

# MTH 9821 - L8

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Why LU decomposition is faster than Cholesky decomposition?

1) Cholesky main diagonal  $\Rightarrow$  need square computation.

LU main diagonal  $\Rightarrow$  do not need square computation. use "1".

2) LU decomposition main diagonal are "1", save computation of division.

3) But Cholesky has a gain: when update a tridiagonal matrix, only need to update the diagonal one.

$$\begin{bmatrix} x & x \\ x & x & x \\ & x & x & x \\ & & x & x & x \\ & & & x & x \end{bmatrix} : \begin{bmatrix} x & x \\ x & x & x \\ & x & x & x \\ & & x & x & x \\ & & & x & x \end{bmatrix} - \begin{pmatrix} x \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} (x \ 0 \ 0 \ 0) = \begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix} - \begin{bmatrix} x & 0 & 0 & 0 \\ 0 & 0 & & \\ 0 & & \ddots & \\ 0 & & & \ddots \end{bmatrix}$$

Solve  $Ax=b$ :  $Ly=b$ ,  $Ux=y$ .

LU decomposition =  $8n + O(1)$ .

$$[L, U] = \text{lu-tridiag-spd}(A) \quad (3n)$$

$$y = \text{forward}(L, b) \quad (2n)$$

$$x = \text{backward}(U, y) \quad (3n)$$

Solve  $Ax=b$ .

$$U = \text{cholesky-tridiag}(A) \quad (4n)$$

Cholesky decomposition =  $10n + O(1)$ .

$$y = \text{forward-sbst}(U^t, b) \quad (3n)$$

$$x = \text{backward-sbst}(U, y) \quad (3n)$$

## Pseudo Code for Cholesky

$$U = \text{cholesky-tridiag}(A)$$

for  $k=1:(n-1)$

$$u(k, k) = \sqrt{A(k, k)} \quad ; \quad u(k, k+1) = \frac{A(k, k+1)}{u(k, k)}$$

$$A(k+1, k+1) = A(k+1, k+1) - (u(k, k+1))^2$$

end.

$$u(n, n) = \sqrt{A(n, n)}$$

$y = \text{forward\_subst}(u^t, b)$

$$y_{(1)} = b_{(1)} / u^t_{(1,1)}$$

for  $i = 2 : m$

$$y_{(i)} = \frac{b_{(i)} - u^t_{(i,i-1)} y_{(i-1)}}{u^t_{(i,i)}}$$

end.

Backward Euler (for European)

for  $m = 1 : M$

$$A u^m = b^m$$

end.

$$b^m = u^{m-1} + \alpha \begin{pmatrix} u_0^m \\ 0 \\ \vdots \\ 0 \\ u_N^m \end{pmatrix} \quad \left. \vphantom{\begin{pmatrix} u_0^m \\ 0 \\ \vdots \\ 0 \\ u_N^m \end{pmatrix}} \right\} N-3$$

$$A = \begin{pmatrix} 1+2\alpha & -\alpha & \dots & 0 \\ -\alpha & 1+2\alpha & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1+2\alpha \end{pmatrix}$$

For American:

$$\begin{cases} u^m \geq \text{early-exercise-premium} \\ A \tilde{u}^m \geq b^m \end{cases}$$

$\therefore$  Early Exercise

$\therefore \tilde{u}^m$  is always greater than  $u^m$ .

Crank - Nicolson.

for  $m = 1 : M$ .

$$A u^m = \tilde{b}^m$$

$$A = \begin{pmatrix} 1+2\alpha & -\frac{\alpha}{2} & \dots & 0 \\ -\frac{\alpha}{2} & 1+2\alpha & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1+2\alpha \end{pmatrix}$$

We have to introduce an iterator solver for linear equation

Find  $x$  such that  $Ax = b$ . solve the recursion

Given  $x_0$ :  $x_{n+1} = R x_n + C$ . for  $n \geq 0$ . until convergence.

Issue: (1) Whether the iteration is convergent?

(2) If convergent, when will it convergent to  $x^*$  that  $Ax^* = b$ ?



### Theorem:

The recursion  $X_{n+1} = RX_n + C$  is convergent iff  $\rho(R) < 1$ .

$\rho(R)$  is called spectral radius of  $R$ .

$\rho(R) = \max |\lambda|$ .  $\lambda$ : value of  $R$ .

<If  $R$  is bigger  $\Rightarrow$  The convergence is faster>.

General splitting technique to generate recursion for solving  $Ax = b$ .

Let  $A = M + N$ .  $(M + N)x = b$ .

$$Mx = -Nx + b$$

$$x = -M^{-1}Nx + M^{-1}b.$$

Recursion:  $X_{n+1} = -M^{-1}NX_n + M^{-1}b$ .  $\forall n \geq 0$

If  $X_n \rightarrow \bar{x}$ , then  $A\bar{x} = b$ .

1)  $M$  must be nonsingular

2)  $\rho(M^{-1}N) < 1$  and smaller

3) Easy to solve  $Mv = w$

$\Rightarrow M$  ideally should be diagonal matrix.

### Jacobi Recursion

Choose  $M = D = \text{diag}(A_{ii})$   $i = 1:n$ .  $\Rightarrow A = L + D + U_A$

$$N = L + U_A$$

Jacobian Recursion:  $X_{n+1} = -D^{-1}(L + U_A)X_n + D^{-1}b$ .  $\forall n \geq 0$ .

### Residual-Based Convergence Criterion

Stop iteration when  $\|b - AX_n\| \leq \text{tol} \|b - AX_0\|$ .

given  $A, b, x_0, \text{tol}$ .  $r_0 = b - Ax_0$ .

$r = r_0$ . stop\_iter\_resid = tol \* norm( $r_0$ )

while norm( $r$ ) > stop\_iter\_resid.

$$x = Rx + C$$

$$r = b - Ax$$

end.

euclidean: all the norms are actually the same.

### Consecutive Approximation Criterion.

Stop iteration when  $\|X_{n+1} - X_n\| \leq \text{tol}$

Given  $A, b, x_0, \text{tol}$ .  $X_{\text{old}} = x_0$ ;  $\text{diff} = 10 \cdot \text{tol}$ .

while ( $\|\text{diff}\| > \text{tol}$ ):

$$X_{\text{new}} = R \cdot X_{\text{old}} + C; \quad \text{diff} = X_{\text{new}} - X_{\text{old}}.$$

$$X_{\text{old}} = X_{\text{new}};$$

end.

### Entry-by-entry recursion

$$(*) \quad \left[ \begin{array}{l} \text{for } j = 1 : P: \\ X_{n+1}(j) = \frac{1}{A(j,j)} \left( \sum_{k=1}^{j-1} A(j,k) \underbrace{X_n(k)}_{X_{n+1}(k) \text{ is a better choice}} + \sum_{k=j+1}^P A(j,k) \cdot X_n(k) \right) + \frac{b(j)}{A(j,j)}. \\ \text{end.} \end{array} \right.$$

### Jacobian Recursion (for convergence proof)

$$X_{n+1} = (L+U)X_n + D^{-1}b.$$

$$L = D^{-1}A$$

$$X_{n+1} = R_J X_n + C_J.$$

$$U = D^{-1}U_A$$

where  $R_J = L+U$ .  $C_J = D^{-1}b$ .

(Another choice for  $M$  besides diagonal matrix is lower triangular).

### Gaussian Seidel Recursion

$$X_{n+1} = -(D+L_A)^{-1} U_A X_n + (D+L_A)^{-1} b. \quad (X_{n+1} = -M^{-1}N X_n + M^{-1}b)$$

$$(D+L_A) X_{n+1} = -U_A X_n + b$$

$$D X_{n+1} = -L_A X_{n+1} - U_A X_n + b.$$

$$X_{n+1} = -D^{-1} (L_A X_{n+1} + U_A X_n) + D^{-1} b.$$

Then: (\*)



Proof:

$$L_A = -DL; \quad U_A = -DU$$

$$X_{n+1} = -(D-DL)^{-1} (-DU)X_n + (D-DL)^{-1}b$$

$$= (I-L)^{-1}D^{-1}DX_n + (I-L)^{-1}D^{-1}b.$$

$$X_{n+1} = (I-L)^{-1}UX_n + (I-L)^{-1}D^{-1}b.$$

$$R_{GS} = (I-L)^{-1}U.$$

SOR (Successive Over Relaxation). <Faster than Jacobian & Gaussian Siedal>

Entry-by-Entry recursion:

for  $j=1:P$ :

$$X_{n+1}(j) = (1-w)X_n(j) - \frac{w}{A(j,j)} \left( \sum_{k=1}^{j-1} A(j,k)X_{n+1}(k) + \sum_{k=j+1}^P A(j,k)X_n(k) + \frac{wb(j)}{A(j,j)} \right).$$

end.

$$X_{n+1, \text{SOR}}(j) = (1-w)X_{n, \text{SOR}}(j) + wX_{n+1, \text{GS}}(j).$$

$$\text{SOR Recursion: } X_{n+1} = (D + wL_A)^{-1} ((1-w)D - wU_A)X_n + w(D + wL_A)^{-1}b.$$

$$X_{n+1} = R_{\text{SOR}}X_n + b_{\text{SOR}}.$$

$$R_{\text{SOR}} = (I - wL)^{-1}((1-w)I + wU).$$

$$\text{If } w=1 \Rightarrow \text{SOR} \equiv \text{Gauss Siedal.}$$

be more efficient

The increase of dimension will increase the complexity, and recursion method will

Convergence Properties Jacobi, GS, SOR.

Theorem 1: SOR convergent  $\Rightarrow 0 < w < 2$ .

Theorem 2: A spd  $\Rightarrow$  SOR convergent for  $0 < w < 2$  (thus, GS convergent).

Theorem 3: A strictly diagonally dominant  
 $\Rightarrow$  Jacobi and GS convergent

Proof theorem 1:

SOR convergent  $\Leftrightarrow \rho(R_{SOR}) < 1$ .

Let  $\lambda_1, \lambda_2, \dots, \lambda_p$  are evalules of  $R_{SOR}$ .  $|\lambda_i| < 1, \forall i=1:p$ .

$$R_{SOR} = (I - \omega L)^{-1} ((1-\omega)I + \omega U).$$

$$\det(R_{SOR}) = \det(I - \omega L)^{-1} \cdot \det((1-\omega)I + \omega U) = (1-\omega)^n = \det(R_{SOR}) = \prod_{i=1}^p \lambda_i$$

$$\prod_{i=1}^p |\lambda_i| = |1-\omega|^n$$

SOR convergent  $\Rightarrow |\lambda_i| < 1 \forall i=1 \dots p$ .

$$\Rightarrow \prod_{i=1}^p |\lambda_i| < 1$$

$$\Rightarrow |1-\omega|^n < 1 \Rightarrow |1-\omega| < 1 \Rightarrow 0 < \omega < 2.$$