

## Recap

Orthogonal Complement of subspace  $(W)$ :

- Denoted  $W^\perp$

$$W^\perp = \{ \text{all } \vec{z} \text{ such that } \vec{z} \perp W \}$$

$$W^\perp = \{ \text{all } \vec{z} \text{ such that } \vec{z} \perp \vec{u} \text{ for any } \vec{u} \in W \}$$

$$\vec{z} \perp \vec{u} \rightarrow \vec{u} \cdot \vec{z} = 0$$

- $\text{proj}_W \vec{z} = 0$  for all  $\vec{z} \in W^\perp$
- $W^\perp$  can be thought of as all area that cannot be described by  $W$ .

$$\underline{\dim W + \dim W^\perp}$$

- Given above it is not ~~sur~~ surprising  
 $\dim W + \dim (W^\perp) = n$  where  
 $W, W^\perp$  are in  $\mathbb{R}^n$

①

### Orthogonal Set

$\{ \vec{u}_1, \dots, \vec{u}_p \}$  is an orthogonal set in  $\mathbb{R}^n$

if  $\vec{u}_i \perp \vec{u}_j$  for all  $i \neq j$   
 $\rightarrow \vec{u}_i \cdot \vec{u}_j = 0$  for all  $i \neq j$

Theorem: An Orthogonal set of non-zero vectors is linearly independent

Theorem: Suppose  $\dim(W) = p$  and  $\{ \vec{u}_1, \dots, \vec{u}_p \}$  is an orthogonal set of non-zero vectors in  $W$   
 $\rightarrow \{ \vec{u}_1, \dots, \vec{u}_p \}$  is a basis for  $W$ .

### Orthogonal Decomposition Theorem

Let  $\{ \vec{u}_1, \dots, \vec{u}_p \}$  be an orthogonal basis for  $W \subseteq \mathbb{R}^n$

For each  $\vec{y}$  in  $\mathbb{R}^n$  it can be decomposed as  $\vec{y} = \vec{\hat{y}} + \vec{z}$

where  $\vec{\hat{y}} \in W$  and  $\vec{z} \in W^\perp$

$$\vec{\hat{y}} = \text{Proj}_W \vec{y}$$

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

(2)

Consider

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix}$$

$$b = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 3 \end{bmatrix}$$

Want to solve  $A\vec{x} = \vec{b}$

$$\left[ \begin{array}{cc|c} 1 & 2 & 1 \\ 1 & 5 & 2 \\ 1 & 7 & 3 \\ 1 & 8 & 3 \end{array} \right] \sim \left[ \begin{array}{cc|c} 1 & 2 & 1 \\ 0 & 3 & 1 \\ 0 & 5 & 2 \\ 0 & 6 & 2 \end{array} \right] \sim \left[ \begin{array}{cc|c} 1 & 2 & 1 \\ 0 & 3 & 1 \\ 0 & 0 & \frac{1}{3} \\ 0 & 0 & 0 \end{array} \right]$$

- Still interested in finding a best solution

- why??

- we could be studying non-deterministic (correlation)

- hours of study vs. exam grade

Def A least-square solution of  $A\vec{x} = b$  is an  $\hat{\vec{x}}$

$$\|\vec{b} - A\hat{\vec{x}}\| \leq \|\vec{b} - A\vec{x}\|$$

for all  $\vec{x} \in \mathbb{R}^n$

-  $\|\cdot\|$  is a distance metric

- In this case, this is the  $n$ -dimensional version of the 1-D least squares metric  $\sqrt{(b - ax)^2}$

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So we want to ~~be~~ find  $\vec{x}$   
 $\min_{\vec{x} \in \mathbb{R}^n} \|\vec{b} - A\vec{x}\|$

- For this we need one more tool  
and the stuff from last lecture

### Best Approximation Theorem

- Let  $W$  as subspace of  $\mathbb{R}^n$
- Let  $\vec{y}$  be a vector of  $\mathbb{R}^n$
- $\rightarrow \|\vec{y} - \text{proj}_W \vec{y}\| \leq \|\vec{y} - \vec{v}\|$

for any  $\vec{v} \neq \text{proj}_W \vec{y}$

So want to change

$$\|\vec{b} - A\vec{x}\| \leq \|\vec{b} - A\vec{x}\| \quad \forall \vec{x} \in \mathbb{R}^n$$

to fit language above

Let  $W = \text{col}(A)$

$$\rightarrow W = \{ A\vec{x} \mid \vec{x} \in \mathbb{R}^n \}$$

$\rightarrow$  let  $\vec{v} \in W$

$\rightarrow$  let  $\vec{b} \in \text{proj}_W \vec{b}$

$$\rightarrow \|\vec{b} - \vec{b}\| \leq \|\vec{b} - \vec{v}\| \quad \text{for all } \vec{v} \in W$$

by best approximation theorem

$$\left\{ c_1 \begin{bmatrix} a_{11} \\ a_{21} \end{bmatrix} + \dots + c_n \begin{bmatrix} a_{1n} \\ a_{2n} \end{bmatrix} \right\}$$

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Does  $\vec{b}$  exist as a ~~set~~ solution to  $A\vec{x}$ ?

$$\vec{b} = \text{proj}_W \vec{b} \quad \text{which by def is in } W$$

$\rightarrow \vec{b}$  is a linear combination of ~~the~~ the columns of  $A$

$\rightarrow A\vec{x} = \vec{b}$  is consistent

$\rightarrow$  follow ~~the~~ close to the same reasoning for  $\vec{v}$  ~~or~~  $A\vec{x} = \vec{v}$

$$\rightarrow \|\vec{b} - A\hat{\vec{x}}\| \leq \|\vec{b} - A\vec{x}\| \text{ for all } \vec{x} \in \mathbb{R}^n$$

where  $A\hat{\vec{x}} = \vec{b} = \text{proj}_W \vec{b}$

How do we calculate  $\vec{b}$  or  $A\hat{\vec{x}}$

- Use orthogonal decomposition

$$\vec{b} = \underbrace{\vec{b}}_{\text{in } W} + \underbrace{\vec{z}}_{\text{in } W^\perp}$$

$$\vec{z} = (\vec{b} - \vec{b})$$

We know  $\vec{z} \in W^\perp$   $\vec{z} \in (\text{col}(A))^\perp$

Recall  $(\text{Col } A)^\perp = \text{Null } A^T$

$$A^T \vec{z} = 0$$
$$A^T (\vec{b} - \vec{b}) = 0$$

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A solution for  $A\vec{x} = \vec{b}$  satisfies

$$A^T(\vec{b} - \vec{\hat{b}}) = 0$$

$$A^T(\vec{b} - A\vec{\hat{x}}) = 0$$

$$A^T\vec{b} - A^T A\vec{\hat{x}} = 0$$

$$\underline{A^T A\vec{\hat{x}} = A^T\vec{b}}$$

↑

is the normal equation  
for  $A\vec{x} = \vec{b}$

Conversely  $A^T A\vec{\hat{x}} = A^T\vec{b}$  satisfies

$$A^T(\vec{b} - A\vec{\hat{x}}) = 0$$

Since  $\text{Null } A^T = (\text{Col}(A))^\perp$

$$\rightarrow (\vec{b} - A\vec{\hat{x}}) \in (\text{Col } A)^\perp = W^\perp$$

$$\rightarrow A\vec{\hat{x}} = \text{proj}_W \vec{b} = \vec{\hat{b}}$$

Back to our problem

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix}$$

$$b = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 3 \end{bmatrix}$$

~~$(A^T A)^{-1} (A^T A)\vec{x} = A^T\vec{b}$~~   
 ~~$(A^T A)^{-1} (A^T A)\vec{x} = A^T\vec{b}$~~

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We want to find an  $\vec{x}$   
such that

$$\begin{aligned}(A^T A) \vec{x} &= A^T \vec{b} \\ (A^T A)^{-1} (A^T A) \vec{x} &= (A^T A)^{-1} A^T \vec{b} \\ \vec{x} &= (A^T A)^{-1} A^T \vec{b}\end{aligned}$$

$$\vec{x} = \begin{pmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 5 & 7 & 8 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 15 \\ 17 \\ 18 \end{bmatrix} \end{pmatrix}^{-1} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 5 & 7 & 8 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 3 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} 2/7 \\ 5/14 \end{bmatrix}$$

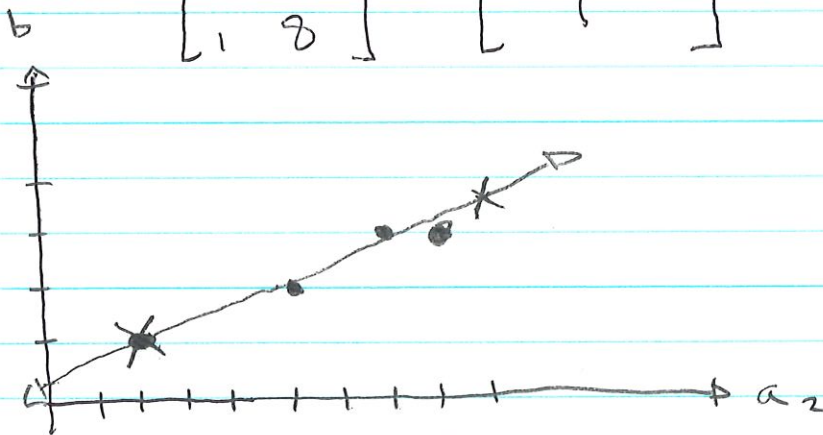
→  $\begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix} \begin{bmatrix} 2/7 \\ 5/14 \end{bmatrix}$  get as close to  $\begin{bmatrix} 1 \\ 2 \\ 3 \\ 3 \end{bmatrix}$  as possible

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Since  $a_1$  is all the ~~same~~ same  
lets just look at ~~the~~  
 $a_2$  vs  $b$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 5 \\ 1 & 7 \\ 1 & 8 \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \end{bmatrix}$$

$a_2$	$b$
2	1
5	2
7	3
8	3



$$b = \frac{2}{7} + \frac{5}{14} a_2$$

In the case  $A^T A$  is not invertible,  
we still want to solve

$$(A^T A) \vec{x} = A^T \vec{b}$$

- ① Find  $A^T A$  which will be a  $n \times n$  matrix
- ② Find  $A^T \vec{b}$  which will be a  $1 \times n$  vector



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③ Put  $A^T A$  and  $A^T b$  in an augmented matrix and solve

$$\left[ \begin{array}{c|c} A^T A & A^T b \end{array} \right]$$

And  $\vec{x}$  can be any solution that satisfies the above.

Theorem:

The set of least squares solutions of  $A\vec{x} = \vec{b}$  = the solution set of  $(A^T A)\vec{x} = A^T \vec{b}$

Theorem Given  $A$  is an  $m \times n$  matrix the following are equivalent

- a)  $A\vec{x} = \vec{b}$  has a unique least square solution
- b) The columns of  $A$  are linearly independent
- c)  $A^T A$  is invertible