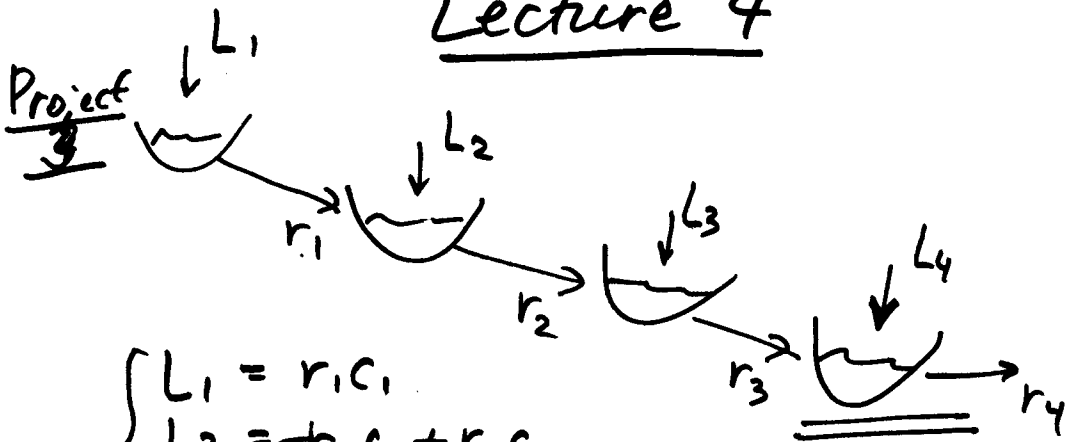


Math 685

Lecture 4



$$\begin{cases} L_1 = r_1 c_1 \\ L_2 = -r_1 c_1 + r_2 c_2 \\ L_3 = -r_2 c_2 + r_3 c_3 \\ L_4 = -r_3 c_3 + r_4 c_4 \end{cases}$$

Remark: Forward error: $\frac{\|\Delta x\|}{\|\tilde{x}\|} \leq \text{cond}(A) \cdot \frac{\|r\|}{\|A\| \cdot \|\tilde{x}\|}$

accuracy sensitivity stability

Backward error: $\frac{\|r\|}{\|A\| \cdot \|\tilde{x}\|} \leq \frac{\|E\|}{\|A\|} \quad (A+E)\tilde{x} = b$

$\|A\|$ -large \Rightarrow Big $\|E\|$.

HW3.

① $\text{cond}(A) = \|A\| \cdot \|A^{-1}\|$

$$\frac{\|\Delta x\|}{\|\tilde{x}\|} \leq \text{cond}(A) \cdot \frac{\|\Delta b\|}{\|b\|}$$

$$\|A\|_1 = 6 \quad \|A^{-1}\|_1 = \frac{1}{2}$$

$$\text{cond}_1(A) = 3$$

$$A^{-1} = \begin{pmatrix} \frac{1}{4} & & 0 \\ & \frac{1}{6} & \\ 0 & & \frac{1}{2} \end{pmatrix}$$

②

$$Ax = b$$
$$D Ax = D b$$

$|D| \neq 0$
 \hookrightarrow diag.

scaling.

$$DAx = Dp$$

$$A = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad D = \begin{pmatrix} 10^4 & 0 \\ 0 & 1 \end{pmatrix} \quad \text{cond}(A) = 1$$

$$\text{Cond}(DA) = 10^4$$

$$DA = \begin{pmatrix} 10^4 & 0 \\ 0 & 1 \end{pmatrix}$$

$$A = \begin{pmatrix} \frac{20}{5} & 0 \\ 0 & 1 \end{pmatrix} \quad D = \begin{pmatrix} 10^{-4} & 0 \\ 0 & 1 \end{pmatrix} \quad DA = \begin{pmatrix} \frac{20 \cdot 10^{-4}}{5} & 0 \\ 0 & 1 \end{pmatrix}$$

$$\begin{pmatrix} 10^{-4} & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 20 & 0 \\ 5 & 1 \end{pmatrix} = \begin{pmatrix} 20 \cdot 10^{-4} & 0 \\ 5 & 1 \end{pmatrix} \quad \begin{pmatrix} \epsilon & 0 \\ 1 & 1 \end{pmatrix}$$

③ $A = LU \quad |A| \neq 0.$

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

$PA = LU$ exists

$A \neq LU$ zero pivot

Q: if ~~A~~ $A = LU$ exists $\Rightarrow |A| \neq 0$?

$$A = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

④ $r = Ax - b$

r -small $\Rightarrow |x - \tilde{x}|$ -small NO.

r -large $\Rightarrow |x - \tilde{x}|$ -large NO.

$$\frac{\|E\|}{\|Ax\|} \geq \frac{\|r\|}{\|A\| \cdot \|\tilde{x}\|}$$

but: YES-
does mean
that backward
error is large
if r is large.

⑤

$Ax = b$ 12-digit precision

Estimated loss of accuracy $\approx \log_{10} \text{cond}(A)$

$$\log_{10} \text{cond}(A) = 12 \Rightarrow \text{cond}(A) \sim 10^{12}$$

$$(\text{\# digits in precision}) - \log_{10} \text{cond}(A) =$$

= \# of sign. digits that
are accurate in your answer

⑥ $(A - uv^T)^{-1} = A^{-1} + A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}$

1) $Ax = b \rightsquigarrow A^{-1}$ by LU decomp.

2) $B = A - uv^T \leftarrow$ rank-1 update

To compute $By = b$: $B = A - uv^T$

$$y = (A - uv^T)^{-1}b$$

SM formula: $y = \underbrace{A^{-1}b}_x + \underbrace{A^{-1}u}_z \underbrace{(1 - v^T A^{-1}u)^{-1}v^T A^{-1}b}_z \underbrace{x}_x$

$$u = \begin{bmatrix} \\ \\ \end{bmatrix} \quad v^T = [\dots] \quad v^T z, v^T x$$

$(1 \times n)(n \times 1) \rightarrow 1 \times 1$

$$\Rightarrow y = x + (\text{const}) \cdot z$$

$$(A - uv^T)^{-1} = A^{-1} + A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}$$

$$I = (A - uv^T)A^{-1} + (A - uv^T)A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}$$

$$I - uv^T A^{-1}$$

$$uv^T A^{-1} = (A - uv^T)A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}$$

$$u = (A - uv^T)A^{-1}u(1 - v^T A^{-1}u)^{-1}$$

$$(1 - v^T A^{-1}u)u = (A - uv^T)A^{-1}u$$

$$= (I - uv^T A^{-1})u = u -$$

$$v^T A^{-1}u = \text{const} = c$$

$$(1 - c)u = u - uc$$

$$cu = uc$$

identity

⑥ $[L, u, P] = \text{lu}(A) \leftarrow$ MATLAB LU decomp.
permutation

$$Ax = b \quad PA = LU$$

$O(n^2)$ effort $PAx = Pb$
 $LUx = Pb$
 \underbrace{LU}_Z

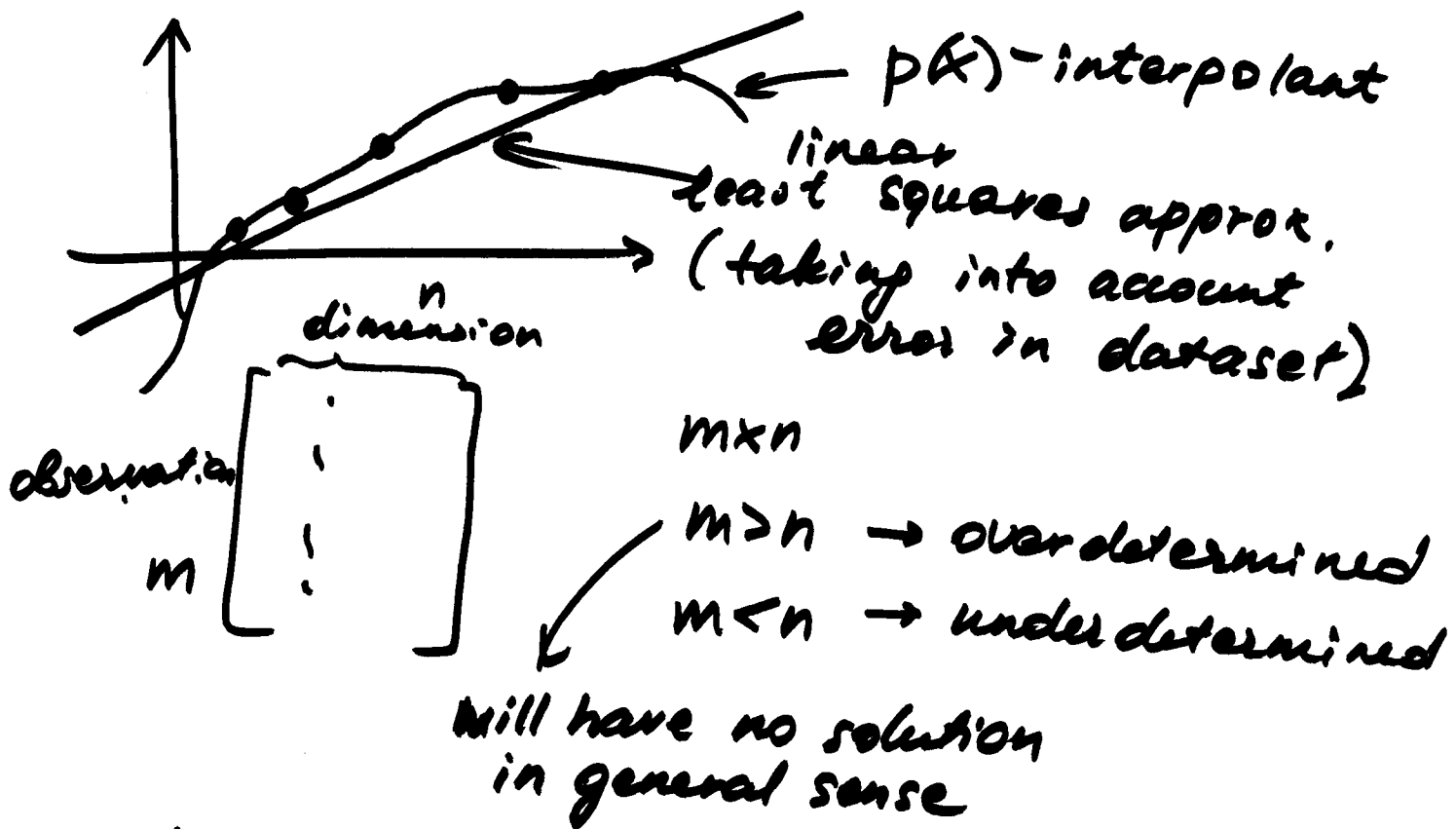
$$\begin{cases} LZ = Pb \leftarrow \text{1st step} \\ Ux = z \leftarrow \text{2nd step} \end{cases}$$

↑ order $O(n^2)$ effort

Sherman-Morrison

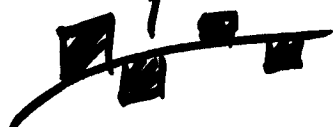
Complexity: $O(n^2)$ vs. $O(n^3)$ for GE.

Least squares.



$Ax \approx b \rightarrow$ looking for best x that is close enough to solution.

$$\min_x \|b - Ax\|_2 = \min_x \left(\sum_{i=1}^n (b_i - Ax_i)^2 \right)^{1/2}$$



$$\sum (y_i - f(t_i, x))^2 \rightarrow \min$$

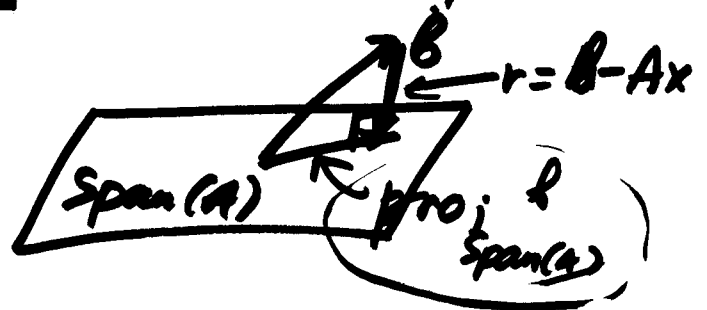
$$f = \underline{a} + \underline{b}t + \underline{c}t^2 \leftarrow (t_i, y_i) = i=1 \dots 5$$

$$\begin{cases} a + bt_1 + ct_1^2 = y_1 \\ a + bt_2 + ct_2^2 = y_2 \\ \vdots \\ a + bt_5 + ct_5^2 = y_5 \end{cases} \rightarrow \begin{bmatrix} a & b & c & & \\ 1 & t_1 & t_1^2 & | & y_1 \\ 1 & t_2 & t_2^2 & | & y_2 \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & t_5 & t_5^2 & | & y_5 \end{bmatrix}$$

Least squares solution:

$$\boxed{A^T A x = A^T b} \leftarrow \text{normal equations}$$

$$A x = b$$



Pseudoinverse: $A^+ = (A^T A)^{-1} A^T$

$$\text{Cond}(A) = \|A\| \cdot \|A^+\| \quad \frac{x = A^+ b}{\text{least squares solution}}$$

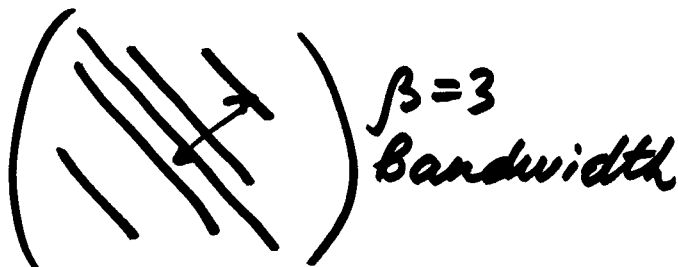
$m \times n, m > n$

$$A^T A x = A^T b$$

$$x = \underbrace{(A^T A)^{-1}}_{\text{SPD}} A^T b \leftarrow \text{normal eqn.}$$

$$(A + E)x \approx b$$

$$\frac{\|\Delta x\|}{\|x\|} \approx (\text{Cond}(A) \cdot \tan(\theta) + \text{Cond}(A)) \cdot \frac{\|E\|}{\|A\|}$$



"sparse" in MATLAB.

$$O(\beta^2 n) - \text{inversion}$$

$$O(\beta n) - \text{storage}$$

$$m \begin{bmatrix} A \\ n \end{bmatrix} \rightarrow \begin{bmatrix} A^T A \\ n \times n \end{bmatrix} \rightarrow \begin{bmatrix} \text{shaded triangle} \end{bmatrix}$$

$x > 0 \quad \boxed{A^T = A}$
 $\boxed{(Ax, x) > 0}$

$$A^T A = L L^T \quad \boxed{A^T A x = A^T b}$$

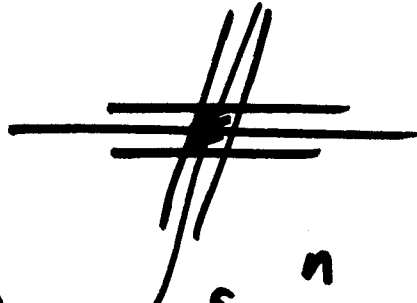
$$L \underbrace{L^T x}_{\vec{z}} = A^T b$$

- 2 steps: 1) $L \vec{z} = A^T b$
 2) $L^T x = \vec{z}$

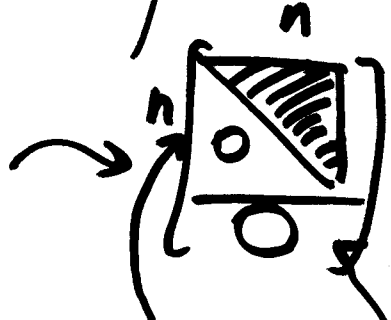


$$p(x) = a + bt + ct^2$$

$$\vec{x} = (0.086 \quad 0.4 \quad 1.429)^T$$



$$A = \begin{bmatrix} & n \\ m & \end{bmatrix}$$



$$\boxed{A = Q_1 R}$$

$$Q \begin{bmatrix} R \\ 0 \end{bmatrix}$$

$$Q = \underbrace{[Q_1]}_n \underbrace{[Q_2]}_{m-n}$$

$$Q_1^T A x = \boxed{R x = c_1} = Q_1^T b$$

LU - by elimination matrices

QR - by orthogonal matrices

$$Q_n \dots Q_2 Q_1 A \rightarrow$$