

# Mathematics for Machine Learning

## — Linear Algebra: Norms, Inner Products & Orthogonality

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## Credits for the resource

- The slides are based on the textbooks:
  - *Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong: Mathematics for Machine Learning. Cambridge University Press. 2020.*
  - *Howard Anton, Chris Rorres, Anton Kaul: Elementary Linear Algebra. Wiley. 2019.*
- We could partially refer to the monograph:  
*Francesco Orabona: A Modern Introduction to Online Learning.*  
<https://arxiv.org/abs/1912.13213>

# Outline

- 1 Norms
- 2 Inner Products
- 3 Lengths & Distances
- 4 Angles and Orthogonality
- 5 Orthonormal Basis
- 6 Inner Product of Functions

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# Norm

## Norm

A norm on a vector space  $V$  is a function

$$\begin{aligned}\|\cdot\| : V &\mapsto \mathbb{R} \\ \mathbf{x} &\mapsto \|\mathbf{x}\|\end{aligned}$$

such that for  $\lambda \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in V$  the following hold:

- $\|\lambda \mathbf{x}\| = |\lambda| \|\mathbf{x}\|$ .
- $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ .
- $\|\mathbf{x}\| \geq 0$  and  $\|\mathbf{x}\| = 0 \Leftrightarrow \mathbf{x} = \mathbf{0}$ .

# $\ell_1$ norm & $\ell_2$ norm

## $\ell_1$ norm (Manhattan Norm)

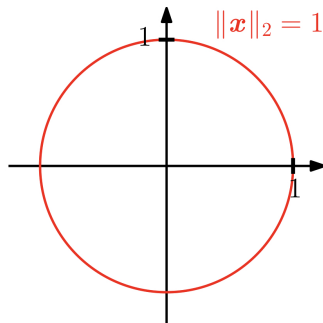
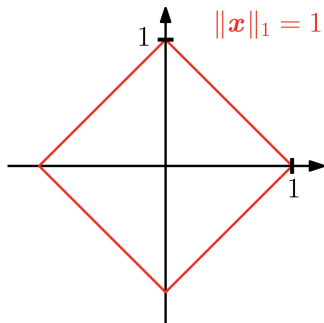
For  $\mathbf{x} \in \mathbb{R}^n$ ,

$$\|\mathbf{x}\|_1 := \sum_{i=1}^n |x_i|.$$

## $\ell_2$ norm

For  $\mathbf{x} \in \mathbb{R}^n$ ,

$$\|\mathbf{x}\|_2 := \sqrt{\sum_{i=1}^n x_i^2} = \sqrt{\mathbf{x}^\top \mathbf{x}}.$$



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# Dot Product

## Dot Product

For  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ ,

$$\mathbf{x}^\top \mathbf{y} = \sum_{i=1}^n x_i y_i.$$

# General Inner Products

## Bilinear Mapping $f$

Given a vector space  $V$ . For all  $\mathbf{x}, \mathbf{y}, \mathbf{z} \in V$ ,  $\lambda, \psi \in \mathbb{R}$ , such that

$$f(\lambda \mathbf{x} + \psi \mathbf{y}, \mathbf{z}) = \lambda f(\mathbf{x}, \mathbf{z}) + \psi f(\mathbf{y}, \mathbf{z})$$

$$f(\mathbf{x}, \lambda \mathbf{y} + \psi \mathbf{z}) = \lambda f(\mathbf{x}, \mathbf{y}) + \psi f(\mathbf{x}, \mathbf{z})$$

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$$f(\mathbf{x}, \lambda \mathbf{y} + \psi \mathbf{z}) = \lambda f(\mathbf{x}, \mathbf{y}) + \psi f(\mathbf{x}, \mathbf{z}) \quad (\text{linear in the 2nd argument})$$

# Symmetric & Positive Definite (1/6)

## Symmetric

Let  $V$  be a vector space and  $f : V \times V \mapsto \mathbb{R}$  be a bilinear mapping. Then  $f$  is **symmetric** if  $f(\mathbf{x}, \mathbf{y}) = f(\mathbf{y}, \mathbf{x})$ .

## Positive Definite

Let  $V$  be a vector space and  $f : V \times V \mapsto \mathbb{R}$  be a bilinear mapping. Then  $f$  is **positive definite** if  $\forall \mathbf{x} \in V \setminus \{\mathbf{0}\}$ , we have

$$f(\mathbf{x}, \mathbf{x}) > 0 \quad \text{and} \quad f(\mathbf{0}, \mathbf{0}) = 0.$$

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## Inner Product

A positive definite & symmetric bilinear mapping  $f : V \times V \mapsto \mathbb{R}$  is called an **inner product** on  $V$  and we write  $f(\mathbf{x}, \mathbf{y})$  as  $\langle \mathbf{x}, \mathbf{y} \rangle$ .

## Symmetric & Positive Definite (2/6)

- Important in machine learning.
  - Matrix decompositions.
  - Key in defining kernels in the SVM (support vector machine).

# An Exercise

## Exercise

Consider  $V = \mathbb{R}^2$ . Define that

$$\langle \mathbf{x}, \mathbf{y} \rangle := x_1 y_1 - (x_1 y_2 + x_2 y_1) + 2x_2 y_2.$$

Show that  $\langle \cdot, \cdot \rangle$  is an inner product.

## Symmetric & Positive Definite (3/6)

Consider an  $n$ -dimensional vector space  $V$  with an inner product  $\langle \cdot \rangle : V \times V \mapsto \mathbb{R}$  and an ordered basis  $B = (\mathbf{b}_1, \dots, \mathbf{b}_n)$  of  $V$ .

- Assume that for  $\mathbf{x}, \mathbf{y} \in V$ ,

- $\mathbf{x} = \sum_{i=1}^n \psi_i \mathbf{b}_i$

- $\mathbf{y} = \sum_{j=1}^n \lambda_j \mathbf{b}_j$

for suitable  $\psi_i, \lambda_j \in \mathbb{R}$ .

- By the bilinearity of the inner product, we have

$$\langle \mathbf{x}, \mathbf{y} \rangle = \left\langle \sum_{i=1}^n \psi_i \mathbf{b}_i, \sum_{j=1}^n \lambda_j \mathbf{b}_j \right\rangle$$



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where  $\hat{\mathbf{x}}$  and  $\hat{\mathbf{y}}$  are the coordinates of  $\mathbf{b}$  w.r.t. the basis  $B$ .

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where  $\hat{\mathbf{x}}$  and  $\hat{\mathbf{y}}$  are the coordinates of  $\mathbf{b}$  w.r.t. the basis  $B$ .

- ★ Note that the symmetry of the inner product implies that  $\mathbf{A}$  is symmetric.

## Symmetric & Positive Definite (4/6)

The positive definiteness of the inner product implies that

$$\forall \mathbf{x} \in V \setminus \{\mathbf{0}\} : \mathbf{x}^\top \mathbf{A} \mathbf{x} > 0.$$

### Symmetric, Positive Definite Matrix

A symmetric matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  that satisfies the property:

$$\forall \mathbf{x} \in V \setminus \{\mathbf{0}\} : \mathbf{x}^\top \mathbf{A} \mathbf{x} > 0.$$

is called **symmetric, positive definite** (or just **positive definite**).

If only  $\geq$  holds, then  $\mathbf{A}$  is called symmetric, **positive semidefinite**.

## Example

Consider the matrices  $\mathbf{A}_1 = \begin{bmatrix} 9 & 6 \\ 6 & 5 \end{bmatrix}$ ,  $\mathbf{A}_2 = \begin{bmatrix} 9 & 6 \\ 6 & 3 \end{bmatrix}$

- $\mathbf{A}_1$  is positive definite (why?)

## Example

Consider the matrices  $\mathbf{A}_1 = \begin{bmatrix} 9 & 6 \\ 6 & 5 \end{bmatrix}$ ,  $\mathbf{A}_2 = \begin{bmatrix} 9 & 6 \\ 6 & 3 \end{bmatrix}$

- $\mathbf{A}_1$  is positive definite (why?)
- $\mathbf{A}_2$  is NOT positive definite (why?)

## Symmetric & Positive Definite (5/6)

If  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is symmetric, positive definite, then

$$\langle \mathbf{x}, \mathbf{y} \rangle = \hat{\mathbf{x}}^\top \mathbf{A} \hat{\mathbf{y}}.$$

## Symmetric & Positive Definite (5/6)

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This defines an inner product w.r.t. an ordered basis  $B$ , where  $\hat{\mathbf{x}}, \hat{\mathbf{y}}$  are the coordinates of  $\mathbf{x}, \mathbf{y}$  w.r.t.  $B$ .

## Symmetric & Positive Definite (6/6)

The following properties hold if  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is symmetric and positive definite.

- $\text{null}(\mathbf{A}) = \{\mathbf{0}\}.$



## Symmetric & Positive Definite (6/6)

The following properties hold if  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is symmetric and positive definite.

- $\text{null}(\mathbf{A}) = \{\mathbf{0}\}$ .
  - Since  $\mathbf{x}^\top \mathbf{A} \mathbf{x} > 0$  for all  $\mathbf{x} > 0 \Rightarrow \mathbf{A} \mathbf{x} \neq \mathbf{0}$  if  $\mathbf{x} \neq \mathbf{0}$ .
- For the diagonal elements  $a_{ii}$  of  $\mathbf{A}$ ,  $a_{ii} = \mathbf{e}_i^\top \mathbf{A} \mathbf{e}_i > 0$ .
  - $\mathbf{e}_i$ : the  $i$ th vector of the standard basis of  $\mathbb{R}^n$ .

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## Remark

- Note that any inner product induces a norm:

$$\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}.$$

### Cauchy-Schwarz Inequality

For an inner product vector space  $(V, \langle \cdot \rangle)$ , the induced norm  $\|\cdot\|$  satisfies the Cauchy-Schwarz inequality

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\| \|\mathbf{y}\|.$$

# Lengths of Vectors

## Example

Compute the length of a vector  $\mathbf{x} = [1, 1]^\top \in \mathbb{R}^2$  using

- Dot product

- $\langle \mathbf{x}, \mathbf{y} \rangle := \mathbf{x}^\top \begin{bmatrix} 1 & \frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix} \mathbf{y} = x_1 y_1 - \frac{1}{2}(x_1 y_2 + x_2 y_1) + x_2 y_2.$

# Distance & Metric

## Distance

Consider an inner product space  $(V, \langle \cdot \rangle)$ . Then, the **distance** between  $\mathbf{x}$  and  $\mathbf{y}$  for  $\mathbf{x}, \mathbf{y} \in V$  is

$$d(\mathbf{x}, \mathbf{y}) := \|\mathbf{x} - \mathbf{y}\| = \sqrt{\langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y} \rangle}.$$

- The mapping  $d : V \times V \mapsto \mathbb{R}$  for which  $(\mathbf{x}, \mathbf{y})$  maps to  $d(\mathbf{x}, \mathbf{y})$  is called a **metric**

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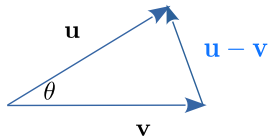
- The mapping  $d : V \times V \mapsto \mathbb{R}$  for which  $(\mathbf{x}, \mathbf{y})$  maps to  $d(\mathbf{x}, \mathbf{y})$  is called a **metric**, which satisfies:
  - *positive definite*:  $d(\mathbf{x}, \mathbf{y}) \geq 0$  for all  $\mathbf{x}, \mathbf{y} \in V$  and  $d(\mathbf{x}, \mathbf{y}) = 0$  iff  $\mathbf{x} = \mathbf{y}$ .
  - *symmetric*:  $d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$  for all  $\mathbf{x}, \mathbf{y} \in V$ .
  - *triangular inequality*:  $d(\mathbf{x}, \mathbf{z}) \leq d(\mathbf{x}, \mathbf{y}) + d(\mathbf{y}, \mathbf{z})$ .

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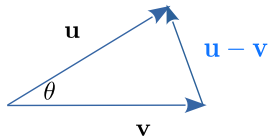
## Recall from Senior High School Math



### Law of Cosines

$$\|\mathbf{u} - \mathbf{v}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2 - 2\|\mathbf{u}\| \|\mathbf{v}\| \cos \theta$$

## Recall from Senior High School Math



### Law of Cosines

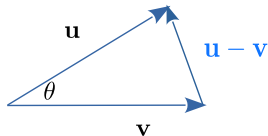
$$\|\mathbf{u} - \mathbf{v}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2 - 2\|\mathbf{u}\| \|\mathbf{v}\| \cos \theta$$

Note:

$$\langle \mathbf{u} - \mathbf{v}, \mathbf{u} - \mathbf{v} \rangle = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2 - 2\langle \mathbf{u}, \mathbf{v} \rangle.$$

Thus,

## Recall from Senior High School Math



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Thus,

$$\langle \mathbf{u}, \mathbf{v} \rangle = \|\mathbf{u}\| \cdot \|\mathbf{v}\| \cos \theta.$$

# Angles

Assume that  $\mathbf{x} \neq \mathbf{0}, \mathbf{y} \neq \mathbf{0}$ . Then by the Cauchy-Schwarz inequality,

$$-1 \leq \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} \leq 1.$$

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Thus, there exists a unique  $\theta \in [0, \pi]$ , such that

$$\cos(\theta) = \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|}.$$

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We call  $\theta$  the **angle** between  $\mathbf{x}$  and  $\mathbf{y}$ .

# Orthogonality

## Orthogonality

- Two vectors  $\mathbf{x}$  and  $\mathbf{y}$  are **orthogonal** if and only if  $\langle \mathbf{x}, \mathbf{y} \rangle = 0$ .
  - We write  $\mathbf{x} \perp \mathbf{y}$ .
- If  $\mathbf{x}$  and  $\mathbf{y}$  are orthogonal and  $\|\mathbf{x}\| = \|\mathbf{y}\| = 1$ , then  $\mathbf{x}$  and  $\mathbf{y}$  are both **orthonormal**.

# Orthogonal Matrix

## Orthogonal Matrix

A square matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is an orthogonal matrix iff its columns are orthonormal so that

$$\mathbf{A}\mathbf{A}^\top = \mathbf{I} = \mathbf{A}^\top \mathbf{A},$$

which implies

$$\mathbf{A}^{-1} = \mathbf{A}^\top.$$

## Remark

Transformations by orthogonal matrices do NOT change the length of a vector.

$$\|\mathbf{A}\mathbf{x}\|^2 = (\mathbf{A}\mathbf{x})^\top (\mathbf{A}\mathbf{x}) =$$



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Let  $\theta$  be the angle between  $\mathbf{Ax}$  and  $\mathbf{Ay}$ , what is  $\cos \theta$ ?

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# Orthonormal Basis

## Orthonormal Basis

Consider an  $n$ -dimensional vector space  $V$  and a basis  $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$  of  $V$ .  
If for all  $i, j = 1, \dots, n$

$$\langle \mathbf{b}_i, \mathbf{b}_j \rangle = 0 \quad \text{for } i \neq j \quad (1)$$

$$\langle \mathbf{b}_i, \mathbf{b}_i \rangle = 1, \quad (2)$$

then the basis is called an **orthonormal basis**.

- Only (1) is satisfied  $\Rightarrow$  orthogonal basis.

## Example

- The standard basis for  $\mathbb{R}^n$ .
- $\mathbf{b}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{b}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}.$

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# Inner Product of Functions

## Inner Product of Functions

Given two functions  $u, v : \mathbb{R} \mapsto \mathbb{R}$ , the inner product of  $u$  and  $v$  can be defined as

$$\langle u, v \rangle := \int_a^b u(x)v(x)dx$$

for lower and upper limits  $a, b < \infty$ .

## Example

### Example (Exercise)

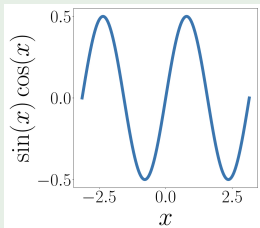
- Choose  $u(x) = \sin(x)$  and  $v(x) = \cos(x)$ .
- Define  $f(x) = u(x)v(x)$ .



## Example

### Example (Exercise)

- Choose  $u(x) = \sin(x)$  and  $v(x) = \cos(x)$ .
- Define  $f(x) = u(x)v(x)$ .



- We can observe that  $f(-x) = -f(x)$
- $\int_{-\pi}^{\pi} u(x)v(x)dx = 0$ .

# Discussions