

Sect 6.3: (Cont...)

Thm:

Let W be a subspace of \mathbb{R}^n , let \underline{y} be any vector in \mathbb{R}^n , and let $\hat{\underline{y}} = \text{proj}_W(\underline{y})$, then $\hat{\underline{y}}$ is the closest point in W to \underline{y} in the sense that

$$\|\underline{y} - \hat{\underline{y}}\| < \|\underline{y} - \underline{v}\|$$

for all \underline{v} in W such that $\underline{v} \neq \hat{\underline{y}}$

Pf.

Let \underline{v} in W with $\underline{v} \neq \hat{\underline{y}}$, then

$\hat{\underline{y}} - \underline{v}$ is in W because W closed under addition

We also know that $\underline{y} - \hat{\underline{y}}$ is orthogonal to W and therefore orthogonal to $\hat{\underline{y}} - \underline{v}$. Then we see

$$\underline{y} - \underline{v} = \underline{y} - \hat{\underline{y}} + \hat{\underline{y}} - \underline{v}$$

$$\underline{y} - \underline{v} = (\underline{y} - \hat{\underline{y}}) + (\hat{\underline{y}} - \underline{v})$$

$\in W^\perp \qquad \in W$

So, by the Pythagorean Thm.

$$\|\underline{y} - \underline{v}\|^2 = \|\underline{y} - \hat{\underline{y}}\|^2 + \|\hat{\underline{y}} - \underline{v}\|^2$$

$$> \|\underline{y} - \hat{\underline{y}}\|^2 \quad \text{because } \|\hat{\underline{y}} - \underline{v}\|^2 > 0$$

We can then define the distance of a vector \underline{y} in \mathbb{R}^n to a subspace W as the distance from \underline{y} to the nearest point W , i.e.,

$$\|\underline{y} - \hat{\underline{y}}\| \text{ where } \hat{\underline{y}} = \text{proj}_W(\underline{y})$$

Ex

Find the distance from \underline{y} to $W = \text{span}\{\underline{u}_1, \underline{u}_2\}$ for

$$\underline{y} = \begin{bmatrix} -1 \\ -5 \\ 10 \end{bmatrix}, \quad \underline{u}_1 = \begin{bmatrix} 5 \\ -2 \\ 1 \end{bmatrix}, \quad \underline{u}_2 = \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}$$

First, we compute $\hat{\underline{y}} = \text{proj}_W(\underline{y})$

$$\begin{aligned} \hat{\underline{y}} &= \frac{\underline{y} \cdot \underline{u}_1}{\underline{u}_1 \cdot \underline{u}_1} \underline{u}_1 + \frac{\underline{y} \cdot \underline{u}_2}{\underline{u}_2 \cdot \underline{u}_2} \underline{u}_2 \\ &= \frac{15}{30} \begin{bmatrix} 5 \\ -2 \\ 1 \end{bmatrix} + \frac{-21}{6} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} 5 \\ -2 \\ 1 \end{bmatrix} + \frac{-7}{2} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} = \begin{bmatrix} -1 \\ -8 \\ 4 \end{bmatrix} \end{aligned}$$

$$\text{Then } \underline{y} - \hat{\underline{y}} = \begin{bmatrix} -1 \\ -5 \\ 10 \end{bmatrix} - \begin{bmatrix} -1 \\ -8 \\ 4 \end{bmatrix} = \begin{bmatrix} 0 \\ 3 \\ 6 \end{bmatrix}$$

And $\|\underline{y} - \hat{\underline{y}}\| = \sqrt{0^2 + 3^2 + 6^2} = \sqrt{45}$
is the distance of \underline{y} to the subspace W

Lastly, we want to relate the formula

$$\hat{y} = \text{proj}_W(y) = (y \cdot \underline{u}_1) \underline{u}_1 + \dots + (y \cdot \underline{u}_p) \underline{u}_p$$

for an orthonormal basis $\{\underline{u}_1 \dots \underline{u}_p\}$ of W and y in \mathbb{R}^n to the orthogonal matrix $U = [\underline{u}_1 \dots \underline{u}_p]$

First, we observe that

$$U^T y = \begin{bmatrix} \underline{u}_1^T \\ \underline{u}_2^T \\ \vdots \\ \underline{u}_p^T \end{bmatrix} y = \begin{bmatrix} \underline{u}_1^T y \\ \underline{u}_2^T y \\ \vdots \\ \underline{u}_p^T y \end{bmatrix} = \begin{bmatrix} \underline{u}_1 \cdot y \\ \underline{u}_2 \cdot y \\ \vdots \\ \underline{u}_p \cdot y \end{bmatrix} = \begin{bmatrix} y \cdot \underline{u}_1 \\ y \cdot \underline{u}_2 \\ \vdots \\ y \cdot \underline{u}_p \end{bmatrix}$$

Multiplying by U we get

$$U(U^T y) = [\underline{u}_1 \ \underline{u}_2 \ \dots \ \underline{u}_p] \begin{bmatrix} y \cdot \underline{u}_1 \\ y \cdot \underline{u}_2 \\ \vdots \\ y \cdot \underline{u}_p \end{bmatrix}$$

$$= (y \cdot \underline{u}_1) \underline{u}_1 + (y \cdot \underline{u}_2) \underline{u}_2 + \dots + (y \cdot \underline{u}_p) \underline{u}_p$$

$$= \text{proj}_W(y)$$

$$= \hat{y}$$

Thus, we've shown that $\hat{y} = \text{proj}_W(y) = U U^T y$ #

Sect. 6.4: Gram-Schmidt Process

Goal: We've shown that orthogonal vectors/sets have lots of nice properties. But, how do we get an orthogonal set from a non-orthogonal set?

Strategy: A series of orthogonal projections.

Thm (Gram-Schmidt Process)

Given a (non-orthogonal) basis $\{x_1, \dots, x_p\}$ for a non-zero subspace W of \mathbb{R}^n , define

$$v_1 = x_1$$

$$v_2 = x_2 - \frac{x_2 \cdot v_1}{v_1 \cdot v_1} v_1$$

← portion of x_2 in the v_1 direction

$$v_3 = x_3 - \frac{x_3 \cdot v_1}{v_1 \cdot v_1} v_1 - \frac{x_3 \cdot v_2}{v_2 \cdot v_2} v_2$$

← portion of x_3 in the v_1 direction

← portion of x_3 in the v_2 direction

⋮

$$v_p = x_p - \frac{x_p \cdot v_1}{v_1 \cdot v_1} v_1 - \dots - \frac{x_p \cdot v_{p-1}}{v_{p-1} \cdot v_{p-1}} v_{p-1}$$

The resulting set $\{v_1, \dots, v_p\}$ is an orthogonal basis for W . We have

$$\text{span} \{v_1, \dots, v_p\} = \text{span} \{x_1, \dots, x_p\} = W$$

$$\text{and } \text{span} \{v_1, \dots, v_k\} = \text{span} \{x_1, \dots, x_k\} \text{ for } 1 \leq k \leq p$$

Ex

$$\text{Let } \underline{x}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \underline{x}_2 = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \underline{x}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \text{ and } W = \text{span} \{ \underline{x}_1, \underline{x}_2, \underline{x}_3 \}$$

Find an orthogonal basis for $W = \text{span} \{ \underline{x}_1, \underline{x}_2, \underline{x}_3 \}$

$$\underline{v}_1 = \underline{x}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\underline{v}_2 = \underline{x}_2 - \frac{\underline{x}_2 \cdot \underline{v}_1}{\underline{v}_1 \cdot \underline{v}_1} \underline{v}_1 = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{3}{4} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -3/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$$

$$\begin{aligned} \underline{v}_3 &= \underline{x}_3 - \frac{\underline{x}_3 \cdot \underline{v}_1}{\underline{v}_1 \cdot \underline{v}_1} \underline{v}_1 - \frac{\underline{x}_3 \cdot \underline{v}_2}{\underline{v}_2 \cdot \underline{v}_2} \underline{v}_2 \\ &= \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} - \frac{2}{4} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{\left(\frac{1}{2}\right)}{\left(\frac{12}{16}\right)} \begin{bmatrix} -3/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0 \\ -2/3 \\ 1/3 \\ 1/3 \end{bmatrix} \end{aligned}$$

↗ $\frac{2}{3}$

Check: $\underline{v}_1 \cdot \underline{v}_2 = \underline{v}_1 \cdot \underline{v}_3 = \underline{v}_2 \cdot \underline{v}_3 = 0$ (orthogonal)

Notes:

- we can modify the Gram-Schmidt Process to produce orthonormal bases by normalizing the basis vectors at each step

Ex (above cont...)

$$\underline{u}_1 = \frac{\underline{v}_1}{\|\underline{v}_1\|} = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1/2 \\ 1/2 \\ 1/2 \\ 1/2 \end{bmatrix}$$

$$\underline{u}_2 = \frac{\underline{v}_2}{\|\underline{v}_2\|} = \frac{1}{\left(\frac{9}{16} + \frac{1}{16} + \frac{1}{16} + \frac{1}{16}\right)^{1/2}} \begin{vmatrix} -3/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{vmatrix} = \begin{vmatrix} -3/\sqrt{12} \\ 1/\sqrt{12} \\ 1/\sqrt{12} \\ 1/\sqrt{12} \end{vmatrix}$$

$$\underline{u}_3 = \frac{\underline{v}_3}{\|\underline{v}_3\|} = \frac{1}{\left(4/9 + 1/9 + 1/9\right)^{1/2}} \begin{vmatrix} 0 \\ -2/3 \\ 1/3 \\ 1/3 \end{vmatrix} = \begin{vmatrix} 0 \\ -2/\sqrt{6} \\ 1/\sqrt{6} \\ 1/\sqrt{6} \end{vmatrix}$$

Check: $\|\underline{u}_1\| = \|\underline{u}_2\| = \|\underline{u}_3\| = 1$ (unit vectors)

$$\underline{u}_1 \cdot \underline{u}_2 = \underline{u}_1 \cdot \underline{u}_3 = \underline{u}_2 \cdot \underline{u}_3 = 0 \quad (\text{orthogonal})$$

- Note that the formula for the k th Gram-Schmidt vector gets longer as k grows. The process gets really costly as the of basis vectors gets large