System of Linear Equations

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1. System of Linear Equations

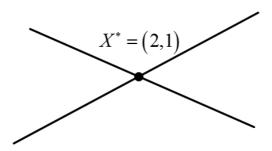
- 1. well-determined linear systems
- 2. under-determined linear systems
- 3. over-determined linear systems

1.1. Well-Determined Linear Systems

· System of linear equations

$$egin{array}{cccc} 2x_1 + 3x_2 &= 7 \ x_1 + 4x_2 &= 6 \end{array} \implies egin{array}{c} x_1^* = 2 \ x_2^* = 1 \end{array}$$

· Geometric analysis



Generalize

$$egin{aligned} a_{11}x_1 + a_{12}x_2 &= b_1 & ext{ Matrix form } \ a_{21}x_1 + a_{22}x_2 &= b_2 & \Longrightarrow & egin{bmatrix} a_{11} & a_{12} \ a_{21} & a_{22} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \end{bmatrix} &= egin{bmatrix} b_1 \ b_2 \end{bmatrix} \end{aligned}$$

$$AX = B$$

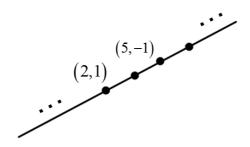
 $\therefore X^* = A^{-1}B \quad \text{if } A^{-1} \text{ exists}$

1.2. Under-Determined Linear Systems

· System of linear equations

$$2x_1 + 3x_2 = 7 \implies \text{Many solutions}$$

· Geometric analysis



Generalize

$$egin{aligned} a_{11}x_1 + a_{12}x_2 &= b_1 & egin{aligned} & \operatorname{Matrix form} \ & \Longrightarrow & \left[egin{aligned} a_{11} & a_{12} \,
ight] \left[egin{aligned} x_1 \ x_2 \end{array}
ight] = b_1 \end{aligned}$$

$$A^TX=B$$

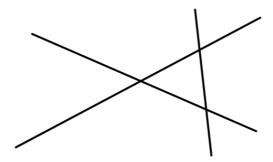
 \therefore Many Solutions when A is fat

1.3. Over-Determined Linear Systems

• System of linear equations

$$egin{array}{lll} 2x_1+3x_2&=7 \ x_1+4x_2&=6&\Longrightarrow& ext{No solutions} \ x_1+x_2&=4 \end{array}$$

· Geometric analysis



Generalize

$$egin{array}{lll} a_{11}x_1 + a_{12}x_2 &= b_1 \ a_{21}x_1 + a_{22}x_2 &= b_2 \ a_{31}x_1 + a_{32}x_2 &= b_3 \end{array} & ext{Matrix form} & egin{bmatrix} a_{11} & a_{12} \ a_{21} & a_{22} \ a_{31} & a_{32} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \end{bmatrix} &= egin{bmatrix} b_1 \ b_2 \ b_3 \end{bmatrix}$$

$$AX = B$$

 \therefore No Solutions when A is skinny

Summary of Linear Systems

$$AX = B$$

· Square: Well-determined Linear Systems

$$egin{bmatrix} a_{11} & a_{12} \ a_{21} & a_{22} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \end{bmatrix} = egin{bmatrix} b_1 \ b_2 \end{bmatrix}$$

· fat: Under-determined Linear Systems

$$\begin{bmatrix} a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

· skinny: Over-determined Linear Systems

$$egin{bmatrix} a_{11} & a_{12} \ a_{21} & a_{22} \ a_{31} & a_{32} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \end{bmatrix} = egin{bmatrix} b_1 \ b_2 \ b_3 \end{bmatrix}$$

2. Optimization Point of View

2.1. Least-Norm Solution

· For Under-Determined Linear System

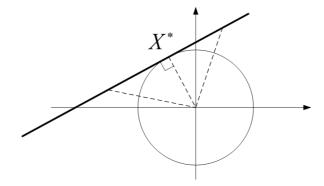
$$\left[egin{array}{cc} a_{11} & a_{12} \end{array}
ight] \left[egin{array}{c} `x_1 \ x_2 \end{array}
ight] = b_1 \quad ext{ or } \quad A^TX = B$$

Find the solution of $A^TX=B$ that minimize $\|X\|$ or $\|X\|^2$

i.e., optimization problem

$$egin{array}{ll} \min & \|X\|^2 \ \mathrm{s.\ t.} & A^TX = B \end{array}$$

· Geometric analysis



· Select one solution among many solutions

$$X^* = (A^T A)^{-1} A^T B$$
 Least norm solution

· Often control problem

2.2. Least-Square Solution

• For Over-Determined Linear System

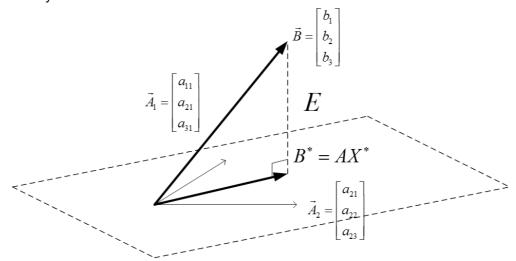
$$egin{bmatrix} a_{11} & a_{12} \ a_{21} & a_{22} \ a_{31} & a_{32} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \end{bmatrix}
eq egin{bmatrix} b_1 \ b_2 \ b_3 \end{bmatrix} & ext{or} & AX
eq B & x_1 \begin{bmatrix} a_{11} \ a_{21} \ a_{31} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \ a_{22} \ a_{32} \end{bmatrix} \
eq egin{bmatrix} b_1 \ b_2 \ b_3 \end{bmatrix}$$

Find X that minimizes $\|E\|$ or $\|E\|^2$

i.e. optimization problem

$$\min_{X} \|E\|^2 = \min_{X} \|AX - B\|^2$$
 $X^* = (A^T A)^{-1} A^T B$
 $B^* = AX^* = A(A^T A)^{-1} A^T B$

· Geometric analysis

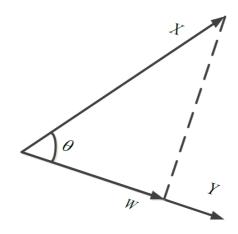


• Often estimation problem

3. Geometic Point of View: Projection

3.1. Vector Projection

ullet The vector projection of a vector X on (or onto) a nonzero vector Y is the orthogonal projection of X onto a straight line parallel to Y



$$egin{aligned} W &= \omega \hat{Y} = \omega rac{Y}{|Y|}, \ ext{where} \ \omega &= |X| \cos heta = |X| rac{X \cdot Y}{|X||Y|} = rac{X \cdot Y}{|Y|} \ W &= \omega \hat{Y} = rac{X \cdot Y}{|Y|} rac{Y}{|Y|} = rac{X \cdot Y}{|Y||Y|} Y = rac{X \cdot Y}{Y \cdot Y} Y = rac{\langle X, Y
angle}{\langle Y, Y
angle} Y \end{aligned}$$

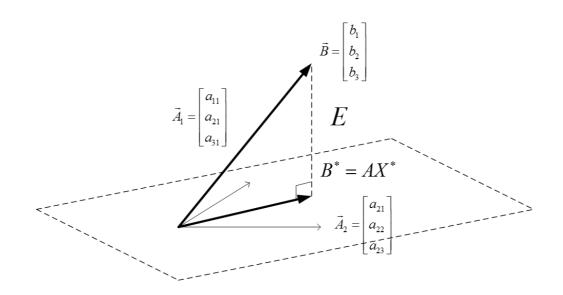
• Another way of computin ω and W

$$egin{aligned} Y \perp (X-W) \ \Longrightarrow Y^T (X-W) &= Y^T \left(X - \omega rac{Y}{|Y|}
ight) = 0 \ \Longrightarrow \omega &= rac{Y^T X}{Y^T Y} |Y| \ \Longrightarrow \omega &= rac{Y^T X}{Y^T Y} |Y| \ W &= \omega rac{Y}{|Y|} &= rac{Y^T X}{Y^T Y} Y = rac{\langle X, Y
angle}{\langle Y, Y
angle} Y \end{aligned}$$

3.2. Orthogonal Projection onto a Subspace

- Projection of B onto a subspace U of span of A_1 and A_2
- · Orthogonality

$$A \perp (AX^* - B)$$
 $A^T (AX^* - B) = 0$
 $A^T AX^* = A^T B$
 $X^* = (A^T A)^{-1} A^T B$
 $B^* = AX^* = A(A^T A)^{-1} A^T B$

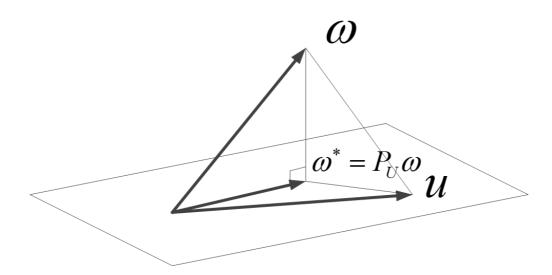


3.3. Towards Minimization Problems

• Suppose U is a subspace of W and $\omega \in W$. Then

$$\|\omega - P_U\omega\|^2 \leq \|\omega - u\|$$

for every $u\in U.$ Furthermore, if $u\in U$ and the inequality above is an equality, then $u=P_u\omega$



3.4. Orthogonal Projection

- Is *P* a linear transformation?
- Any projection matrix P satisfies the two properties:
 - $lacksquare P^2=P$
 - lacksquare P is symmetric
- It is also true that any matrix that satisfies these two properties is the projection matrix for some subspace \mathbb{R}^n

In [3]:

%%javascript
\$.getScript('https://kmahelona.github.io/ipython_notebook_goodies/ipython_notebook_toc.
js')