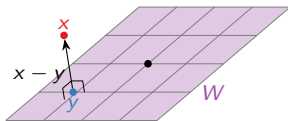


## Section 6.2

### Orthogonal Sets

# Best Approximation

Due to measurement error, the measured  $x$  is not actually in the subspace it must lie on (*for theoretical reasons*).



Best approximation:  $y$  is the *closest point* to  $x$  on  $W$ .

Replace  $x$  with its orthogonal projection  $y$  onto  $W$ .

How do you know that  $y$  is the closest point?

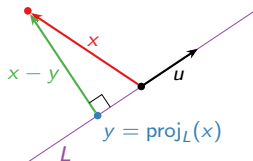
# Orthogonal Projection onto a Line

## 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  $L$** .



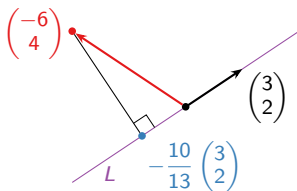
Choose term 'ortogonal' because  $x - y$  is in  $L^\perp$ .

# Orthogonal Projection onto a Line

## Example

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

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



# Orthogonal Sets

## Definition

A set of *nonzero* vectors is **orthogonal** if each pair of vectors is orthogonal. Such set 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:

## Orthogonal bases

Linearly independent

An *orthogonal set of vectors*  $\mathcal{B} = \{u_1, u_2, \dots, u_m\}$  is linearly independent. Therefore  **$\mathcal{B}$  forms a basis** for  $W = \text{Span } \mathcal{B}$ .

## $\mathcal{B}$ -coordinates for Orthogonal bases

### 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

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

### An advantage

For orthogonal bases, it's *easy to compute the  $\mathcal{B}$ -coordinates* of a vector  $x$  in  $W$ :

$$\left( \frac{x \cdot u_1}{u_1 \cdot u_1}, \frac{x \cdot u_2}{u_2 \cdot u_2}, \dots, \frac{x \cdot u_m}{u_m \cdot u_m} \right).$$

# Orthogonal Bases

Geometric reason

## Theorem

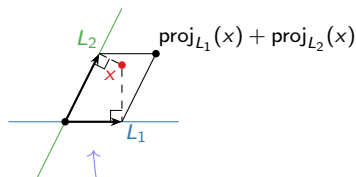
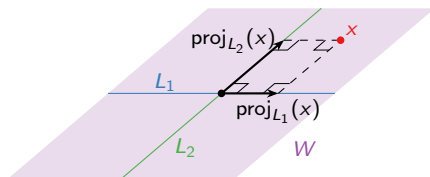
Let  $\mathcal{B} = \{u_1, u_2, \dots, u_m\}$  be an orthogonal set, and let  $x$  be a vector in  $W = \text{Span } \mathcal{B}$ . Then

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

$\swarrow \text{proj}_{L_2}(u_2)$

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

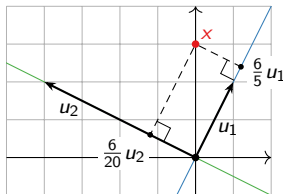
$$\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} -4 \\ 2 \end{pmatrix} \right\}.$$

**Old way:**

$$\left( \begin{array}{cc|c} 1 & -4 & 0 \\ 2 & 2 & 3 \end{array} \right) \xrightarrow{\text{rref}} .$$

**New way:** Exploit that  $\mathcal{B}$  is an *orthogonal basis*.

$$x = \frac{x \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{x \cdot u_2}{u_2 \cdot u_2} u_2$$



$$\Rightarrow [x]_{\mathcal{B}} = \begin{pmatrix} 6/5 \\ 6/20 \end{pmatrix}.$$

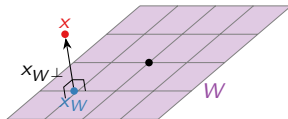
# Orthogonal Bases

## Example

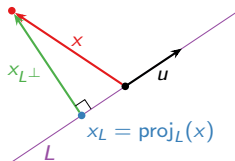
## Section 6.3

### Orthogonal Projections

# Motivation



Example with a line: The closest point to  $x$  in  $L$  is  $\text{proj}_L(x) = \frac{x \cdot u}{u \cdot u} u$



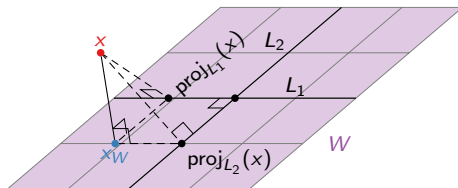
# Orthogonal Projections

## 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

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

The orthogonal projection is formed by adding orthogonal projections onto perpendicular lines.



# Orthogonal Projections

## Best approximation

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  $W^\perp$ .

## 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

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

# Orthogonal Projections

## Properties

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.  $\text{proj}_W$  is a *linear* transformation.
2. For every  $x$  in  $W$ , we have  $\text{proj}_W(x) = x$ .
3. For every  $x$  in  $W^\perp$ , we have  $\text{proj}_W(x) = 0$ .
4. The range of  $\text{proj}_W$  is  $W$ .

The following is *the property we wanted* 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

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





# 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:

# Orthogonal Projections

## Matrix facts

Let  $A$  be the matrix for  $\text{proj}_W$ , where  $W$  is an  $m$ -dimensional subspace of  $\mathbf{R}^n$ .

Facts:

1.  $A$  is diagonalizable with eigenvalues 0 and 1;
2. it is similar to the diagonal matrix with  $m$  ones and  $n - m$  zeros on the diagonal, and
3.  $A^2 = A$ .

**Example:** If  $W$  is a plane in  $\mathbf{R}^3$ , then  $A$  is similar to projection onto the  $xy$ -plane:

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

# Orthogonal Projections

## Minimum distance

What is the (minimum) *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:* From  $e_1$  to its closest point on  $W$ :

$$\text{dist}(e_1, \text{proj}_W(e_1)) = \|(e_1)_{W^\perp}\|.$$

