

## EECS 16A

Module 3, Lecture 4.

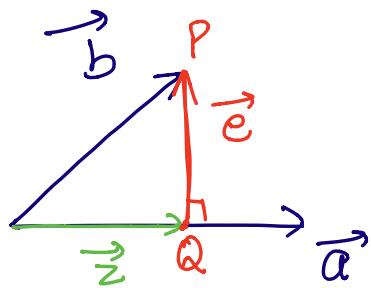
Today: • Least Squares / Projection

Last time : ① 1D projection

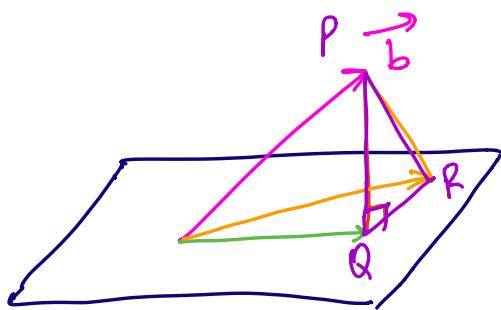
: ② shortest distance from a point to a line is given by the perpendicular from the point to the line.

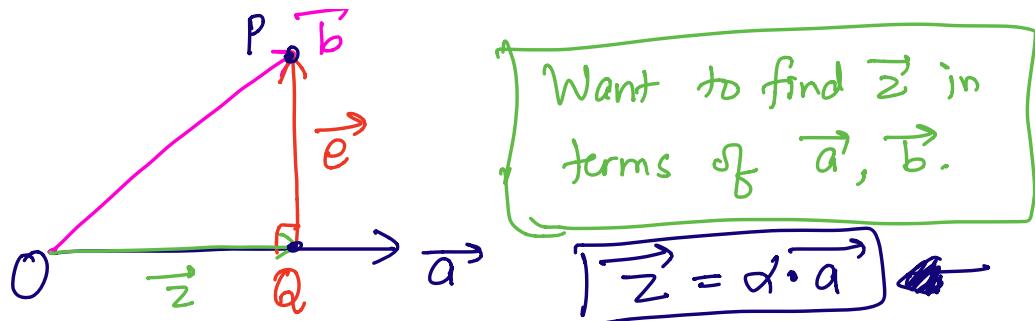
↳ Generalizes:

shortest distance from a point to a hyperplane / vector space is given by the "orthogonal" projection of the point onto the hyperplane.



$$\begin{aligned}\vec{e} &= \text{error} \\ \vec{z} + \vec{e} &= \vec{b} \\ \vec{e} &= \vec{b} - \vec{z} \\ \vec{z} &= \alpha \cdot \vec{a}\end{aligned}$$





$$\vec{z} + \vec{e} = \vec{b}$$

$$\vec{z} = \vec{b} - \vec{e}$$

$\langle \vec{e}, \vec{a} \rangle = 0$  : Must be true since we want

$$\Rightarrow \langle \vec{b} - \vec{z}, \vec{a} \rangle = 0 \quad \vec{e} \text{ orthogonal to } \vec{a}.$$

$$\Rightarrow \langle \vec{a}, \vec{b} - \vec{z} \rangle = 0 \quad ) \text{ inner products don't care about order.}$$

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

$$\Rightarrow \vec{a}^T (\vec{b} - \alpha \cdot \vec{a}) = 0$$

$$\Rightarrow \vec{a}^T \vec{b} - \alpha \cdot \vec{a}^T \vec{a} = 0$$

$$\Rightarrow \langle \vec{a}, \vec{b} \rangle - \alpha \|\vec{a}\|^2 = 0$$

$$\alpha = \frac{\langle \vec{a}, \vec{b} \rangle}{\|\vec{a}\|^2} \quad \text{SCALAR}$$

$$\boxed{\vec{z} = \alpha \cdot \vec{a}} = \vec{z} = \underbrace{\frac{\langle \vec{a}, \vec{b} \rangle}{\|\vec{a}\|^2}}_{\sim} \cdot \vec{a}$$

$$\|\vec{z}\| = \|\alpha \vec{a}\| = |\alpha| \cdot \|\vec{a}\|$$

$$= \frac{|\langle \vec{a}, \vec{b} \rangle|}{\|\vec{a}\|^2} \cdot \cancel{\|\vec{a}\|}$$

$$= \frac{|\langle \vec{a}, \vec{b} \rangle|}{\|\vec{a}\|}$$

1D Projections or Least Squares.

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Systems:

$$\textcircled{A} \vec{x} \approx \textcircled{b}$$

In GPS: have multiple satellites.

$A$  is no longer just a vector, but  
is an actual matrix.

$$\textcircled{a} \vec{x} = \vec{b}$$

## Moving beyond 1D.

Thm: Consider matrix  $A$ ,  $\vec{y} \in \text{Colspace}(A)$ .

$$A = \left[ \vec{q}_1, \vec{q}_2, \dots, \vec{q}_n \right].$$

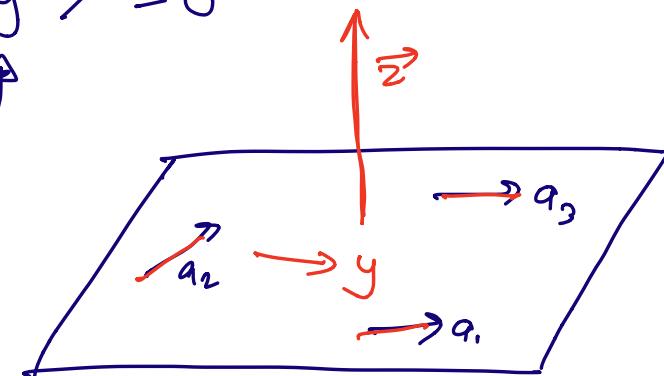
Then, consider  $\vec{z}$

$$\langle \vec{z}, \vec{q}_1 \rangle = 0 \quad \dots$$

$$\langle \vec{z}, \vec{q}_n \rangle = 0$$

$$\langle \vec{z}, \vec{q}_2 \rangle = 0$$

Then:  $\langle \vec{z}, \vec{y} \rangle = 0$



Proof:

Known:

$$\vec{y} \in \text{Col}(A)$$

$$\vec{y} \text{ is a lin. comb of } \vec{q}_1, \vec{q}_2, \dots, \vec{q}_n = 2 \cdot \vec{q}_1$$

eg.  $A \cdot \vec{b}$   
 $A \cdot (2\vec{b})$

$$\vec{y} = c_1 \cdot \vec{q}_1 + c_2 \cdot \vec{q}_2 + \dots + c_n \cdot \vec{q}_n$$

$$\langle \vec{z}, \vec{q}_1 \rangle = 0 \dots \langle \vec{z}, \vec{q}_n \rangle = 0$$

Want:

$$\langle \vec{z}, \vec{y} \rangle = 0$$

$$\langle \vec{z}, \vec{y} \rangle$$

Inner products are linear operations.

$$= \langle \vec{z}, c_1 \vec{q}_1 + c_2 \vec{q}_2 + \dots + c_n \vec{q}_n \rangle$$

$$= \langle \vec{z}, c_1 \vec{q}_1 \rangle + \langle \vec{z}, c_2 \vec{q}_2 \rangle + \dots + \langle \vec{z}, c_n \vec{q}_n \rangle$$

$$= c_1 \langle \vec{z}, \vec{q}_1 \rangle + c_2 \langle \vec{z}, \vec{q}_2 \rangle + \dots + c_n \langle \vec{z}, \vec{q}_n \rangle$$

$$= c_1 \cdot 0 + c_2 \cdot 0 + \dots + c_n \cdot 0$$

$$= 0$$

QED.

### Least Squares-Algorithm

Trilateration  $\Rightarrow$

$$A \vec{x} = \vec{b} + \vec{e}$$

Noisy equations

Many equations. More equations than unknowns

A :  $m \times n$

$$\begin{matrix} m \\ & A \\ & | \\ & n \end{matrix} \quad \begin{matrix} \vec{x} \\ = \\ \vec{b} \end{matrix} \quad \begin{matrix} m \times 1 \end{matrix}$$

$m > n$

m equations  
n unknowns

Overdetermined  
System.

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Square:

$$\begin{matrix} n \times n \\ n \times 1 \\ n \times 1 \end{matrix} = \begin{matrix} n \times 1 \end{matrix}$$

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Least-Squares: Find  $\vec{x}$ , such that

$A\vec{x}$  is close to  $\vec{b}$

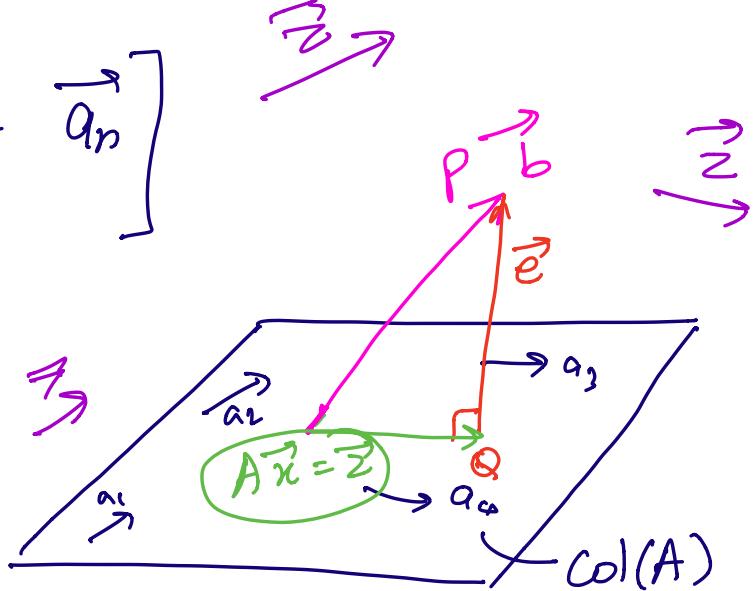
$$\vec{b} - A\vec{x} = \vec{e}$$

$$A\vec{x} = \vec{z}$$

$$\|\vec{A}\vec{x} - \vec{b}\| = (\|\vec{e}\|) \text{ to be minimized.}$$

$$A = \left[ \vec{a}_1, \vec{a}_2 \dots \vec{a}_n \right]$$

What is  
 $\vec{A}\vec{x} = \vec{z}$



$$\left[ \vec{a}_1 \vec{a}_2 \dots \vec{a}_n \right] \left[ \vec{x} \right] = \text{col}(A)$$

We are searching over  $\vec{z} \in \text{col}(A)$

because  $\vec{A}\vec{x}$  represents all vectors in the  $\text{col}(A)$ .

$$\vec{z} + \vec{e} = \vec{b}$$

$$\vec{e} = \vec{b} - \vec{z}$$

$$\langle \vec{a}_1, \vec{e} \rangle = 0 \Rightarrow \langle \vec{a}_1, \vec{b} - \vec{z} \rangle = 0$$

$$\langle \vec{a}_2, \vec{e} \rangle = 0$$

⋮  
⋮

$$\langle \vec{a}_n, \vec{e} \rangle = 0 \Rightarrow \langle \vec{a}_n, \vec{b} - \vec{z} \rangle = 0$$

$$\boxed{\begin{aligned}\vec{a}_1^T (\vec{b} - \vec{z}) &= 0 \\ \vec{a}_2^T (\vec{b} - \vec{z}) &= 0 \\ &\vdots \\ \vec{a}_n^T (\vec{b} - \vec{z}) &= 0\end{aligned}}$$

$$A = [\vec{a}_1 \dots \vec{a}_n]$$

$$A^T = \left[ \begin{array}{c} \vec{a}_1^T \\ \vec{a}_2^T \\ \vdots \\ \vec{a}_n^T \end{array} \right]$$

$$A = m \times n$$

$$A^T : n \times m$$

$$\left[ \begin{array}{c} \vec{a}_1^T \\ \vec{a}_2^T \\ \vdots \\ \vec{a}_n^T \end{array} \right] \left[ \begin{array}{c} \vec{b} - \vec{z} \end{array} \right] = 0$$

$$\underbrace{A^T}_{n \times m} \underbrace{\left( \overrightarrow{b} - \overrightarrow{z} \right)}_{m \times 1} = 0$$

$$A^T \left( \overrightarrow{b} - A \overrightarrow{x} \right) = 0$$

$$A^T \overrightarrow{b} - A^T A \cdot \underbrace{\overrightarrow{x}}_m = 0$$

$$A^T A \overrightarrow{x} = A^T \overrightarrow{b}$$

$$A \overrightarrow{x} = \overrightarrow{b}$$

$$A^T \cdot A : n \times n$$

$n \times m \quad m \times n$

Use inversion! if  $A^T A$  is invertible:

$$\overrightarrow{x} = (A^T A)^{-1} A^T \cdot \overrightarrow{b} !!!$$

"General least squares algorithm"

$$\overrightarrow{z} = A \overrightarrow{x} = A (A^T A)^{-1} A^T \cdot \overrightarrow{b}$$

Example:

$$A = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$2 \times 1$

$$\vec{b} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$m=2$

$n=1$

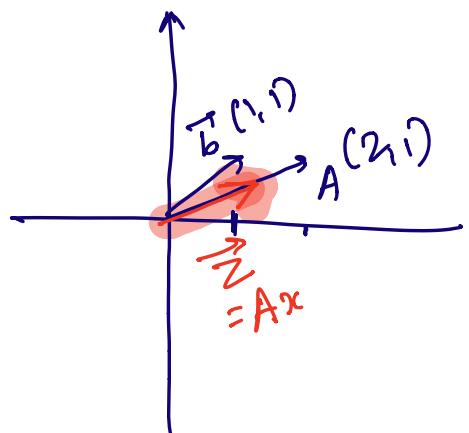
$$" A \vec{x} = \vec{b} "$$

$$\boxed{\begin{bmatrix} 2 \\ 1 \end{bmatrix} \boxed{x}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Gaussian Elimination

$$\left[ \begin{array}{c|c} 2 & 1 \\ 1 & 1 \end{array} \right] \rightarrow \left[ \begin{array}{c|c} 1 & 1/2 \\ 1 & 1 \end{array} \right] \rightarrow \left[ \begin{array}{c|c} 1 & 1/2 \\ 0 & 1/2 \end{array} \right]$$

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



$$A^T = \begin{bmatrix} 2 & 1 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$= 5$$

$$(A^T A)^{-1} = \frac{1}{5}$$

$$A^T \cdot \vec{b} = \begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 3$$

$$\hat{x} = \frac{1}{5} \circ 3 = \frac{3}{5}$$

$$\vec{z} = A \hat{x} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \cdot \frac{3}{5}$$

$$\begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$