



NTNU
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TMA4115 - Calculus 3
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Yesterday's lecture

Yesterday we introduced and studied

- *the inner product,*
- *the length of a vector,*
- *orthogonality and orthogonal sets in \mathbb{R}^n ,*
- *the orthogonal complement of a subspace,*
- *orthogonal bases and orthonormal bases,*
- *orthogonal matrices.*



Today's lecture

Today we shall introduce and study

- *orthogonal projections,*
- *the Gram-Schmidt process,*
- *QR factorization.*



Orthogonal complements

Let W be a subspace of \mathbb{R}^n . The set of all vectors \mathbf{z} that are orthogonal to W is called the *orthogonal complement* of W and is denoted by W^\perp .

W^\perp is a subspace of \mathbb{R}^n .



The orthogonal complements of $\text{Row}(A)$ and $\text{Col}(A)$

Theorem 3

Let A be an $m \times n$ matrix. Then

- 1 $(\text{Row}(A))^\perp = \text{Nul}(A)$.
- 2 $(\text{Col}(A))^\perp = \text{Nul}(A^T)$.



Orthogonal sets and bases

- A set of vectors $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ in \mathbb{R}^n is said to be an *orthogonal set* if each pair of distinct vectors from the set is orthogonal, that is, if $\mathbf{v}_i \cdot \mathbf{v}_j = 0$ whenever $i \neq j$.
- An *orthogonal basis* for a subspace W of \mathbb{R}^n is a basis for W that is also an orthogonal set.
- $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthogonal basis for W if and only if $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthogonal set and $\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_p\} = W$.

Theorem 5

Let $\mathcal{B} = \{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ be an orthogonal basis for a subspace W of \mathbb{R}^n and let \mathbf{y} be in W . Then the coordinates c_1, \dots, c_p of \mathbf{y} relative to \mathcal{B} is given by $c_j = \frac{\mathbf{y} \cdot \mathbf{v}_j}{\mathbf{v}_j \cdot \mathbf{v}_j}$.



Orthonormal sets and bases

- An *orthonormal set* is an orthogonal set of unit vectors.
- $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthonormal set if and only if

$$\mathbf{v}_i \cdot \mathbf{v}_j = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

- An *orthonormal basis* for a subspace W of \mathbb{R}^n is a basis for W that is also an orthonormal set.
- $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthonormal basis for W if and only if $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthonormal set and $\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_p\} = W$.
- If $\mathcal{B} = \{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ be an orthonormal basis for a subspace W of \mathbb{R}^n and \mathbf{y} is in W , then the coordinates c_1, \dots, c_p of \mathbf{y} relative to \mathcal{B} is given by $c_j = \mathbf{y} \cdot \mathbf{v}_j$.



Matrices with orthonormal columns

Theorem 6

An $m \times n$ matrix U has orthonormal columns if and only if $U^T U = I_n$.

Theorem 7

Let U be an $m \times n$ matrix with orthonormal columns and let \mathbf{x} and \mathbf{y} be in \mathbb{R}^n . Then

- 1 $(U\mathbf{x}) \cdot (U\mathbf{y}) = \mathbf{x} \cdot \mathbf{y}$.
- 2 $\|U\mathbf{x}\| = \|\mathbf{x}\|$.
- 3 $(U\mathbf{x}) \cdot (U\mathbf{y}) = 0$ if and only if $\mathbf{x} \cdot \mathbf{y} = 0$.



Orthogonal matrices

A square matrix with **orthonormal** columns is called an *orthogonal matrix*.

A square matrix U is orthogonal if and only if U is invertible and $U^{-1} = U^T$.



Orthogonal projections

- Let \mathbf{u} and \mathbf{y} be vectors in \mathbb{R}^n and assume that $\mathbf{u} \neq \mathbf{0}$.
- Let $L = \text{Span}\{\mathbf{u}\}$.
- The vector $\text{proj}_L \mathbf{y} = \frac{\mathbf{y} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}} \mathbf{u}$ is called the *orthogonal projection* of \mathbf{y} onto L (or onto \mathbf{u}).
- If $\mathbf{z} = \mathbf{y} - \text{proj}_L \mathbf{y}$, then \mathbf{z} is orthogonal to \mathbf{u} and $\mathbf{y} = \text{proj}_L \mathbf{y} + \mathbf{z}$.
- The vector $\mathbf{z} = \mathbf{y} - \text{proj}_L \mathbf{y}$ is called the component of \mathbf{y} orthogonal to L (or to \mathbf{u}).
- $\|\mathbf{z}\|$ is called the *distance from \mathbf{y} to L* .



Example

Let $\mathbf{y} = \begin{bmatrix} 5 \\ 2 \end{bmatrix}$ and $\mathbf{u} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$. Let us compute the distance from \mathbf{y} to the line through \mathbf{u} and the origin.



Solution

The line through \mathbf{u} and the origin is the line $L = \text{Span}\{\mathbf{u}\}$.

$$\text{proj}_L \mathbf{y} = \frac{\mathbf{y} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}} \mathbf{u} = \frac{7}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 7/2 \\ 7/2 \end{bmatrix}$$

so the distance from \mathbf{y} to L is

$$\begin{aligned} \|\mathbf{y} - \text{proj}_L \mathbf{y}\| &= \left\| \begin{bmatrix} 3/2 \\ -3/2 \end{bmatrix} \right\| \\ &= \sqrt{(3/2)^2 + (-3/2)^2} = \sqrt{9/2} = \frac{3}{\sqrt{2}}. \end{aligned}$$



The orthogonal decomposition theorem

Theorem 8

Let W be a subspace of \mathbb{R}^n and let \mathbf{y} be in \mathbb{R}^n .

- 1 Then \mathbf{y} can be written uniquely in the form $\mathbf{y} = \mathbf{w} + \mathbf{z}$ where \mathbf{w} is in W and \mathbf{z} is in W^\perp .
- 2 If $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ is an orthogonal basis for W , then $\mathbf{w} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \dots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p$ and $\mathbf{z} = \mathbf{y} - \mathbf{w}$.

The vector $\mathbf{w} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \dots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p$ is called the *orthogonal projection of \mathbf{y} onto W* and is denoted by $\text{proj}_W \mathbf{y}$.



Proof of Theorem 8

Let $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ be an orthogonal basis for W and let

$$\mathbf{w} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \dots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p.$$

Then \mathbf{w} is in W . Let $\mathbf{z} = \mathbf{y} - \mathbf{w}$. Then

$\mathbf{z} \cdot \mathbf{u}_k = \mathbf{y} \cdot \mathbf{u}_k - \mathbf{y} \cdot \mathbf{u}_k = 0$ for each k , so \mathbf{z} is in W^\perp .

Suppose $\mathbf{y} = \mathbf{w}' + \mathbf{z}'$ where \mathbf{w}' is in W and \mathbf{z}' is in W^\perp . Then

$\mathbf{w} - \mathbf{w}' = \mathbf{z}' - \mathbf{z}$ is both in W and in W^\perp , so

$\mathbf{w} - \mathbf{w}' = \mathbf{z}' - \mathbf{z} = \mathbf{0}$, from which it follows that $\mathbf{w} = \mathbf{w}'$ and

$\mathbf{z} = \mathbf{z}'$.



The best approximation theorem

Theorem 9

Let W be a subspace of \mathbb{R}^n , let \mathbf{y} be in \mathbb{R}^n , and let $\mathbf{w} = \text{proj}_W \mathbf{y}$.

Then \mathbf{w} is the closest point in W to \mathbf{y} in the sense that $\|\mathbf{y} - \mathbf{w}\| < \|\mathbf{y} - \mathbf{x}\|$ for all \mathbf{x} in W distinct from \mathbf{w} .



Proof of Theorem 9

Let \mathbf{x} be a vector in W distinct from \mathbf{w} . Then $\mathbf{w} - \mathbf{x}$ is in W and $\mathbf{y} - \mathbf{w}$ is in W^\perp , so $\mathbf{w} - \mathbf{x}$ and $\mathbf{y} - \mathbf{w}$ are orthogonal. It follows that

$$\|\mathbf{y} - \mathbf{x}\|^2 = \|(\mathbf{y} - \mathbf{w}) + (\mathbf{w} - \mathbf{x})\|^2 = \|\mathbf{y} - \mathbf{w}\|^2 + \|\mathbf{w} - \mathbf{x}\|^2.$$

Since $\mathbf{x} \neq \mathbf{w}$, it follows that $\|\mathbf{w} - \mathbf{x}\| > 0$, and thus that $\|\mathbf{y} - \mathbf{w}\| < \|\mathbf{y} - \mathbf{x}\|$.



Example

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

$W = \text{Span}\{\mathbf{u}_1, \mathbf{u}_2\}$. Let us find the closest point in W to \mathbf{y} .



Solution

The closest point in W to \mathbf{y} is $\text{proj}_W \mathbf{y}$. We have that $\mathbf{u}_1 \cdot \mathbf{u}_2 = 0$, so $\{\mathbf{u}_1, \mathbf{u}_2\}$ is an orthogonal basis for W . It follows that

$$\begin{aligned}\text{proj}_W \mathbf{y} &= \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \frac{\mathbf{y} \cdot \mathbf{u}_2}{\mathbf{u}_2 \cdot \mathbf{u}_2} \mathbf{u}_2 \\ &= \frac{9}{30} \begin{bmatrix} 2 \\ 5 \\ -1 \end{bmatrix} + \frac{3}{6} \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} -2/5 \\ 2 \\ 1/5 \end{bmatrix}.\end{aligned}$$



Orthogonal projections onto orthonormal bases

Theorem 10

Let $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ be an orthonormal basis for a subspace W of \mathbb{R}^n and let \mathbf{y} be in \mathbb{R}^n .

- 1 Then $\text{proj}_W \mathbf{y} = (\mathbf{y} \cdot \mathbf{u}_1)\mathbf{u}_1 + \dots + (\mathbf{y} \cdot \mathbf{u}_p)\mathbf{u}_p$.
- 2 If $U = [\mathbf{u}_1 \dots \mathbf{u}_p]$, then $\text{proj}_W \mathbf{y} = UU^T \mathbf{y}$.



Proof of Theorem 10

Let $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ be an orthonormal basis for W . Then

$\mathbf{u}_k \cdot \mathbf{u}_k = 1$ for each k , so

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

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

Let $U = [\mathbf{u}_1 \dots \mathbf{u}_p]$. Then

$$\begin{aligned} UU^T \mathbf{y} &= [\mathbf{u}_1 \dots \mathbf{u}_p][\mathbf{u}_1 \dots \mathbf{u}_p]^T \mathbf{y} = [\mathbf{u}_1 \dots \mathbf{u}_p] \begin{bmatrix} \mathbf{u}_1 \cdot \mathbf{y} \\ \vdots \\ \mathbf{u}_p \cdot \mathbf{y} \end{bmatrix} \\ &= (\mathbf{y} \cdot \mathbf{u}_1) \mathbf{u}_1 + \dots + (\mathbf{y} \cdot \mathbf{u}_p) \mathbf{u}_p = \text{proj}_W \mathbf{y} \end{aligned}$$

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



Example

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

$W = \text{Span}\{\mathbf{u}_1, \mathbf{u}_2\}$. Let us use Theorem 10 to find the closest point in W to \mathbf{y} .



Solution

$\|\mathbf{u}_1\|^2 = \mathbf{u}_1 \cdot \mathbf{u}_1 = 30$ and $\|\mathbf{u}_2\|^2 = \mathbf{u}_2 \cdot \mathbf{u}_2 = 6$, so

$\left\{ \begin{bmatrix} 2/\sqrt{30} \\ 5/\sqrt{30} \\ -1/\sqrt{30} \end{bmatrix}, \begin{bmatrix} -2/\sqrt{6} \\ 1/\sqrt{6} \\ 1/\sqrt{6} \end{bmatrix} \right\}$ is an orthonormal basis for W .

$$\text{Let } U = \begin{bmatrix} 2/\sqrt{30} & -2/\sqrt{6} \\ 5/\sqrt{30} & 1/\sqrt{6} \\ -1/\sqrt{30} & 1/\sqrt{6} \end{bmatrix}.$$



Solution

Then

$$\begin{aligned}UU^T &= \begin{bmatrix} 2/\sqrt{30} & -2/\sqrt{6} \\ 5/\sqrt{30} & 1/\sqrt{6} \\ -1/\sqrt{30} & 1/\sqrt{6} \end{bmatrix} \begin{bmatrix} 2/\sqrt{30} & 5/\sqrt{30} & -1/\sqrt{30} \\ -2/\sqrt{6} & 1/\sqrt{6} & 1/\sqrt{6} \end{bmatrix} \\ &= \frac{1}{30} \begin{bmatrix} 24 & 0 & -12 \\ 0 & 30 & 0 \\ -12 & 0 & 6 \end{bmatrix}\end{aligned}$$

$$\text{so } \text{proj}_W \mathbf{y} = UU^T \mathbf{y} = \frac{1}{30} \begin{bmatrix} 24 & 0 & -12 \\ 0 & 30 & 0 \\ -12 & 0 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} -2/5 \\ 2 \\ 1/5 \end{bmatrix}.$$



An algorithm for producing an orthogonal basis for a subspace of \mathbb{R}^n

Let $\{\mathbf{x}_1, \dots, \mathbf{x}_p\}$ be a basis for a subspace W of \mathbb{R}^n .

- 1 Let $\mathbf{v}_1 = \mathbf{x}_1$ and $W_1 = \text{Span}\{\mathbf{v}_1\}$.
- 2 Let $\mathbf{v}_2 = \mathbf{x}_2 - \text{proj}_{W_1} \mathbf{x}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1$ and $W_2 = \text{Span}\{\mathbf{v}_1, \mathbf{v}_2\}$.
- 3 If appropriate, scale \mathbf{v}_2 to simplify later calculations.
- 4 Let $\mathbf{v}_3 = \mathbf{x}_3 - \text{proj}_{W_2} \mathbf{x}_3 = \mathbf{x}_3 - \frac{\mathbf{x}_3 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \frac{\mathbf{x}_3 \cdot \mathbf{v}_2}{\mathbf{v}_2 \cdot \mathbf{v}_2} \mathbf{v}_2$, let $W_3 = \text{Span}\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$, and scale \mathbf{v}_3 to simplify later calculations (if appropriate).



An algorithm for producing an orthogonal basis for a subspace of \mathbb{R}^n

- 5 Continue like this and produce vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p$ where, for $1 < k \leq p$, \mathbf{v}_k is an appropriate multiple of $\mathbf{x}_k - \text{proj}_{\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_{k-1}\}} \mathbf{x}_k = \mathbf{x}_k - \frac{\mathbf{x}_k \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \dots - \frac{\mathbf{x}_k \cdot \mathbf{v}_{k-1}}{\mathbf{v}_{k-1} \cdot \mathbf{v}_{k-1}} \mathbf{v}_{k-1}$.
- 6 Then $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthogonal basis for W .



The Gram-Schmidt process

Theorem 11

Let $\{\mathbf{x}_1, \dots, \mathbf{x}_p\}$ be a linearly independent subset of \mathbb{R}^n . Let

$$\mathbf{v}_1 = \mathbf{x}_1$$

$$\mathbf{v}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1}$$

\vdots

$$\mathbf{v}_p = \mathbf{x}_k - \frac{\mathbf{x}_p \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \dots - \frac{\mathbf{x}_p \cdot \mathbf{v}_{p-1}}{\mathbf{v}_{p-1} \cdot \mathbf{v}_{p-1}} \mathbf{v}_{p-1}$$

Then $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ is an orthogonal set, and
 $\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_k\} = \text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$ for $1 \leq k \leq p$.



Proof of Theorem 11

Let $W_k = \text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$ for each $1 \leq k \leq p$. Then $\{\mathbf{v}_1\}$ is an orthogonal basis for W_1 .

Suppose that $1 \leq k < p$ and that $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is an orthogonal basis for W_k . Then $\mathbf{v}_{k+1} = \mathbf{x}_{k+1} - \text{proj}_{W_k} \mathbf{x}_{k+1}$ is orthogonal to W_k and in W_{k+1} , so $\{\mathbf{v}_1, \dots, \mathbf{v}_{k+1}\}$ is an orthogonal set in W_{k+1} . Since $\dim(W_{k+1}) = k + 1$, it follows that $\{\mathbf{v}_1, \dots, \mathbf{v}_{k+1}\}$ is an orthogonal basis for W_{k+1} .

It follows that $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is an orthogonal basis for W_k for all $1 \leq k \leq p$.



Example

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

$$W = \text{Span}\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}.$$

Let us find an orthogonal basis for W .



Solution

$\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}$ is linearly independent and therefore a basis for W . Let $\mathbf{v}_1 = \mathbf{x}_1$ and $W_1 = \text{Span}\{\mathbf{v}_1\} = \text{Span}\{\mathbf{x}_1\}$.

Let

$$\mathbf{v}_2 = \mathbf{x}_2 - \text{proj}_{W_1} \mathbf{x}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{3}{4} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} -3 \\ 1 \\ 1 \\ 1 \end{bmatrix},$$

$$\mathbf{v}'_2 = 4\mathbf{v}_2 = \begin{bmatrix} -3 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \text{ and}$$

$$W_2 = \text{Span}\{\mathbf{v}_1, \mathbf{v}'_2\} = \text{Span}\{\mathbf{v}_1, \mathbf{v}_2\} = \text{Span}\{\mathbf{x}_1, \mathbf{x}_2\}.$$



Solution

Let

$$\begin{aligned}\mathbf{v}_3 &= \mathbf{x}_3 - \text{proj}_{W_2} \mathbf{x}_3 \\ &= \mathbf{x}_3 - \frac{\mathbf{x}_3 \cdot \mathbf{v}_1}{\mathbf{v}_1 \cdot \mathbf{v}_1} \mathbf{v}_1 - \frac{\mathbf{x}_3 \cdot \mathbf{v}'_2}{\mathbf{v}'_2 \cdot \mathbf{v}'_2} \mathbf{v}'_2 \\ &= \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} - \frac{2}{4} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{2}{12} \begin{bmatrix} -3 \\ 1 \\ 1 \\ 1 \end{bmatrix} \\ &= \frac{1}{3} \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix}\end{aligned}$$



Solution (cont.)

and $\mathbf{v}'_3 = 3\mathbf{v}_3 = \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix}$. Then

$\{\mathbf{v}_1, \mathbf{v}'_2, \mathbf{v}'_3\} = \left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} -3 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix} \right\}$ is an orthogonal basis

for W .



The QR factorization

Theorem 12

If A is an $m \times n$ matrix with linearly independent columns, then A can be factored as $A = QR$, where

- Q is an $m \times n$ matrix whose columns form an orthonormal basis for $\text{Col}(A)$,
- R is an $n \times n$ upper triangular invertible matrix with positive entries on its diagonal.



Proof of Theorem 12

Let $A = [\mathbf{x}_1 \dots \mathbf{x}_n]$ and let $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ be an orthogonal set such that $\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_k\} = \text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$ for each $1 \leq k \leq p$.

Then we have for each $1 \leq k \leq p$ that there exist scalars $r_{1k}, r_{2k}, \dots, r_{kk}$ such that $\mathbf{x}_k = r_{1k}\mathbf{v}_1 + \dots + r_{kk}\mathbf{v}_k$.

We must have that $r_{kk} \neq 0$ because otherwise \mathbf{x}_k would be in $\text{Span}\{\mathbf{v}_1, \dots, \mathbf{v}_{k-1}\} = \text{Span}\{\mathbf{x}_1, \dots, \mathbf{x}_{k-1}\}$ which would contradict the assumption that $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ is linearly independent.

We may assume that $r_{kk} > 0$, because if $r_{kk} < 0$, then we can replace \mathbf{v}_k by $-\mathbf{v}_k$ and r_{kk} by $-r_{kk}$, and then $r_{kk} > 0$.



Proof of Theorem 12 (cont.)

$$\text{Let } Q = [\mathbf{v}_1 \dots \mathbf{v}_n] \text{ and } R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ 0 & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & r_{nn} \end{bmatrix}.$$

$$\text{Then } QR = [\mathbf{x}_1 \dots \mathbf{x}_n] = A.$$



Example

Let us find a QR factorization of $A = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$.



Solution

$$\text{Let } \mathbf{x}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \mathbf{x}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \mathbf{v}_1 = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix},$$

$$\mathbf{v}_2 = \frac{1}{\sqrt{12}} \begin{bmatrix} -3 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \mathbf{v}_3 = \frac{1}{\sqrt{6}} \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix}.$$



Solution (cont.)

Then $A = [\mathbf{x}_1 \ \mathbf{x}_2 \ \mathbf{x}_3]$, and $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$ is an orthonormal set such that

$$\mathbf{x}_1 = 2\mathbf{v}_1$$

$$\mathbf{x}_2 = \frac{3}{2}\mathbf{v}_1 + \frac{\sqrt{3}}{2}\mathbf{v}_2$$

$$\mathbf{x}_3 = \mathbf{v}_1 + \frac{1}{\sqrt{3}}\mathbf{v}_2 + \frac{\sqrt{2}}{\sqrt{3}}\mathbf{v}_3$$



Solution (cont.)

So if we let $Q = [\mathbf{v}_1 \ \mathbf{v}_2 \ \mathbf{v}_3] = \begin{bmatrix} 1 & -3 & 0 \\ 2 & \sqrt{12} & -2 \\ 1 & \sqrt{12} & \sqrt{6} \\ 2 & \sqrt{12} & \sqrt{6} \\ 1 & \sqrt{12} & \sqrt{6} \\ 2 & \sqrt{12} & \sqrt{6} \end{bmatrix}$ and

$R = \begin{bmatrix} 2 & \frac{3}{2} & 1 \\ 0 & \frac{\sqrt{3}}{2} & \frac{1}{\sqrt{3}} \\ 0 & 0 & \frac{\sqrt{2}}{\sqrt{3}} \end{bmatrix}$, then $QR = A$ is a QR factorization of A .



Problem 6 from June 2010

Let A be the following matrix; find a basis for each of the spaces $\text{Nul}(A)$, $\text{Col}(A)$, $(\text{Col}(A))^\perp$, and $\text{Row}(A)$.

$$A = \begin{bmatrix} 1 & 2 & 0 & 1 & 2 & 1 \\ 3 & 6 & 1 & 0 & 2 & -1 \\ 4 & 8 & 2 & -2 & 0 & -4 \end{bmatrix}$$

Find the orthogonal projection of $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ on to $\text{Col}(A)$.



Solution

We start by reducing A to its reduced echelon form.

$$\begin{bmatrix} 1 & 2 & 0 & 1 & 2 & 1 \\ 3 & 6 & 1 & 0 & 2 & -1 \\ 4 & 8 & 2 & -2 & 0 & -4 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & 0 & 1 & 2 & 1 \\ 0 & 0 & 1 & -3 & -4 & -4 \\ 0 & 0 & 2 & -6 & -8 & -8 \end{bmatrix} \rightarrow$$

$$\begin{bmatrix} 1 & 2 & 0 & 1 & 2 & 1 \\ 0 & 0 & 1 & -3 & -4 & -4 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$



Solution

We see that $\left\{ \begin{bmatrix} -2 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 3 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -2 \\ 0 \\ 4 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 4 \\ 0 \\ 1 \end{bmatrix} \right\}$ is a basis for

$\text{Nul}(A)$, that $\left\{ \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} \right\}$ is a basis for $\text{Col}(A)$,



Solution (cont.)

and that $\left\{ \begin{bmatrix} 1 \\ 2 \\ 0 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -3 \\ -4 \\ -4 \end{bmatrix} \right\}$ is a basis for $\text{Row}(A)$.



Solution (cont.)

$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ is in $(\text{Col}(A))^\perp$ if and only if

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 3 \\ 4 \end{bmatrix} = x_1 + 3x_2 + 4x_3 = 0 \text{ and}$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} = x_2 + 2x_3 = 0.$$

We reduce the coefficient matrix of the system

$$x_1 + 3x_2 + 4x_3 = 0$$

$$x_2 + 2x_3 = 0$$

to its reduced echelon form.



Solution (cont.)

$$\begin{bmatrix} 1 & 3 & 4 \\ 0 & 1 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & -2 \\ 0 & 1 & 2 \end{bmatrix}$$

We see that $(\text{Col}(A))^\perp = \text{Span} \left\{ \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} \right\}$, so $\left\{ \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} \right\}$ is a basis for $(\text{Col}(A))^\perp$.



Solution (cont.)

The orthogonal projection of $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ on to $(\text{Col}(A))^\perp$ is

$$\frac{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}}{\begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix}} \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} \text{ so the orthogonal projection of}$$

$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \text{ on to } \text{Col}(A) \text{ is } \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 2 \\ -2 \\ 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} -2 \\ 2 \\ 8 \end{bmatrix}.$$



Problem 5 from June 2011

Let V be the column space of the matrix

$$\begin{bmatrix} 1 & 3 & 0 & 1 \\ 2 & 1 & 5 & -3 \\ -1 & -1 & -2 & 1 \end{bmatrix}$$

and let

$$\mathbf{b} = \begin{bmatrix} 1 \\ 7 \\ 3 \end{bmatrix}.$$

Find the nearest point in V to \mathbf{b} (that is, the orthogonal projection of \mathbf{b} on to V).



Solution

We start by reducing the matrix to an echelon form.

$$\begin{bmatrix} 1 & 3 & 0 & 1 \\ 2 & 1 & 5 & -3 \\ -1 & -1 & -2 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 3 & 0 & 1 \\ 0 & -5 & 5 & -5 \\ 0 & 2 & -2 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 3 & 0 & 1 \\ 0 & 1 & -1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

We see that $\left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} \right\}$ is a basis for V . We then find an orthogonal basis for V by using the Gram-Schmidt

process on $\left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} \right\}$.



Solution (cont.)

$$\begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} - \frac{\begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}}{\begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \\ -1 \end{bmatrix} - \frac{6}{6} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}$$

so $\left\{ \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}, \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} \right\}$ is an orthogonal basis for V .



Solution (cont.)

We then have that

$$\begin{aligned}\text{proj}_V \mathbf{b} &= \frac{\begin{bmatrix} 1 \\ 7 \\ 3 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}}{\begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix}} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} + \frac{\begin{bmatrix} 1 \\ 7 \\ 3 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}}{\begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}} \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} \\ &= \frac{12}{6} \begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} + \frac{-5}{5} \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 5 \\ -2 \end{bmatrix}.\end{aligned}$$



Problem 5 from December 2010

Let $V \subseteq \mathbb{R}^4$ be the solution space of the linear system

$$\begin{aligned}x + y - z + w &= 0 \\x + 2y - 2z + w &= 0\end{aligned}$$

- 1 Find an orthogonal basis for V .
- 2 Find the orthogonal projection of $\mathbf{b} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$ on to V .
- 3 Find an orthogonal basis for \mathbb{R}^4 in which the first two first basis vectors are the once we found in (1).



Solution

We start by reducing the coefficient matrix of the system to its reduced echelon form.

$$\begin{bmatrix} 1 & 1 & -1 & 1 \\ 1 & 2 & -2 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & -1 & 1 \\ 0 & 1 & -1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & -1 & 0 \end{bmatrix}$$

We see that $\left\{ \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \right\}$ is a basis for V and that it is orthogonal.



Solution (cont.)

The orthogonal projection of \mathbf{b} on to V is

$$\frac{\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}}{\begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}} \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix} + \frac{\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}}{\begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}} \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}$$



Solution (cont.)

Let A be the coefficient matrix of the system. Then

$$V^\perp = (\text{Nul}(A))^\perp = \text{Row}(A) = \text{Span} \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \\ 0 \end{bmatrix} \right\}, \text{ so}$$

$$\left\{ \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ -1 \\ 0 \end{bmatrix} \right\} \text{ is an orthogonal basis for } \mathbb{R}^4.$$



Plan for next week

Wednesday we shall look at

- *least-squares problems*,
- applications to linear models.

Sections 6.5–6.6 in “Linear Algebras and Its Applications” (pages 360–375).

Thursday we shall introduce and study

- *symmetric matrices*,
- *quadratic forms*.

Sections 7.1–7.2 in “Linear Algebras and Its Applications” (pages 393–407).

