

# Announcements

Wednesday, November 15

- ▶ The third midterm is on **this Friday, November 17**.
  - ▶ The exam covers §§3.1, 3.2, 5.1, 5.2, 5.3, and 5.5.
  - ▶ About half the problems will be conceptual, and the other half computational.
- ▶ There is a practice midterm posted on the website. It is identical in format to the real midterm (although there may be  $\pm 1-2$  problems).
- ▶ Study tips:
  - ▶ There are lots of problems at the end of each section in the book, and at the end of the chapter, for practice.
  - ▶ Make sure to **learn the theorems** and **learn the definitions**, and understand what they mean. There is a reference sheet on the website.
  - ▶ Sit down to do the practice midterm in 50 minutes, with no notes.
  - ▶ Come to office hours!
- ▶ WeBWork 5.3, 5.5 are due Wednesday at 11:59pm.
- ▶ **Double Rabinoffice hours this week:** Monday, 1–3pm; Tuesday, 9–11am; Thursday, 9–11am; Thursday, 12–2pm.
- ▶ My review session **tomorrow**, 7–8pm, Howie L4.  
TA review session **tonight**, 4–6pm, in the Culc.

# Chapter 6

## Orthogonality and Least Squares

# Section 6.1

Inner Product, Length, and Orthogonality

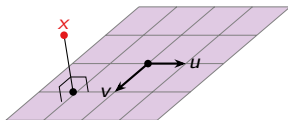
# Orientation

Recall: This course is about learning to:

- ▶ Solve the matrix equation  $Ax = b$
- ▶ Solve the matrix equation  $Ax = \lambda x$
- ▶ Almost solve the equation  $Ax = b$

We are now aiming at the last topic.

Idea: In the real world, data is imperfect. Suppose you measure a data point  $x$  which you know for theoretical reasons must lie on a plane spanned by two vectors  $u$  and  $v$ .



Due to measurement error, though, the measured  $x$  is not actually in  $\text{Span}\{u, v\}$ . In other words, the equation  $au + bv = x$  has no solution. What do you do? The real value is probably the *closest* point to  $x$  on  $\text{Span}\{u, v\}$ . Which point is that?

# The Dot Product

We need a notion of *angle* between two vectors, and in particular, a notion of *orthogonality* (i.e. when two vectors are perpendicular). This is the purpose of the dot product.

## Definition

The **dot product** of two vectors  $x, y$  in  $\mathbf{R}^n$  is

$$x \cdot y = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \cdot \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \stackrel{\text{def}}{=} x_1y_1 + x_2y_2 + \cdots + x_ny_n.$$

Thinking of  $x, y$  as column vectors, this is the same as  $x^T y$ .

## Example

$$\begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} \cdot \begin{pmatrix} 4 \\ 5 \\ 6 \end{pmatrix} = (1 \quad 2 \quad 3) \begin{pmatrix} 4 \\ 5 \\ 6 \end{pmatrix} =$$

## Properties of the Dot Product

Many usual arithmetic rules hold, as long as you remember you can only dot two vectors together, and that the result is a scalar.

- ▶  $x \cdot y = y \cdot x$
- ▶  $(x + y) \cdot z = x \cdot z + y \cdot z$
- ▶  $(cx) \cdot y = c(x \cdot y)$

Dotting a vector with itself is special:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = x_1^2 + x_2^2 + \cdots + x_n^2.$$

Hence:

- ▶  $x \cdot x \geq 0$
- ▶  $x \cdot x = 0$  if and only if  $x = 0$ .

**Important:**  $x \cdot y = 0$  does *not* imply  $x = 0$  or  $y = 0$ . For example,  $\begin{pmatrix} 1 \\ 0 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ 1 \end{pmatrix} = 0$ .

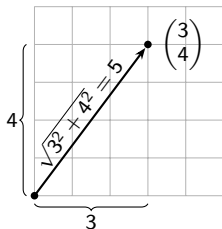
# The Dot Product and Length

## Definition

The **length** or **norm** of a vector  $x$  in  $\mathbf{R}^n$  is

$$\|x\| = \sqrt{x \cdot x} = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}.$$

Why is this a good definition? The Pythagorean theorem!



$$\left\| \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right\| = \sqrt{3^2 + 4^2} = 5$$

## Fact

If  $x$  is a vector and  $c$  is a scalar, then  $\|cx\| = |c| \cdot \|x\|$ .

$$\left\| \begin{pmatrix} 6 \\ 8 \end{pmatrix} \right\| = \left\| 2 \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right\| =$$

# The Dot Product and Distance

## Definition

The **distance** between two points  $x, y$  in  $\mathbf{R}^n$  is

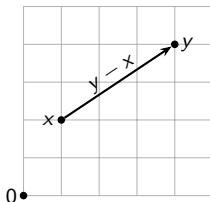
$$\text{dist}(x, y) = \|y - x\|.$$

This is just the length of the vector from  $x$  to  $y$ .

## Example

Let  $x = (1, 2)$  and  $y = (4, 4)$ . Then

$$\text{dist}(x, y) =$$





# Unit Vectors

## Definition

A **unit vector** is a vector  $v$  with length  $\|v\| = 1$ .

## Example

The unit coordinate vectors are unit vectors:

$$\|e_1\| = \left\| \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \right\| = \sqrt{1^2 + 0^2 + 0^2} = 1$$

## Definition

Let  $x$  be a nonzero vector in  $\mathbf{R}^n$ . The **unit vector in the direction of  $x$**  is the vector  $\frac{x}{\|x\|}$ .

This is in fact a unit vector:

$$\text{scalar} \left\| \frac{x}{\|x\|} \right\| = \frac{1}{\|x\|} \|x\| = 1.$$

# Unit Vectors

## Example

### Example

What is the unit vector in the direction of  $x = \begin{pmatrix} 3 \\ 4 \end{pmatrix}$ ?

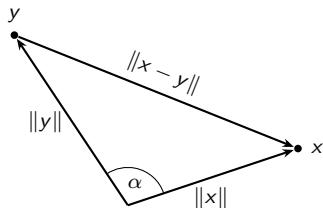
# Orthogonality

## Definition

Two vectors  $x, y$  are **orthogonal** or **perpendicular** if  $x \cdot y = 0$ .

*Notation:*  $x \perp y$  means  $x \cdot y = 0$ .

Why is this a good definition? The Pythagorean theorem / law of cosines!



Law of cosines:

$$\|x - y\|^2 = \|x\|^2 + \|y\|^2 - 2\|x\| \|y\| \cos \alpha$$

$$\alpha = 90^\circ \iff \cos \alpha = 0$$

**Fact:**  $x \perp y \iff \|x - y\|^2 = \|x\|^2 + \|y\|^2$

# Orthogonality

## Example

**Problem:** Find *all* vectors orthogonal to  $v = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}$ .

# Orthogonality

## Example

**Problem:** Find *all* vectors orthogonal to both  $v = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}$  and  $w = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ .

# Orthogonality

## General procedure

**Problem:** Find all vectors orthogonal to some number of vectors  $v_1, v_2, \dots, v_m$  in  $\mathbf{R}^n$ .

This is the same as finding all vectors  $x$  such that

$$0 = v_1^T x = v_2^T x = \dots = v_m^T x.$$

Putting the *row* vectors  $v_1^T, v_2^T, \dots, v_m^T$  into a matrix, this is the same as finding all  $x$  such that

$$\begin{pmatrix} -v_1^T - \\ -v_2^T - \\ \vdots \\ -v_m^T - \end{pmatrix} x = \begin{pmatrix} v_1 \cdot x \\ v_2 \cdot x \\ \vdots \\ v_m \cdot x \end{pmatrix} = 0.$$

### Important

The set of all vectors orthogonal to some vectors  $v_1, v_2, \dots, v_m$  in  $\mathbf{R}^n$  is the *null space* of the  $m \times n$  matrix you get by “turning them sideways and smooching them together:”

$$\begin{pmatrix} -v_1^T - \\ -v_2^T - \\ \vdots \\ -v_m^T - \end{pmatrix}.$$

In particular, this set is a subspace!

# Orthogonal Complements

## Definition

Let  $W$  be a subspace of  $\mathbf{R}^n$ . Its **orthogonal complement** is

$$W^\perp = \{v \text{ in } \mathbf{R}^n \mid v \cdot w = 0 \text{ for all } w \text{ in } W\} \quad \text{read "W perp".}$$

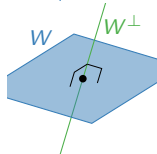
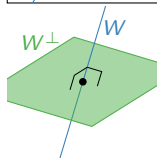
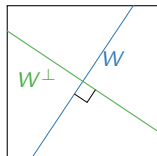
$W^\perp$  is orthogonal complement  
 $A^T$  is transpose

## Pictures:

The orthogonal complement of a **line** in  $\mathbf{R}^2$  is the perpendicular **line**. [interactive]

The orthogonal complement of a **line** in  $\mathbf{R}^3$  is the perpendicular **plane**. [interactive]

The orthogonal complement of a **plane** in  $\mathbf{R}^3$  is the perpendicular **line**. [interactive]







# Orthogonal Complements

## Basic properties

Let  $W$  be a subspace of  $\mathbf{R}^n$ .

Facts:

1.  $W^\perp$  is also a subspace of  $\mathbf{R}^n$
2.  $(W^\perp)^\perp = W$
3.  $\dim W + \dim W^\perp = n$
4. If  $W = \text{Span}\{v_1, v_2, \dots, v_m\}$ , then

$$\begin{aligned}W^\perp &= \text{all vectors orthogonal to each } v_1, v_2, \dots, v_m \\&= \{x \text{ in } \mathbf{R}^n \mid x \cdot v_i = 0 \text{ for all } i = 1, 2, \dots, m\} \\&= \text{Nul} \begin{pmatrix} -v_1^T & - \\ -v_2^T & - \\ \vdots & \\ -v_m^T & - \end{pmatrix}.\end{aligned}$$

# Orthogonal Complements

## Computation

Problem: if  $W = \text{Span} \left\{ \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\}$ , compute  $W^\perp$ .

[interactive]

$$\text{Span}\{v_1, v_2, \dots, v_m\}^\perp = \text{Nul} \begin{pmatrix} -v_1^T & - \\ -v_2^T & - \\ \vdots & \\ -v_m^T & - \end{pmatrix}$$

# Orthogonal Complements

Row space, column space, null space

## Definition

The **row space** of an  $m \times n$  matrix  $A$  is the span of the *rows* of  $A$ . It is denoted  $\text{Row } A$ . Equivalently, it is the column span of  $A^T$ :

$$\text{Row } A = \text{Col } A^T.$$

It is a subspace of  $\mathbf{R}^n$ .

We showed before that if  $A$  has rows  $v_1^T, v_2^T, \dots, v_m^T$ , then

$$\text{Span}\{v_1, v_2, \dots, v_m\}^\perp = \text{Nul } A.$$

Hence we have shown:

**Fact:**  $(\text{Row } A)^\perp = \text{Nul } A$ .

Replacing  $A$  by  $A^T$ , and remembering  $\text{Row } A^T = \text{Col } A$ :

**Fact:**  $(\text{Col } A)^\perp = \text{Nul } A^T$ .

Using property 2 and taking the orthogonal complements of both sides, we get:

**Fact:**  $(\text{Nul } A)^\perp = \text{Row } A$  and  $\text{Col } A = (\text{Nul } A^T)^\perp$ .

# Orthogonal Complements

Reference sheet

## Orthogonal Complements of Most of the Subspaces We've Seen

For any vectors  $v_1, v_2, \dots, v_m$ :

$$\text{Span}\{v_1, v_2, \dots, v_m\}^\perp = \text{Nul} \begin{pmatrix} -v_1^T & - \\ -v_2^T & - \\ \vdots & \\ -v_m^T & - \end{pmatrix}$$

For any matrix  $A$ :

$$\text{Row } A = \text{Col } A^T$$

and

$$\begin{aligned} (\text{Row } A)^\perp &= \text{Nul } A & \text{Row } A &= (\text{Nul } A)^\perp \\ (\text{Col } A)^\perp &= \text{Nul } A^T & \text{Col } A &= (\text{Nul } A^T)^\perp \end{aligned}$$