

Vector and Matrix Linear Algebra

Introduction to Optimization for Machine Learning
M1 MLSD/AMSD

October 17, 2023

Roadmap

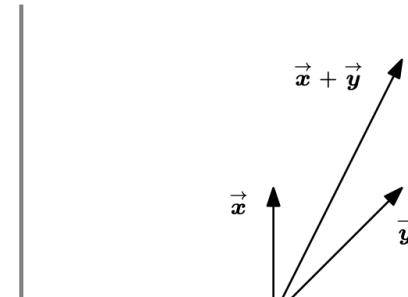
- (1) Systems of Linear Equations
- (2) Matrices
- (3) Solving Systems of Linear Equations
- (4) Vector Spaces
- (5) Linear Independence
- (6) Basis and Rank

Roadmap

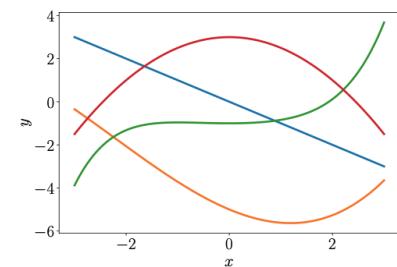
- (1) Systems of Linear Equations
- (2) Matrices
- (3) Solving Systems of Linear Equations
- (4) Vector Spaces
- (5) Linear Independence
- (6) Basis and Rank

Linear Algebra

- Algebra: a set of objects and a set of rules or operations to manipulate those objects
- Linear algebra
 - Object: vectors \mathbf{v}
 - Operations: their additions ($\mathbf{v} + \mathbf{w}$) and scalar multiplication ($k\mathbf{v}$)
- Examples
 - Geometric vectors
 - Polynomials
 - Audio signals
 - Elements of \mathbb{R}^n



(a) Geometric vectors.



(b) Polynomials.

System of Linear Equations

- For unknown variables $(x_1, \dots, x_n) \in \mathbb{R}^n$,

$$a_{11}x_1 + \dots + a_{1n}x_n = b_1$$

⋮

$$a_{m1}x_1 + \dots + a_{mn}x_n = b_m$$

- Three cases of solutions

- No solution

$$\begin{aligned}x_1 + x_2 + x_3 &= 3 \\x_1 - x_2 + 2x_3 &= 2 \\2x_1 + 3x_3 &= 1\end{aligned}$$

- Unique solution

$$\begin{aligned}x_1 + x_2 + x_3 &= 3 \\x_1 - x_2 + 2x_3 &= 2 \\x_2 + 3x_3 &= 1\end{aligned}$$

- Infinitely many solutions

$$\begin{aligned}x_1 + x_2 + x_3 &= 3 \\x_1 - x_2 + 2x_3 &= 2 \\2x_1 + 3x_3 &= 5\end{aligned}$$

Matrix Representation

- A collection of linear equations

$$a_{11}x_1 + \cdots + a_{1n}x_n = b_1$$

⋮

$$a_{m1}x_1 + \cdots + a_{mn}x_n = b_m$$

- Matrix representations:

$$\begin{pmatrix} a_{11} \\ \vdots \\ a_{m1} \end{pmatrix} x_1 + \cdots + \begin{pmatrix} a_{1n} \\ \vdots \\ a_{mn} \end{pmatrix} x_n = \begin{pmatrix} b_1 \\ \vdots \\ b_m \end{pmatrix} \iff \underbrace{\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}}_x = \underbrace{\begin{pmatrix} b_1 \\ \vdots \\ b_m \end{pmatrix}}_b$$

- Understanding \mathbf{A} is the key to answering various questions about this linear system
 $\mathbf{Ax} = \mathbf{b}$.

Roadmap

- (1) Systems of Linear Equations
- (2) Matrices
- (3) Solving Systems of Linear Equations
- (4) Vector Spaces
- (5) Linear Independence
- (6) Basis and Rank

Matrix: Addition and Multiplication

- For two matrices $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $\mathbf{B} \in \mathbb{R}^{m \times n}$,

$$\mathbf{A} + \mathbf{B} := \begin{pmatrix} a_{11} + b_{11} & \cdots & a_{1n} + b_{1n} \\ \vdots & & \vdots \\ a_{m1} + b_{m1} & \cdots & a_{mn} + b_{mn} \end{pmatrix} \in \mathbb{R}^{m \times n}$$

- For two matrices $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $\mathbf{B} \in \mathbb{R}^{n \times k}$, the elements c_{ij} of the product $\mathbf{C} = \mathbf{AB} \in \mathbb{R}^{m \times k}$ is:

$$c_{ij} = \sum_{l=1}^n a_{il} b_{lj}, \quad i = 1, \dots, m, \quad j = 1, \dots, k.$$

- Example. $\mathbf{A} = \begin{pmatrix} 1 & 2 & 3 \\ 3 & 2 & 1 \end{pmatrix}$ and $\mathbf{B} = \begin{pmatrix} 0 & 2 \\ 1 & -1 \\ 0 & 1 \end{pmatrix}$, compute \mathbf{AB} and \mathbf{BA} .

Identity Matrix and Matrix Properties

- A square matrix¹ \mathbf{I}_n with $I_{ii} = 1$ and $I_{ij}=0$ for $i \neq j$, where n is the number of rows and columns. For example,

$$\mathbf{I}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad \mathbf{I}_4 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

- **Associativity:** For $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{B} \in \mathbb{R}^{n \times p}$, $\mathbf{C} \in \mathbb{R}^{p \times q}$, $(\mathbf{AB})\mathbf{C} = \mathbf{A}(\mathbf{BC})$
- **Distributivity:** For $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{m \times n}$, and $\mathbf{C}, \mathbf{D} \in \mathbb{R}^{n \times p}$,
(i) $(\mathbf{A} + \mathbf{B})\mathbf{C} = \mathbf{AC} + \mathbf{BC}$ and (ii) $\mathbf{A}(\mathbf{C} + \mathbf{D}) = \mathbf{AC} + \mathbf{AD}$
- **Multiplication with the identity matrix:** For $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{I}_m \mathbf{A} = \mathbf{A} \mathbf{I}_n = \mathbf{A}$

¹# of rows = # of cols

Inverse and Transpose

- For a square matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$, \mathbf{B} is the **inverse** of A , denoted by \mathbf{A}^{-1} , if

$$\mathbf{AB} = \mathbf{I}_n = \mathbf{BA}.$$

- Called **regular/invertible/nonsingular**, if it exists.
- If it exists, it is unique.
- How to compute? For 2×2 matrix,

$$\mathbf{A}^{-1} = \frac{1}{a_{11}a_{22} - a_{12}a_{21}} \begin{pmatrix} a_{22} & -a_{12} \\ -a_{21} & a_{11} \end{pmatrix}$$

- For a matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{B} \in \mathbb{R}^{n \times m}$ with $b_{ij} = a_{ji}$ is the **transpose** of \mathbf{A} , which we denote by \mathbf{A}^T .

- Example.** For $\mathbf{A} = \begin{pmatrix} 0 & 2 \\ 1 & -1 \\ 0 & 1 \end{pmatrix}$,

$$\mathbf{A}^T = \begin{pmatrix} 0 & 1 & 0 \\ 2 & -1 & 1 \end{pmatrix}$$

- If $\mathbf{A} = \mathbf{A}^T$, \mathbf{A} is called **symmetric**.

Inverse and Transpose: More Properties

- $\mathbf{A}\mathbf{A}^{-1} = \mathbf{I} = \mathbf{A}^{-1}\mathbf{A}$
- $(\mathbf{AB})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$
- $(\mathbf{A} + \mathbf{B})^{-1} \neq \mathbf{A}^{-1} + \mathbf{B}^{-1}$
- $(\mathbf{A}^T)^T = \mathbf{A}$
- $(\mathbf{A} + \mathbf{B})^T = \mathbf{A}^T + \mathbf{B}^T$
- $(\mathbf{AB})^T = \mathbf{B}^T\mathbf{A}^T$
- If \mathbf{A} is invertible, so is \mathbf{A}^T .

Scalar Multiplication

- Multiplication by a scalar $\lambda \in \mathbb{R}$ to $\mathbf{A} \in \mathbb{R}^{m \times n}$

- Example. For $\mathbf{A} = \begin{pmatrix} 0 & 2 \\ 1 & -1 \\ 0 & 1 \end{pmatrix}$, $3 \times \mathbf{A} = \begin{pmatrix} 0 & 6 \\ 3 & -3 \\ 0 & 3 \end{pmatrix}$

- **Associativity**

- $(\lambda\psi)\mathbf{C} = \lambda(\psi\mathbf{C})$
- $\lambda(\mathbf{B}\mathbf{C}) = (\lambda\mathbf{B})\mathbf{C} = \mathbf{B}(\lambda\mathbf{C}) = (\mathbf{B}\mathbf{C})\lambda$
- $(\lambda\mathbf{C})^T = \mathbf{C}^T\lambda^T = \mathbf{C}^T\lambda = \lambda\mathbf{C}^T$

- **Distributivity**

- $(\lambda + \psi)\mathbf{C} = \lambda\mathbf{C} + \psi\mathbf{C}$
- $\lambda(\mathbf{B} + \mathbf{C}) = \lambda\mathbf{B} + \lambda\mathbf{C}$

Roadmap

- (1) Systems of Linear Equations
- (2) Matrices
- (3) Solving Systems of Linear Equations
- (4) Vector Spaces
- (5) Linear Independence
- (6) Basis and Rank

Algorithms for Solving System of Linear Equations

1. Pseudo-inverse

$$\mathbf{A}\mathbf{x} = \mathbf{b} \iff \mathbf{A}^T \mathbf{A}\mathbf{x} = \mathbf{A}^T \mathbf{b} \iff \mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$$

- $(\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T$: *Moore-Penrose pseudo-inverse*
- many computations: matrix product, inverse, etc

2. Gaussian elimination

- intuitive and constructive way
- cubic complexity (in terms of # of simultaneous equations)

3. Iterative methods

- practical ways to solve indirectly
 - (a) stationary iterative methods: Richardson method, Jacobi method, Gaus-Seidel method, successive over-relaxation method
 - (b) Krylov subspace methods: conjugate gradients, generalized minimal residual, biconjugate gradients

Roadmap

- (1) Systems of Linear Equations
- (2) Matrices
- (3) Solving Systems of Linear Equations
- (4) Vector Spaces
- (5) Linear Independence
- (6) Basis and Rank

Vector Spaces

Definition. A real-valued vector space $V = (\mathcal{V}, +, \cdot)$ is a set \mathcal{V} with two operations

- (a) $+ : \mathcal{V} \times \mathcal{V} \mapsto \mathcal{V}$ (vector addition)
- (b) $\cdot : \mathbb{R} \times \mathcal{V} \mapsto \mathcal{V}$ (scalar multiplication),

where

1. **Distributivity.**
 - $\forall \lambda \in \mathbb{R}, \mathbf{x}, \mathbf{y} \in \mathcal{V}, \lambda \cdot (\mathbf{x} + \mathbf{y}) = \lambda \cdot \mathbf{x} + \lambda \mathbf{y}$
 - $\forall \lambda, \psi \in \mathbb{R}, \mathbf{x} \in \mathcal{V}, (\lambda + \psi) \cdot \mathbf{x} = \lambda \cdot \mathbf{x} + \psi \cdot \mathbf{x}$
2. **Associativity.** $\forall \lambda, \psi \in \mathbb{R}, \mathbf{x} \in \mathcal{V}, \lambda \cdot (\psi \cdot \mathbf{x}) = (\lambda\psi) \cdot \mathbf{x}$
3. **Neutral element.** $\forall \mathbf{x} \in \mathcal{V}, 1 \cdot \mathbf{x} = \mathbf{x}$

Example

- $\mathcal{V} = \mathbb{R}^n$ with
 - Vector addition: $\mathbf{x} + \mathbf{y} = (x_1 + y_1, \dots, x_n + y_n)$
 - Scalar multiplication: $\lambda \mathbf{x} = (\lambda x_1, \dots, \lambda x_n)$

- $\mathcal{V} = \mathbb{R}^{m \times n}$ with

- Vector addition: $\mathbf{A} + \mathbf{B} = \begin{pmatrix} a_{11} + b_{11} & \cdots & a_{1n} + b_{1n} \\ \vdots & & \vdots \\ a_{m1} + b_{m1} & \cdots & a_{mn} + b_{mn} \end{pmatrix}$

- Scalar multiplication: $\lambda \mathbf{A} = \begin{pmatrix} \lambda a_{11} & \cdots & \lambda a_{1n} \\ \vdots & & \vdots \\ \lambda a_{m1} & \cdots & \lambda a_{mn} \end{pmatrix}$

Roadmap

- (5) Systems of Linear Equations
- (5) Matrices
- (5) Solving Systems of Linear Equations
- (5) Vector Spaces
- (5) **Linear Independence**
- (5) Basis and Rank

Linear Independence

- **Definition.** For a vector space V and vectors $\mathbf{x}_1, \dots, \mathbf{x}_n \in V$, every $\mathbf{v} \in V$ of the form $\mathbf{v} = \lambda_1 \mathbf{x}_1 + \dots + \lambda_k \mathbf{x}_k$ with $\lambda_1, \dots, \lambda_k \in \mathbb{R}$ is a **linear combination** of the vectors $\mathbf{x}_1, \dots, \mathbf{x}_n \in V$.
- **Definition.** If there is a non-trivial linear combination such that $\mathbf{0} = \sum_{i=1}^k \lambda_i \mathbf{x}_i$ with at least one $\lambda_i \neq 0$, the vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ are **linearly dependent**. If only the trivial solution exists, i.e., $\lambda_1 = \dots = \lambda_k = 0$, $\mathbf{x}_1, \dots, \mathbf{x}_n$ are **linearly independent**.
- **Meaning.** A set of linearly independent vectors consists of vectors that have no redundancy.
- **Useful fact.** The vectors $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ are linearly dependent, iff (at least) one of them is a linear combination of the others.
 - $x - 2y = 2$ and $2x - 4y = 4$ are linearly dependent.

Rank (1)

- **Definition.** The rank of $\mathbf{A} \in \mathbb{R}^{m \times n}$ denoted by $\text{rk}(\mathbf{A})$ is # of linearly independent columns
 - Same as the number of linearly independent rows

- $\mathbf{A} = \begin{pmatrix} 1 & 2 & 1 \\ -2 & -3 & 1 \\ 3 & 5 & 0 \end{pmatrix}$

Thus, $\text{rk}(\mathbf{A}) = 2$.

- $\text{rk}(\mathbf{A}) = \text{rk}(\mathbf{A}^T)$

Rank (2)

- The columns (resp. rows) of \mathbf{A} span a subspace U (resp. W) with $\dim(U) = \text{rk}(\mathbf{A})$ (resp. $\dim(W) = \text{rk}(\mathbf{A})$), and a basis of U (resp. W) can be found by Gauss elimination of \mathbf{A} (resp. \mathbf{A}^T).
- For all $\mathbf{A} \in \mathbb{R}^{n \times n}$, $\text{rk}(\mathbf{A}) = n$, iff \mathbf{A} is regular (invertible).
- The linear system $\mathbf{Ax} = \mathbf{b}$ is solvable, iff $\text{rk}(\mathbf{A}) = \text{rk}(\mathbf{A}|\mathbf{b})$.
- For $\mathbf{A} \in \mathbb{R}^{m \times n}$, the subspace of solutions for $\mathbf{Ax} = \mathbf{0}$ possesses dimension $n - \text{rk}(\mathbf{A})$.
- $\mathbf{A} \in \mathbb{R}^{m \times n}$ has full rank if its rank equals the largest possible rank for a matrix of the same dimensions. The rank of the full-rank matrix \mathbf{A} is $\min(\# \text{ of cols}, \# \text{ of rows})$.