

# Lecture 4.1: Inner product

Optimization and Computational Linear Algebra for Data Science

# The Euclidean dot product

## Definition

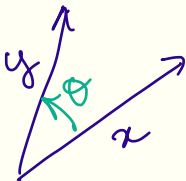
We define the Euclidean dot product of two vectors  $x$  and  $y$  of  $\mathbb{R}^n$  as:

$$\underline{x \cdot y} = \sum_{i=1}^n x_i y_i = \underline{x_1 y_1} + \cdots + \underline{x_n y_n}.$$

Remarks:

- $x \cdot x = \|x\|_2^2$
- $x \cdot y = \|x\|_2 \|y\|_2 \cos \theta$

$$x \cdot y > 0$$



$$x \cdot y = 0$$



$$x \cdot y < 0$$



# Inner product

Let  $V$  be a vector space.

## Definition

An inner product on  $V$  is a function  $\langle \cdot, \cdot \rangle$  from  $V \times V$  to  $\mathbb{R}$  that verifies the following points:

1. **Symmetry:**  $\langle u, v \rangle = \langle v, u \rangle$  for all  $u, v \in V$ .
2. **Linearity:**  $\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle$  and  $\langle \alpha v, w \rangle = \alpha \langle v, w \rangle$  for all  $u, v, w \in V$  and  $\alpha \in \mathbb{R}$ .
3. **Positive definiteness:**  $\langle v, v \rangle \geq 0$  with equality if and only if  $v = 0$ .

Ex: for  $V = \mathbb{R}^n$ , the Euclidean dot prod.  
 $\langle x, y \rangle = x \cdot y$ , is an inner product on  $\mathbb{R}^n$

# Other example

If  $V$  is the set of all random variables (on a probability space  $\Omega$ ) that have a finite second moment, then

rand. var.  $\langle X, Y \rangle \stackrel{\text{def}}{=} \mathbb{E}[XY]$  mean value of  $XY$

is an inner product on  $V$ .

- Symmetry  $\langle X, Y \rangle = \mathbb{E}[XY] = \mathbb{E}[YX] = \langle Y, X \rangle$
- Linearity: exercise!
- $\langle X, X \rangle = \mathbb{E}[X^2] \geq 0$

if  $\mathbb{E}[X^2] = 0$  then  $X = 0$

# Norm induced by an inner product

## Proposition

If  $\langle \cdot, \cdot \rangle$  is an inner product on  $V$  then

$$\underline{\underline{\|v\|}} \stackrel{\text{def}}{=} \sqrt{\langle v, v \rangle}$$

is a norm on  $V$ . We say that the norm  $\| \cdot \|$  is induced by the inner product  $\langle \cdot, \cdot \rangle$ .

Example: On  $V = \mathbb{R}^n$ , the Euclidean norm  $\| \cdot \|_2$  is induced by the Euclidean dot product:

$$\|x\|_2 = \sqrt{x \cdot x}$$

# Example

Consider again the set  $V$  of all random variables (on a probability space  $\Omega$ ) that have a finite second moment, with the inner product:

$$\langle X, Y \rangle \stackrel{\text{def}}{=} \mathbb{E}[XY]. \quad \parallel$$

$$\rightarrow \|X\| = \sqrt{\langle X, X \rangle} = \sqrt{\mathbb{E}[X^2]}$$

second moment  
of  $X$ .

# Cauchy Schwarz inequality

## Theorem (Cauchy-Schwarz inequality)

Let  $\|\cdot\|$  be the norm induced by the inner product  $\langle \cdot, \cdot \rangle$  on the vector space  $V$ . Then for all  $x, y \in V$ :

$$\underline{|\langle x, y \rangle|} \leq \underline{\|x\| \|y\|}. \quad (1)$$

Moreover, there is equality in (1) if and only if  $x$  and  $y$  are linearly dependent, i.e.  $x = \alpha y$  or  $y = \alpha x$  for some  $\alpha \in \mathbb{R}$ .

Ex:  $V = \mathbb{R}^n$

$$|x \cdot y| = | \|x\|_2 \|y\|_2 \cos(\theta) | \leq \|x\|_2 \|y\|_2$$

# Examples

In the case  $\langle X, Y \rangle = \underline{\mathbb{E}[XY]}$ :

Cauchy - Schwarz gives:

$$|\mathbb{E}[XY]| \leq \sqrt{\mathbb{E}[X^2]} \sqrt{\mathbb{E}[Y^2]}$$

Replace:  $X$  by  $X - \mathbb{E}X$  and  $Y$  by  $Y - \mathbb{E}Y$

$$|\mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)]| \leq \sqrt{\mathbb{E}[(X - \mathbb{E}X)^2]} \sqrt{\mathbb{E}[(Y - \mathbb{E}Y)^2]}$$

$$|\text{Cov}(X, Y)| \leq \text{Var}(X) \text{Var}(Y)$$



# Examples