

Nov 4, 2020

$$\begin{bmatrix} A \end{bmatrix} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} b \end{bmatrix}$$

$$\min_x \left\| \begin{bmatrix} A \end{bmatrix} \begin{bmatrix} x \end{bmatrix} - \begin{bmatrix} b \end{bmatrix} \right\|_2$$

$$\lambda \begin{bmatrix} A \end{bmatrix} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} b \end{bmatrix}$$

$$PA = LU = \begin{bmatrix} \text{matrix} \end{bmatrix} \begin{bmatrix} \text{matrix} \end{bmatrix}$$

$$A = QR = \begin{bmatrix} \text{matrix} \end{bmatrix} \begin{bmatrix} \text{matrix} \end{bmatrix}$$

$$A = QTQ^H \quad T = \begin{bmatrix} \text{matrix} \end{bmatrix}$$

$$L(Ux) = P^T b$$

$$Rx = Q^T b$$

$$\lambda = T_{ii} \quad Ty = \lambda y \\ x = Qy$$

direct methods

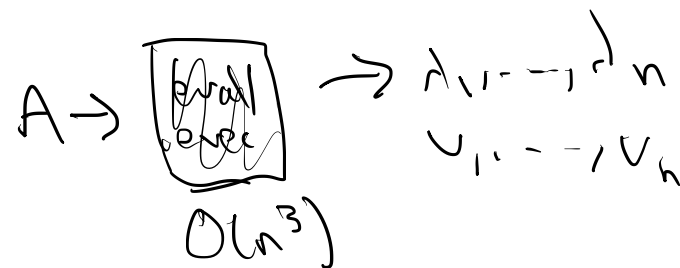
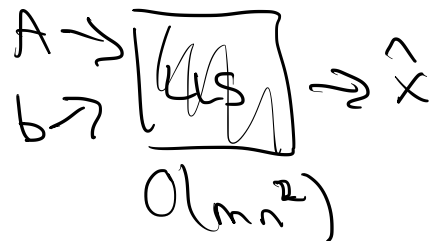
A → factorization → easy  $O(n^3)$   $O(mn^2)$

benefits: ① can be fast (n small)

② reliable: stability

③ reuse:  $Ax = c \Rightarrow LUx = P^T c \quad O(n^2)$

Mostly "black box" performance



Not totally black boxes

① reuse

②  $k_2(A) = \|A\|_2 \|A^{-1}\|$  on sensitivity  
 $Ax = b$ , LLS

③ whether or not LLS is "good"

$A^T b \approx 0 \iff b \perp \text{Range}(A) \Rightarrow$  no "good" solution

④  $\min_x \left\| \begin{matrix} \overset{n}{A} \\ \underset{n}{x} \end{matrix} - \begin{matrix} \overset{m}{b} \\ \underset{m}{0} \end{matrix} \right\|_2^2 + \lambda \|x\|_2$

$\iff \min_x \left\| \begin{matrix} \overset{n}{A} \\ \underset{m}{\lambda I} \end{matrix} x - \begin{matrix} \overset{m}{b} \\ \underset{m}{0} \end{matrix} \right\|_2 \quad O((m+n)n^2) = O(n^3)$

$\lambda \rightarrow 0 \quad ((A^T)^+)^T b \quad O(mn^2)$

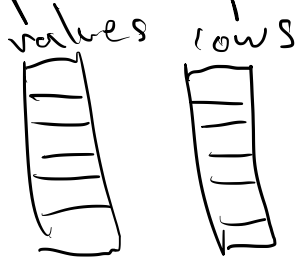
⑤ sparse  $A$ ,  $Ax = b$   
 $PAQ = LU$



# Sparse matrices cause problems for direct methods

Example: English Wikipedia (2013) 4.2M pages 101M links

Compressed sparse column (CSC)



col ptr



col 2  
in indices  
4 to 6

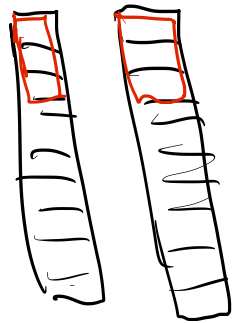
$2 \cdot 101M = 8$  bytes per value

$\approx 1.5$  GB

LU factors  $(4.2M)^2 \cdot 8$  bytes per entry

$\approx 128$  TB

One fast thing:  $y = Ax = \sum_j A(:,j) x_j$



$$A_{10,1} = 1$$

$$A_{1358,1} = 1$$

$$A_{400221,1} = 1$$

$$y = 0$$
$$y_{10} + = x_1$$

$$y_{1358} + = x_1$$

$$y_{400221} + = x_1$$

$O(\text{nnz}(A))$

# Black box for iterative solvers

$$x \rightarrow \boxed{\text{matrix}} \rightarrow Ax \quad x \rightarrow \boxed{\text{matrix}} \rightarrow A^T x \quad (x^T A)$$

① A sparse  $Ax$  in  $O(\text{nnz}(A))$  time

② sparse + low rank

$$\boxed{A} = \boxed{S} + \boxed{L} \boxed{R} \quad Ax = \underbrace{Sx}_{\text{nnz}(S)} + \underbrace{L(Rx)}_{O(nk)}$$

③ Low displacement rank

Toeplitz:  $T_{ij} = t_{i-j}$


 $O(n \log n)$

④ Kernel  $K_{ij} = \frac{1}{\|x_i - x_j\|_2}$

$x_1, \dots, x_n \in \mathbb{R}^2$   
quasi-uniformly  $O(n)$  (approx)

⑤ Product structure

$$A \otimes B = \begin{pmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & & \vdots \\ a_{n1}B & \dots & a_{nn}B \end{pmatrix} \quad \text{nnz}(A \otimes B) = O(n^4)$$

$$\text{vec} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} a \\ c \\ b \\ d \end{pmatrix}$$

$$(A \otimes B) \text{vec}(C) = \text{vec}(B C A^T)$$

$O(n^3)$

## Iterative solvers

- ① Splitting / stationary
- ② Krylov subspace methods  
 $b, Ab, A^2b, A^3b, \dots$
- ③ Geometric methods (multigrid)