

Linear algebra for AI and ML  
(September - 29)

Stephen Boyd (2018)  
(Applied LA & least squares)

Gr. Strang  
Linear algebra and learning  
from data (2020)

(MIT-OCW) (2019)

# Linear algebra for AI ML

- Basics of LA
  - vectors / Matrices / Vector spaces / basis / dimension / subspaces
  - Linear transformation / affine transformation
  - (Linear functional)  $\leftarrow$  inner product, norm ( $\ell_2$  / spectral)
  - Matrix representation of linear transformation
  - Gram orthogonalization / orthogonal matrices
  - K-mean clustering

- Solving systems of linear equations
$$Ax = b \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m$$
$$\text{To find } x \in \mathbb{R}^n$$

$\rightarrow$  Existence and uniqueness of solution.

$$\left\{ \begin{array}{l} (x\text{-linear combination of columns of } A) \\ \langle \text{rows of } A, x \rangle = b_i \end{array} \right\}$$

$$ax=b; \quad a, b \in \mathbb{R} \quad x = a^{-1}b = b/a$$

→ Left inverse / right inverse / inverse of matrix.

For square matrices  $n \times n$

→ Methods to compute the solution.

→ Gaussian elimination  $\equiv$  LU decomposition of  $A$ .

→ In case,  $A$  is symmetric,  $U = L^T$

$$\underline{A = LL^T}$$

: Cholesky decomposition of  $A$ .

→ QR decomposition (Gram-Schmidt orthogonalization)

$$A = QR \quad \left( \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \end{array} \right)$$

↑  
orthogonal

$$\begin{aligned} Ax &= b \\ \underline{Rx} &= \underline{Q^T b} \end{aligned}$$

- rotator matrices / reflector matrices

Sensitivity analysis:

$$Ax=b$$

$A$  and  $b$  are NOT known exactly.

→ numerical inaccuracies in storing data ( $1/3$ ).

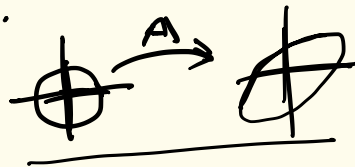
→ measurement inaccuracies.

$$(A + \Delta A) \hat{x} = (b + \Delta b)$$

$$Ax = b$$

maxmag(A), minmag(A), condition numbers.

$$\frac{\|\delta x\|_2}{\|x\|_2} \leq \underbrace{\kappa_2(A)}_{\uparrow} \left[ \underbrace{\frac{\|\delta b\|_2}{\|b\|_2}}_{\uparrow} + \underbrace{\frac{\|\delta A\|_2}{\|A\|_2}}_{\uparrow} \right]$$



we will visit again.

$\kappa(A) \uparrow \Rightarrow \frac{\|\delta x\|}{\|x\|}$  may be large.

$\kappa(A) \uparrow \Rightarrow A$  is "close" to being singular/non-invertible.

LS problems:

$$\begin{bmatrix} \vdots \\ \text{red line} \\ \vdots \end{bmatrix} \begin{bmatrix} \vdots \\ \text{red line} \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ \text{red dot} \\ \vdots \end{bmatrix}$$

$Ax = b$

(non-square)

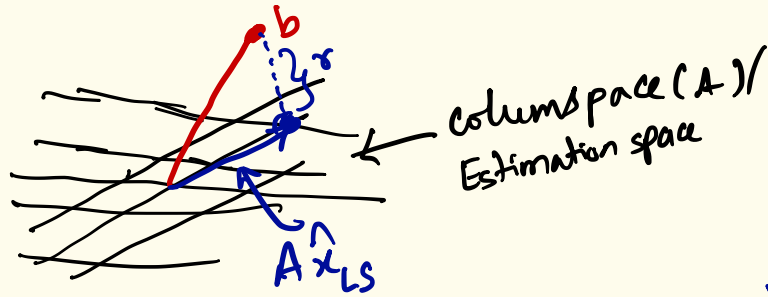
(A has linearly indep. columns)

→ overdetermined

→ Existence of soln. ✓

$$\min_{x \in \mathbb{R}^n} \|b - Ax\|_2^2$$

$$x_{LS} = \underbrace{(A^T A)^{-1}}_{\text{matrix}} A^T b$$



$$r \perp A \hat{x}_{LS}$$

$$\downarrow$$

$$(A^T A) x_{LS} = A^T b$$

normal eq<sup>n</sup>

## Application of LS problems:

- i) LS data fitting &
- ii) LS classification (boolean/multiclass)
- iii) multi-objective LS problem

$$J_1, \dots, J_r$$

- iv) constrained LS problem  
splines, (minimum norm solution)

$$\lambda \uparrow \infty$$

(KKT matrix)

Pending: Sensitivity of LS problem!

$$y = f(x)$$

$$f_1, f_2, \dots, f_p$$

$$f \approx \underbrace{\alpha_1 f_1 + \alpha_2 f_2 + \dots + \alpha_p f_p}$$