

# Welcome to Ma221! Lecture 23, Fall 24

## Splitting Methods for $Ax=b$

Def:  $A = M - K$ ,  $M$  nonsingular

$$Ax=b \rightarrow Mx = Kx + b$$

$$\rightarrow Mx_{i+1} = Kx_i + b$$

$$(*) \quad x_{i+1} = M^{-1}Kx_i + M^{-1}b \\ = Rx_i + c$$

Def: spectral radius of  $R = \rho(R) = \max_{\lambda \text{ eval of } R} |\lambda|$

Thm: (\*) converges to  $A^{-1}b$  for all  $x_0$   
if and only if  $\rho(R) < 1$

$$A = \begin{bmatrix} & & -U' \\ & D & \\ -L' & & \end{bmatrix} = D - L' - U' = D(I - L - U)$$

Jacobi, in words:

for  $j = 1$  to  $n$  pick  $x_{i+1}(j)$  to  
exactly solve equation  $j$

as a splitting:  $A = M - K = D - (L' + U')$

$$R_J = D^{-1}(L' + U') = L + U$$

Gauss-Seidel, in words:

Improve on Jacobi by using most recently updated values of  $x$

as a splitting:  $A = (D-L') - U' = M-K$

$$\begin{aligned}R_{GS} &= M^{-1}K = (D-L')^{-1}U' \\ &= (D(I-L))^{-1}U' \\ &= (I-L)^{-1}U\end{aligned}$$

SOR( $w$ ): Successive Overrelaxation:

In words: weighted linear combination of  $x_i$  and result of GS

$$x_{i+1}^{SOR(w)}(j) = (1-w)x_i(j) + w x_{i+1}^{GS}(j)$$

$w = 1 \Rightarrow$  same as GS

$w < 1 \Rightarrow$  "underrelaxation", not useful

$w > 1 \Rightarrow$  "overrelaxation", go further in same direction as GS

Later: how to choose  $w$  optimally for Poisson

As a loop

for  $j = 1:n$

$$x_{i+1}(j) = (1-w)x_i(j) +$$

$$w(b_j - \sum_{k < j} A(j,k)x_{i+1}(k)$$

$$- \sum_{k > j} A(j,k)x_i(k)) / A(j,j)$$

As a splitting: Multiply inner loop by  $A(j,j)$

$$(D - wL')x_{i+1} = ((I - w)Dx_i + wU'x_i) + wb$$

divide by  $w$

$$A = \left(\frac{1}{w}D - L'\right) - \left(\frac{1}{w}D - D + U'\right)$$

$$= M - K$$

$$R^{\text{SOR}(w)} = M^{-1}K = \left(\frac{1}{w}D - L'\right)^{-1} \left(\frac{1}{w}D - D + U'\right)$$

$$= (I - wL)^{-1} ((1-w)I + wU)$$

For 2D Poisson, red-black ordering  
 for all **reds**:  $\text{red} \equiv j+k \text{ even}, \text{black} \equiv j+k \text{ odd}$

$$V_{i+1}(j,k) = (1-w)V_i(j,k) +$$

$$w(V_i(j-1,k) + V_i(j+1,k)$$

$$+ V_i(j,k-1) + V_i(j,k+1))$$

$$+ h^2 F(j,k) / 4$$

old black data

for all blacks:

$$V_{i+1}(j,k) = (1-w)V_i(j,k) +$$

$$w(V_{i+1}(j-1,k) + V_{i+1}(j+1,k)$$

$$+ V_{i+1}(j,k-1) + V_{i+1}(j,k+1))$$

$$+ h^2 F(j,k) / 4$$

updated **red** data

# Convergence of Splitting Methods In general, and for 2D Poisson

$$\text{Jacobi: } T_{n \times n} = M - K = 4I - (4I - T_{n \times n})$$

$$R = M^{-1}K = I - \frac{1}{4}T_{n \times n}$$

$$\Rightarrow \text{evals of } R \text{ are } 1 - \frac{1}{4}(\lambda_i + \bar{\lambda}_i)$$

$\lambda_i$  are evals of  $T_n$

$$\lambda_i = 2\left(1 - \cos \frac{i\pi}{n+1}\right)$$

$$\Rightarrow \rho(R) = 1 - \frac{1}{4} 2 \cdot \lambda_{\min}$$

$$= 1 - \frac{1}{2} \lambda_{\min}$$

$$= 1 - \left(1 - \cos \frac{\pi}{n+1}\right)$$

$$= \cos \frac{\pi}{n+1} \approx 1 - \frac{\pi^2}{2(n+1)^2} \text{ when } n \gg 1$$

$\rho(R)$  gets closer to 1 as  $n$  grows  
 $\Rightarrow$  slower convergence

$$\rho(R) = 1 - x \quad x \ll 1$$

$$\rho(R)^m = (1-x)^m = (1-x)^{\frac{1}{x} \cdot mx} \\ \approx e^{-mx}$$

$$\text{for } e^{-mx} = e^{-1} \Rightarrow m = \frac{1}{x}$$

$$\text{for Jacobi } \frac{1}{x} = \frac{2(n+1)^2}{\pi^2} \text{ for } n \gg 1 \\ = O(n^2) = O(N)$$

Cost to reduce error by any constant  
also proportional to cost of  $N$  steps

$$\begin{aligned}\text{cost} &= \# \text{iteration} \cdot \# \text{ flops per iteration} \\ &= O(N) \cdot O(N) \\ &= O(N^2)\end{aligned}$$

Typical behavior: slower convergence  
for larger problems (except multigrid!)

GS: Assuming updates in red/black order  
 $\rho(R_{GS}) = (\rho(R_J))^2$

$\Rightarrow$  1 step of GS same as  
2 steps of J  
only 2x faster

SOR( $\omega$ ): Again with Red-Black ordering  
optimal  $\omega$ , much faster

$$\rho(R_{\text{SOR}(\omega_{\text{opt}})}) \approx 1 - \frac{2\pi}{n}$$

$\Rightarrow O(n) = O(N^{1/2})$  steps to converge

$\Rightarrow \text{cost} = O(N^{3/2})$  to converge

Next: Present (and prove some of)  
general convergence theory  
for J, GS, SOR( $\omega$ )  
more details for Poisson

Thm 1: If  $A$  strictly row diagonally dominant

$$|A_{ii}| > \sum_{j \neq i} |A_{ij}|$$

then  $J$  and GS converge,

GS at least as fast as Jacobi

$$\|R_{GS}\|_{\infty} \leq \|R_J\|_{\infty} < 1$$

Proof: just for  $J$  (see Thm 6.2 in text)

Splitting:  $A = D - (D - A)$

$$R_J = D^{-1}(D - A) = I - D^{-1}A$$

$$\|R_J\|_{\infty} = \max_j \sum_i |R(j,i)|$$

$$= \left| 1 - \frac{A(j,j)}{A(j,j)} \right| + \sum_{i \neq j} \left| \frac{A(j,i)}{A(j,j)} \right| \quad \text{for some } j$$

$$= 0 + \frac{1}{|A(j,j)|} \sum_{i \neq j} |A(j,i)| < 1$$

by strict diagonal dominance

$$\Rightarrow \|R_J\|_{\infty} < 1 \Rightarrow \text{converges}$$

2D Poisson: not strictly row diag. dominant

because most rows are  $[-1 \ -1 \ 4 \ -1 \ -1]$

Def: If  $|A(j,j)| \geq \sum_{i \neq j} |A(j,i)|$  for all  $j$

with strict inequality at least once

$\Rightarrow A$  weakly row diagonally dominant

Not enough by itself for Jacobi to converge

$$A = \left[ \begin{array}{cc|c} 1 & -1 & 0 \\ 1 & 1 & 0 \\ \hline 0 & 0 & 1 \end{array} \right] \Rightarrow R = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\Rightarrow R^5 = R \Rightarrow R^i \text{ does not converge to } 0$$

Need one more property of  $A$ , based on sparsity!

Def: A matrix is irreducible if there is no permutation  $P$  such that

$$PAP^T = \begin{bmatrix} \square & \square & \square \\ \square & \square & \square \\ \square & \square & \square \end{bmatrix} \text{ is block triangular}$$

Equivalently, the directed graph corresponding to  $A$  ( $A(i,j) \neq 0 \Leftrightarrow$  edge from  $i$  to  $j$ )

is strongly connected:

i.e. path from each  $i$  to each  $j$

Model Problem is irreducible because graph is 1D, 2D, 3D, ... mesh

Model Problem also weakly diagonally dominant

Thm: If  $A$  is weakly row diagonally dominant and irreducible then  $\rho(R_G) < \rho(R_J) < 1$  so GS and J both converge, GS faster

(Thm 6.3 in text)

Thm:  $A$  s.p.d.  $\Rightarrow$  SOR( $\omega$ ) converges iff  $0 < \omega < 2$

In particular SOR(1) = GS converges  
(Thm 6.5 text)

Convergence of SOR( $\omega$ ) for 2D Poisson

One more graph theory property:

Def: A matrix has "Property A" if there is a permutation  $P$  such that

$$PAP^T = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \text{ s.t. } A_{11} \text{ and } A_{22} \text{ are diagonal}$$

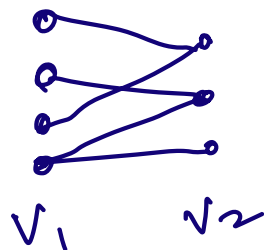
Graph Theory version:  $A$  is "bipartite" if can partition nodes (rows + cols)

$$V = V_1 \cup V_2$$

such that all edges in graph go from

$V_1$  to  $V_2$  or  $V_2$  to  $V_1$ ,

none from  $V_1$  to  $V_1$  or  $V_2$  to  $V_2$



for 1D Poisson

odd vertices =  $V_1$

even vertices =  $V_2$





for 2D Poisson: odd = black =  $V_1$   
 even = red =  $V_2$

Same idea for 3D Poisson

Thm: Suppose  $A$  has "Property A"  
 and we do SOR( $w$ ) updating all vertices  
 in  $V_1$  before  $V_2$ . Then evals  $\rho$  of  $R_S$   
 and evals  $\lambda$  of  $R_{SOR(w)}$  are related by

$$(*) (\lambda + w - 1)^2 = \lambda w^2 \rho^2$$

If  $w=1$ , so SOR(1) = GS then  $\lambda = \rho^2$

$$\Rightarrow \rho(R_{SOR(1)}) = \rho(R_{GS}) = (\rho(R_S))^2$$

$\Rightarrow$  GS converges twice as fast as J

proof: number vertices in  $V_1$  before  $V_2$

$$\Rightarrow A = \left[ \begin{array}{c|c} A_{11} & A_{12} \\ \hline A_{21} & A_{22} \end{array} \right], A_{ii} \text{ diagonal}$$

$$\text{for 2D Poisson } A = 4I + \left[ \begin{array}{c|c} 0 & A_{12} \\ \hline A_{21} & 0 \end{array} \right]$$

$$= 4I + \left[ \begin{array}{c|c} 0 & 0 \\ \hline A_{21} & 0 \end{array} \right] + \left[ \begin{array}{c|c} 0 & A_{12} \\ \hline 0 & 0 \end{array} \right]$$

$$= D - L' - U'$$

$\lambda$  eval of  $R_{SOR(w)} \Rightarrow$

$$\begin{aligned}
0 &= \det(\lambda I - R_{\text{SOR}}(\omega)) \\
&= \det(\lambda I - (I - \omega L)^{-1}((1 - \omega)I + \omega U)) \\
&= \det((I - \omega L) \quad \quad \quad) \\
&= \det(\lambda I - \omega \lambda L - (1 - \omega)I - \omega U) \\
&= \det((\lambda - 1 + \omega)I - \omega \lambda L - \omega U) \\
&= \det(\sqrt{\lambda} \omega \left( \frac{\lambda - 1 + \omega}{\sqrt{\lambda} \omega} I - \sqrt{\lambda} L - \frac{1}{\sqrt{\lambda}} U \right)) \\
&= (\sqrt{\lambda} \omega)^n \det\left( \frac{\lambda - 1 + \omega}{\sqrt{\lambda} \omega} I - \sqrt{\lambda} L - \frac{1}{\sqrt{\lambda}} U \right)
\end{aligned}$$

$$D = \begin{bmatrix} I & 0 \\ 0 & \frac{1}{\sqrt{\lambda}} I \end{bmatrix}$$

$$\begin{aligned}
D(\sqrt{\lambda} L)D^{-1} &= \begin{bmatrix} I & 0 \\ 0 & \frac{1}{\sqrt{\lambda}} I \end{bmatrix} \begin{bmatrix} 0 & 0 \\ \sqrt{\lambda} A_{21} & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & \sqrt{\lambda} I \end{bmatrix} \\
&= \begin{bmatrix} 0 & 0 \\ A_{21} & 0 \end{bmatrix} = L
\end{aligned}$$

$$D\left(\frac{1}{\sqrt{\lambda}} U\right)D^{-1} = U$$

$$\Rightarrow c \cdot \det(D(\quad)D^{-1})$$

$$= c \cdot \det\left(\frac{\lambda - 1 + \omega}{\sqrt{\lambda} \omega} I - \underbrace{L - U}_{= -R_j}\right)$$

$$= c \cdot \det\left(\frac{\lambda - 1 + \omega}{\sqrt{\lambda} \omega} I - R_j\right)$$

to be zero, this is eval of  $R_j$

$$\Rightarrow \frac{\lambda - 1 + \omega}{\sqrt{\lambda} \omega} = \mu, \text{ same as } (*) \text{ above}$$

QED

Since we know all evals  $\nu$  of  $R_i$  for Poisson  
 can choose  $\omega$  to minimize max eval  
 $\lambda$  of  $R_{SOR(\omega)}$

Thm Suppose  $A$  has  $\ast$  property  $A^{\ast}$  and  
 $SOR(\omega)$  updates  $V_1$  before  $V_2$ ,  
 and  $\nu = \rho(R_j) < 1$  so Jacobi converges

$$\text{then } \omega_{opt} = \frac{2}{1 + \sqrt{1 - \nu^2}}$$

$$\rho(R_{SOR(\omega_{opt})}) = \omega_{opt} - 1 = \frac{\nu^2}{(1 + \sqrt{1 - \nu^2})^2}$$

$$\text{for 2D Poisson: } \omega_{opt} = \frac{2}{1 + \sin(\frac{\pi}{n+1})} \approx 2$$

$$\rho(R_{SOR(\omega_{opt})}) = \frac{\cos^2(\frac{\pi}{n+1})}{(1 + \sin(\frac{\pi}{n+1}))^2} \approx 1 - \frac{2\pi}{n+1}$$

if  $n$  large

$\Rightarrow$  #steps to converge

$\sim \sqrt{\text{\#steps for Jacobi to converge}}$   
 or GS

Thm 6.5:  $A$  s.p.d  $\Rightarrow$

$$\rho(R_{SOR(\omega)}) < 1 \quad \text{if } 0 < \omega < 2$$

$$\omega = 1 \Rightarrow \rho(R_{SOR(1)}) = \rho(R_{GS}) < 1$$

$$\text{pf: } R = R_{\text{SOR}(\omega)} \quad A = D - L' - U' = D(I - L - U)$$

$$A = M - K = \left(\frac{1}{\omega}D - L'\right) - \left(\left(\frac{1}{\omega} - 1\right)D + U'\right)$$

$$1) Q = A^{-1}(2M - A) \dots \text{show } \text{Re}(\lambda_i(Q)) > 0 \quad \forall i$$

$$2) R = (Q - I)(Q + I)^{-1} \dots \text{implies } |\lambda_i(R)| < 1$$

$$1) Qx = \lambda x \Rightarrow (2M - A)x = \lambda Ax$$

$$x^*(2M - A)x = \lambda x^*Ax$$

$$\text{conjugate transpose: } \overline{x^*(2M - A)x} = \overline{\lambda x^*Ax}$$

$$\text{add, divide by 2: } x^*(M + M^* - A)x = \text{Re}(\lambda)(x^*Ax)$$

$$\text{Re}(\lambda) = \frac{x^*(M + M^* - A)x}{x^*Ax} = \frac{x^*\left(\frac{2}{\omega}D - L' - U' - (D - L' - U')\right)x}{x^*Ax}$$

$$= \frac{x^*\left(\left(\frac{2}{\omega} - 1\right)D\right)x}{x^*Ax}$$

$$0 < \omega < 2 \Rightarrow \frac{2}{\omega} - 1 > 0 \Rightarrow$$

$$\left(\frac{2}{\omega} - 1\right)D \text{ s.p.d.}$$

$$= \frac{\text{pos}}{\text{pos}} = \text{pos}$$

$$\begin{aligned} 2) (Q - I)(Q + I)^{-1} &= (2A^{-1}M - 2I)(2A^{-1}M)^{-1} \\ &= I - M^{-1}A = I - M^{-1}(M - K) \\ &= M^{-1}K = R \end{aligned}$$

HWQ 4.5 (spectral mapping thm)

$$\lambda(R) = \frac{\lambda(Q) - 1}{\lambda(Q) + 1} \quad \text{for all evals}$$

$$|\lambda(R)|^2 = \frac{|\lambda(Q) - 1|^2}{|\lambda(Q) + 1|^2}$$
$$= \frac{(\operatorname{Re} \lambda(Q) - 1)^2 + (\operatorname{Im} \lambda(Q))^2}{(\operatorname{Re} \lambda(Q) + 1)^2 + (\operatorname{Im} \lambda(Q))^2}$$

since  $\operatorname{Re} \lambda(Q) > 0$

$< 1$

QED