

# Math 2270-1

Notes of 11/8/19

## Orthogonal Projections

- We start with revisiting the idea of projecting a point  $\mathbf{y}$  in  $\mathbb{R}^2$  onto a line through the origin.
- The projection of  $\mathbf{y}$  is the point on the line that is closest to  $\mathbf{y}$ .

- This idea can be generalized to projecting a point  $\mathbf{y}$  in  $\mathbb{R}^n$  onto a subspace of  $\mathbb{R}^n$ .
- **Theorem 8.** Let  $W$  be a subspace of  $\mathbb{R}^n$ . Then each  $\mathbf{y}$  in  $\mathbb{R}^n$  can be written uniquely in the form

$$\mathbf{y} = \hat{\mathbf{y}} + \mathbf{z} \quad (1)$$

where  $\hat{\mathbf{y}}$  is in  $W$  and  $\mathbf{z}$  is in  $W^\perp$ .

- This is the **orthogonal Decomposition theorem**. The vector  $\hat{\mathbf{y}}$  in (1) is called the **orthogonal projection of  $\mathbf{y}$  onto  $W$** .
- The textbook uses the notation

$$\hat{\mathbf{y}} = \text{proj}_W \mathbf{y}.$$

- The textbook proves the Theorem by actually computing  $\hat{\mathbf{y}}$  and  $\mathbf{z}$ :
- In fact, if  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_p\}$  is any orthogonal basis of  $W$ , then

$$\begin{aligned} \hat{\mathbf{y}} &= \frac{\mathbf{y} \bullet \mathbf{u}_1}{\mathbf{u}_1 \bullet \mathbf{u}_1} \mathbf{u}_1 + \frac{\mathbf{y} \bullet \mathbf{u}_2}{\mathbf{u}_2 \bullet \mathbf{u}_2} \mathbf{u}_2 + \dots + \frac{\mathbf{y} \bullet \mathbf{u}_p}{\mathbf{u}_p \bullet \mathbf{u}_p} \mathbf{u}_p \\ &= \sum_{i=1}^p \frac{\mathbf{y} \bullet \mathbf{u}_i}{\mathbf{u}_i \bullet \mathbf{u}_i} \mathbf{u}_i \end{aligned}$$

and

$$\mathbf{z} = \mathbf{y} - \hat{\mathbf{y}}.$$

- However, the uniqueness of the decomposition (1) shows that the orthogonal projections depends only on  $W$  and not on its basis.



- Example 2, textbook. Let

$$\mathbf{u}_1 = \begin{bmatrix} 2 \\ 5 \\ -1 \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}, \quad \text{and} \quad \mathbf{y} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}.$$

# Geometric Interpretation of Orthogonal Projection

- Note that if the dimension of  $W$  is one, and  $\{\mathbf{u}\}$  is a basis of  $W$  then the orthogonal projection of  $\mathbf{y}$  onto  $W$  is just

$$\hat{\mathbf{y}} = \frac{\mathbf{u} \bullet \mathbf{y}}{\mathbf{u} \bullet \mathbf{u}} \mathbf{u}.$$

- Thus the terms  $\frac{\mathbf{u}_i \bullet \mathbf{y}}{\mathbf{u}_i \bullet \mathbf{u}_i} \mathbf{u}_i$  in

$$\hat{\mathbf{y}} = \sum_{i=1}^p \frac{\mathbf{u}_i \bullet \mathbf{y}}{\mathbf{u}_i \bullet \mathbf{u}_i} \mathbf{u}_i$$

are just the projections of  $\mathbf{y}$  onto the spaces  $\text{span}\{\mathbf{u}_i\}$ .

- As in our initial example, the orthogonal projection  $\hat{\mathbf{y}}$  of  $\mathbf{y}$  onto  $W$  is the point in  $W$  that is closest to  $\mathbf{y}$ . This is the contents of
- **Best Approximation Theorem** (Theorem 9, p. 352) Let  $W$  be a subspace of  $\mathbb{R}^n$ , let  $\mathbf{y}$  be any vector in  $\mathbb{R}^n$ , and let  $\hat{\mathbf{y}}$  be the orthogonal projection of  $\mathbf{y}$  onto  $W$ . Then  $\hat{\mathbf{y}}$  is the closest point  $W$  to  $\mathbf{y}$ , in the sense that

$$\|\mathbf{y} - \mathbf{v}\| > \|\mathbf{y} - \hat{\mathbf{y}}\|$$

for all  $\mathbf{v}$  in  $W$  distinct from  $\hat{\mathbf{y}}$ .

- This is a simple consequence of the Pythagorean Theorem.

- Example 4, p. 353, textbook. Let

$$\mathbf{y} = \begin{bmatrix} -1 \\ -5 \\ 10 \end{bmatrix}, \mathbf{u}_1 = \begin{bmatrix} 5 \\ -2 \\ 1 \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \quad \text{and} \quad W = \text{Span}\{\mathbf{u}_1, \mathbf{u}_2\}$$

Compute the point  $\hat{y}$  in  $W$  that is closest to  $\mathbf{y}$  and its distance from  $\mathbf{y}$ .

- Formulas simplify if our basis is orthonormal, rather than just orthogonal.
- **Theorem 10**, p. 353. If  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_p\}$  is an orthonormal basis for a subspace  $W$  of  $\mathbb{R}^n$ , then

$$\hat{\mathbf{y}} = \text{proj}_W \mathbf{y} = \sum_{i=1}^p (\mathbf{y} \bullet \mathbf{u}_i) \mathbf{u}_i.$$

If  $U = [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_p]$ , then

$$\text{proj}_W \mathbf{y} = UU^T \mathbf{y}$$

for all  $\mathbf{y}$  in  $\mathbb{R}^n$ .



- Next question: How do we get orthonormal bases?