ and $c_2 > 0$ such that $c_1 \|\mathbf{x}\|_* \leq \|\mathbf{x}\|_{\dagger} \leq c_2 \|\mathbf{x}\|_*$.

Example

$$\begin{aligned} \|\mathbf{x}\|_2 &\leq \|\mathbf{x}\|_1 \leq \sqrt{n} \|\mathbf{x}\|_2; \quad \|\mathbf{x}\|_{\infty} \leq \|\mathbf{x}\|_2 \leq \sqrt{n} \|\mathbf{x}\|_{\infty}; \\ \|\mathbf{x}\|_{\infty} &\leq \|\mathbf{x}\|_1 \leq n \|\mathbf{x}\|_{\infty}; \quad \|\mathbf{x}\|_{\infty} \leq \|\mathbf{x}\|_2 \leq n \|\mathbf{x}\|_1; \end{aligned}$$

Inner Products and Norms

Definition (continuity)

A function $\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is continuous at $\mathbf{x} \in \mathbb{R}^n$ if: for all $\varepsilon > 0$, there exists $\delta > 0$ such that $\|\mathbf{y} - \mathbf{x}\| < \delta \Rightarrow \|\mathbf{f}(\mathbf{y}) - \mathbf{f}(\mathbf{x})\| < \varepsilon$.

Definition (inner product in \mathbb{C}^n)

In the complex vector space \mathbb{C}^n , inner product $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^n x_i \bar{y}_i$, where the bar denotes complex conjugation.

Property

Inner product on \mathbb{C}^n is a complex-valued function admitting properties:

- ① $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0$, “=” holds if and only if $\mathbf{x} = \mathbf{0}$.
- ② $\langle \mathbf{x}, \mathbf{y} \rangle = \overline{\langle \mathbf{y}, \mathbf{x} \rangle}$.
- ③ $\langle \mathbf{x} + \mathbf{y}, \mathbf{z} \rangle = \langle \mathbf{x}, \mathbf{z} \rangle + \langle \mathbf{y}, \mathbf{z} \rangle$.
- ④ $\langle r\mathbf{x}, \mathbf{y} \rangle = r\langle \mathbf{x}, \mathbf{y} \rangle$, where $r \in \mathbb{C}$.

Homework

Exercise in text book: 2.3, 2.5, 2.10

