

Announcements

November 21

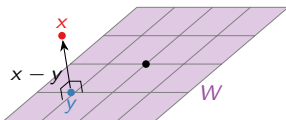
- ▶ Please fill out the CIOS form online.
 - ▶ It is important for me to get responses from most of the class: I use these for preparing future iterations of this course.
 - ▶ If we get an 80% response rate before the final, I'll drop the *two* lowest quiz grades instead of one.
- ▶ The written assignment is due the Monday after Thanksgiving.
 - ▶ See the Piazza post for details.
- ▶ The next WeBWork assignment is due on Friday, December 2, at 6am.
- ▶ Office hours: none this week.
 - ▶ As always, TAs' office hours are posted on the website.
 - ▶ Math Lab is also a good place to visit.

Section 6.2

Orthogonal Sets

Best Approximation

Suppose you measure a data point x which you know for theoretical reasons must lie on a subspace W .



Due to measurement error, though, the measured x is not actually in W . Best approximation: y is the *closest* point to x on W .

How do you know that y is the closest point? The vector from y to x is orthogonal to W : it is in the *orthogonal complement* W^\perp .

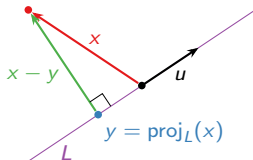
Orthogonal Projection onto a Line

Theorem

Let $L = \text{Span}\{u\}$ be a line in \mathbf{R}^n , and let x be in \mathbf{R}^n . The closest point to x on L is the point

$$\text{proj}_L(x) = \frac{x \cdot u}{u \cdot u} u.$$

This point is called the **orthogonal projection** of x onto L .



Why? Let $y = \text{proj}_L(x)$. We have to verify that $x - y$ is in L^\perp . This means proving that $u \cdot (x - y) = 0$.

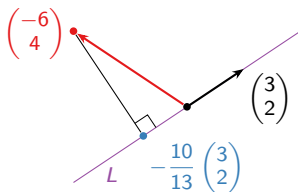
$$u \cdot (x - y) = u \cdot \left(x - \frac{x \cdot u}{u \cdot u} u \right) = u \cdot x - \frac{x \cdot u}{u \cdot u} (u \cdot u) = u \cdot x - x \cdot u = 0.$$

Orthogonal Projection onto a Line

Example

Compute the orthogonal projection of $x = \begin{pmatrix} -6 \\ 4 \end{pmatrix}$ onto the line L spanned by $u = \begin{pmatrix} 3 \\ 2 \end{pmatrix}$.

$$y = \text{proj}_L(x) = \frac{x \cdot u}{u \cdot u} u = \frac{-18 + 8}{9 + 4} \begin{pmatrix} 3 \\ 2 \end{pmatrix} = -\frac{10}{13} \begin{pmatrix} 3 \\ 2 \end{pmatrix}.$$



Orthogonal Sets

Definition

A set of *nonzero* vectors is **orthogonal** if each pair of vectors is orthogonal. It is **orthonormal** if, in addition, each vector is a unit vector.

Example: $\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} \right\}$ is an orthogonal set. Check:

$$\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} = 0 \quad \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} = 0 \quad \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} = 0.$$

Lemma

An orthogonal set of vectors is linearly independent.

Suppose $\{u_1, u_2, \dots, u_m\}$ is orthogonal. We need to show that the equation

$$c_1 u_1 + c_2 u_2 + \cdots + c_m u_m = 0$$

has only the trivial solution $c_1 = c_2 = \cdots = c_m = 0$.

$$0 = u_1 \cdot (c_1 u_1 + c_2 u_2 + \cdots + c_m u_m) = c_1(u_1 \cdot u_1) + 0 + 0 + \cdots + 0.$$

Hence $c_1 = 0$. Similarly for the other c_i .

Orthogonal Bases

An orthogonal set $\mathcal{B} = \{u_1, u_2, \dots, u_m\}$ forms a basis for its span W . An advantage of orthogonal bases is it's *very easy* to compute the \mathcal{B} -coordinates of a vector in W .

Theorem

Let $\mathcal{B} = \{u_1, u_2, \dots, u_m\}$ be an orthogonal set, and let x be a vector in $W = \text{Span } \mathcal{B}$. Then

$$x = \sum_{i=1}^m \frac{x \cdot u_i}{u_i \cdot u_i} u_i = \frac{x \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{x \cdot u_2}{u_2 \cdot u_2} u_2 + \cdots + \frac{x \cdot u_m}{u_m \cdot u_m} u_m.$$

In other words, the \mathcal{B} -coordinates of x are $\frac{x \cdot u_1}{u_1 \cdot u_1}, \frac{x \cdot u_2}{u_2 \cdot u_2}, \dots, \frac{x \cdot u_m}{u_m \cdot u_m}$.

Why? If $x = c_1 u_1 + c_2 u_2 + \cdots + c_m u_m$, then

$$x \cdot u_1 = c_1(u_1 \cdot u_1) + 0 + \cdots + 0 \implies c_1 = \frac{x \cdot u_1}{u_1 \cdot u_1}.$$

Similarly for the other c_i .

Orthogonal Bases

Geometric Reason

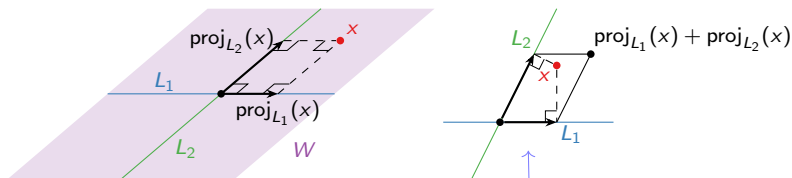
Theorem

Let $\mathcal{B} = \{u_1, u_2, \dots, u_m\}$ be an orthogonal set, and let x be a vector in $W = \text{Span } \mathcal{B}$. Then

$$x = \sum_{i=1}^m \frac{x \cdot u_i}{u_i \cdot u_i} u_i = \frac{x \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{x \cdot u_2}{u_2 \cdot u_2} u_2 + \cdots + \frac{x \cdot u_m}{u_m \cdot u_m} u_m.$$

If L_i is the line spanned by u_i , then this says

$$x = \text{proj}_{L_1}(x) + \text{proj}_{L_2}(x) + \cdots + \text{proj}_{L_m}(x).$$



Warning: this only works for an *orthogonal* basis.

Orthogonal Bases

Example

Problem: find the \mathcal{B} -coordinates of $x = \begin{pmatrix} 0 \\ 3 \end{pmatrix}$, where

$$\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} -4 \\ 2 \end{pmatrix} \right\}.$$

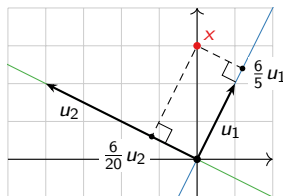
Old way:

$$\left(\begin{array}{cc|c} 1 & -4 & 0 \\ 2 & 2 & 3 \end{array} \right) \xrightarrow{\text{rref}} \left(\begin{array}{cc|c} 1 & 0 & 6/5 \\ 0 & 1 & 6/20 \end{array} \right) \Rightarrow [x]_{\mathcal{B}} = \begin{pmatrix} 6/5 \\ 6/20 \end{pmatrix}.$$

New way: note \mathcal{B} is an *orthogonal* basis.

$$x = \frac{x \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{x \cdot u_2}{u_2 \cdot u_2} u_2 = \frac{3 \cdot 2}{1^2 + 2^2} u_1 + \frac{3 \cdot 2}{(-4)^2 + 2^2} u_2 = \frac{6}{5} u_1 + \frac{6}{20} u_2.$$

So the \mathcal{B} -coordinates are $\frac{6}{5}, \frac{6}{20}$.



Orthogonal Bases

Example

Problem: find the \mathcal{B} -coordinates of $x = (6, 1, -8)$ where

$$\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} \right\}.$$

Answer:

$$\begin{aligned} [x]_{\mathcal{B}} &= \left(\frac{x \cdot u_1}{u_1 \cdot u_1}, \frac{x \cdot u_2}{u_2 \cdot u_2}, \frac{x \cdot u_3}{u_3 \cdot u_3} \right) \\ &= \left(\frac{6 \cdot 1 + 1 \cdot 1 - 8 \cdot 1}{1^2 + 1^2 + 1^2}, \frac{6 \cdot 1 + 1 \cdot (-2) - 8 \cdot 1}{1^2 + (-2)^2 + 1^2}, \frac{6 \cdot 1 + 1 \cdot 0 + (-8) \cdot (-1)}{1^2 + 0^2 + (-1)^2} \right) \\ &= \left(-\frac{1}{3}, -\frac{2}{3}, 7 \right). \end{aligned}$$

Check:

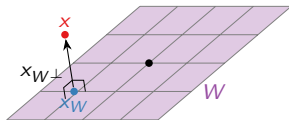
$$\begin{pmatrix} 6 \\ 1 \\ -8 \end{pmatrix} = -\frac{1}{3} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix} + 7 \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}.$$

Section 6.3

Orthogonal Projections

Idea Behind Orthogonal Projections

If x is not in a subspace W , then y in W is the closest to x if $x - y$ is in W^\perp :



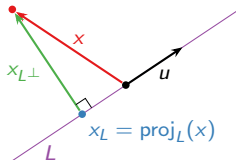
Reformulation: Every vector x can be decomposed uniquely as

$$x = x_W + x_{W^\perp}$$

where $x_W = y$ is the closest vector to x in W , and $x_{W^\perp} = x - y$ is in W^\perp .

Example: Let $u = \begin{pmatrix} 3 \\ 2 \end{pmatrix}$ and let $L = \text{Span}\{u\}$. Let $x = \begin{pmatrix} -6 \\ 4 \end{pmatrix}$. Then the closest point to x in L is $\text{proj}_L(x) = \frac{x \cdot u}{u \cdot u} u$, so

$$x_L = \text{proj}_L(x) = -\frac{10}{13} \begin{pmatrix} 3 \\ 2 \end{pmatrix} \quad x_{L^\perp} = x - \text{proj}_L(x) = \begin{pmatrix} -6 \\ 4 \end{pmatrix} + \frac{10}{13} \begin{pmatrix} 3 \\ 2 \end{pmatrix}.$$



Orthogonal Projections

Definition

Let W be a subspace of \mathbf{R}^n , and let $\{u_1, u_2, \dots, u_m\}$ be an *orthogonal* basis for W . The **orthogonal projection** of a vector x onto W is

$$\text{proj}_W(x) \stackrel{\text{def}}{=} \sum_{i=1}^m \frac{x \cdot u_i}{u_i \cdot u_i} u_i.$$

Question: What is the difference between this and the formula for $[x]_B$ from before?

Theorem

Let W be a subspace of \mathbf{R}^n , and let x be a vector in \mathbf{R}^n . Then $\text{proj}_W(x)$ is the closest point to x in W . Therefore

$$x_W = \text{proj}_W(x) \quad x_{W^\perp} = x - \text{proj}_W(x).$$

Why? Let $y = \text{proj}_W(x)$. We need to show that $x - y$ is in W^\perp . In other words, $u_i \cdot (x - y) = 0$ for each i . Let's do u_1 :

$$u_1 \cdot (x - y) = u_1 \cdot \left(x - \sum_{i=1}^m \frac{x \cdot u_i}{u_i \cdot u_i} u_i \right) = u_1 \cdot x - \frac{x \cdot u_1}{u_1 \cdot u_1} (u_1 \cdot u_1) - 0 - \dots = 0.$$

Orthogonal Projections

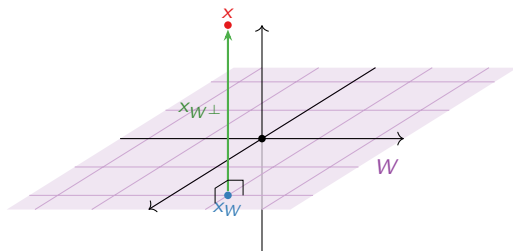
Easy Example

What is the projection of $x = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}$ onto the xy -plane?

Answer: The xy -plane is $W = \text{Span}\{e_1, e_2\}$, and $\{e_1, e_2\}$ is an orthogonal basis.

$$x_W = \text{proj}_W \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} = \frac{x \cdot e_1}{e_1 \cdot e_1} e_1 + \frac{x \cdot e_2}{e_2 \cdot e_2} e_2 = \frac{1 \cdot 1}{1^2} e_1 + \frac{1 \cdot 2}{1^2} e_2 = \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}.$$

So this is the same projection as before.



Orthogonal Projections

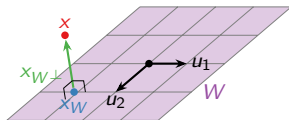
More complicated example

What is the projection of $x = \begin{pmatrix} -1.1 \\ 1.4 \\ 1.45 \end{pmatrix}$ onto $W = \text{Span} \left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1.1 \\ -0.2 \end{pmatrix} \right\}$?

Answer: The basis is orthogonal, so

$$\begin{aligned} x_W &= \text{proj}_W \begin{pmatrix} -1.1 \\ 1.4 \\ 1.45 \end{pmatrix} = \frac{x \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{x \cdot u_2}{u_2 \cdot u_2} u_2 \\ &= \frac{(-1.1)(1)}{1^2} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + \frac{(1.4)(1.1) + (1.45)(-0.2)}{1.1^2 + (-0.2)^2} \begin{pmatrix} 0 \\ 1.1 \\ -0.2 \end{pmatrix} \end{aligned}$$

This turns out to be equal to $u_2 - 1.1u_1$.



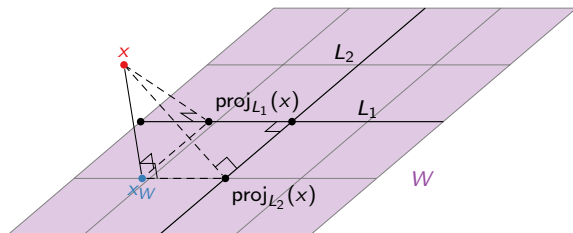
Orthogonal Projections

Picture

Let W be a subspace of \mathbf{R}^n , and let $\{u_1, u_2, \dots, u_m\}$ be an orthogonal basis for W . Let $L_i = \text{Span}\{u_i\}$. Then

$$\text{proj}_W(x) = \sum_{i=1}^m \frac{x \cdot u_i}{u_i \cdot u_i} u_i = \sum_{i=1}^m \text{proj}_{L_i}(x).$$

So the orthogonal projection is formed by adding orthogonal projections onto perpendicular lines.



Orthogonal Projections

Properties

First we restate the property we've been using all along.

Best Approximation Theorem

Let W be a subspace of \mathbf{R}^n , and let x be a vector in \mathbf{R}^n . Then $y = \text{proj}_W(x)$ is the closest point in W to x , in the sense that

$$\text{dist}(x, y') \geq \text{dist}(x, y) \quad \text{for all } y' \text{ in } W.$$

We can think of orthogonal projection as a *transformation*:

$$\text{proj}_W: \mathbf{R}^n \longrightarrow \mathbf{R}^n \quad x \mapsto \text{proj}_W(x).$$

Theorem

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

1. proj_W is a *linear* transformation.
2. For every x in W , we have $\text{proj}_W(x) = x$.
3. The range of proj_W is W .

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

Poll

Let A be the matrix for proj_W . What is A^2 equal to?

- A. A B. A^{-1} C. $-A$ D. 0 E. I_n F. $-I_n$

For any x in \mathbf{R}^n , $\text{proj}_W(x)$ is in W .

Hence $\text{proj}_W(\text{proj}_W(x)) = \text{proj}_W(x)$.

So $\text{proj}_W \circ \text{proj}_W = \text{proj}_W$.

The matrix for $\text{proj}_W \circ \text{proj}_W$ is A^2 .

Therefore $A^2 = A$.

Orthogonal Projections

Matrices

What is the matrix for $\text{proj}_W: \mathbf{R}^3 \rightarrow \mathbf{R}^3$, where

$$W = \text{Span} \left\{ \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\}?$$

Answer: Recall how to compute the matrix for a linear transformation:

$$A = \begin{pmatrix} \left. \text{proj}_W(e_1) \right| & \left. \text{proj}_W(e_2) \right| & \left. \text{proj}_W(e_3) \right| \end{pmatrix}.$$

We compute:

$$\text{proj}_W(e_1) = \frac{e_1 \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{e_1 \cdot u_2}{u_2 \cdot u_2} u_2 = \frac{1}{2} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} + \frac{1}{3} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 5/6 \\ 1/3 \\ -1/6 \end{pmatrix}$$

$$\text{proj}_W(e_2) = \frac{e_2 \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{e_2 \cdot u_2}{u_2 \cdot u_2} u_2 = 0 + \frac{1}{3} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1/3 \\ 1/3 \\ 1/3 \end{pmatrix}$$

$$\text{proj}_W(e_3) = \frac{e_3 \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{e_3 \cdot u_2}{u_2 \cdot u_2} u_2 = -\frac{1}{2} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} + \frac{1}{3} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -1/6 \\ 1/3 \\ 5/6 \end{pmatrix}$$

$$\text{Therefore } A = \begin{pmatrix} 5/6 & 1/3 & -1/6 \\ 1/3 & 1/3 & 1/3 \\ -1/6 & 1/3 & 5/6 \end{pmatrix}.$$

Orthogonal Projections

Minimum distance

What is the distance from e_1 to $W = \text{Span} \left\{ \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\}$?

Answer: The closest point from e_1 to W is $\text{proj}_W(e_1) = \begin{pmatrix} 5/6 \\ 1/3 \\ -1/6 \end{pmatrix}$. The distance from e_1 to this point is

$$\begin{aligned} \text{dist}(e_1, \text{proj}_W(e_1)) &= \left\| \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} - \begin{pmatrix} 5/6 \\ 1/3 \\ -1/6 \end{pmatrix} \right\| = \left\| \begin{pmatrix} 1/6 \\ -1/3 \\ -1/6 \end{pmatrix} \right\| \\ &= \sqrt{(1/6)^2 + (-1/3)^2 + (-1/6)^2} \\ &= \frac{1}{\sqrt{6}}. \end{aligned}$$