

## Lec 19 Accelerating Convergence

Lemma Consider the split  $A = D + L + U$ . Then  $Ax = b$  may be written:

$$(D + \omega L)x = -[(\omega - 1)D + \omega U]x + \omega b. \quad (*)$$

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$$Ax = b$$

$$\Leftrightarrow \omega Ax = \omega b$$

$$\Leftrightarrow \omega(D + L + U)x = \omega b$$

$$\Leftrightarrow (\omega D + \omega L)x = -\omega Ux + \omega b$$

$$\omega D + \omega L + \underbrace{D - D}$$

$$\begin{aligned} \Leftrightarrow (D + \omega L)x &= -\omega Dx + Dx - \omega Ux + \omega b \\ &= -[(\omega - 1)D + \omega U]x + \omega b \end{aligned}$$

□

As before, we can solve (\*) iteratively via:

$$\boxed{(D + \omega L)x_{k+1} = -[(\omega - 1)D + \omega U]x_k + \omega b} \quad (**)$$

Note: This reduces to Gauss-Seidel when  $\omega = 1$  (see (400) on p3 of L18).

In fact, we can interpret  $(\#1)$  as averaging the current iterate  $x_k$  and the next iterate  $x_{k+1}$ . To see this, consider:

$$x_{k+1} = w g_{GS}(x_k, x_{k+1}) + (1-w)x_k \quad \otimes$$

where (by  $(\#6)$  on p3 of L8):

$$g_{GS}(x_k, x_{k+1}) = D^{-1}[-Lx_{k+1} - Ux_k + b]$$

Sub into  $\otimes$ , and premultiply by  $D$ , to get:

$$D x_{k+1} = w [-Lx_{k+1} - Ux_k + b] + (1-w)Dx_k$$

Bring  $x_{k+1}$  to LHS to get:

$$\begin{aligned} (D + wL)x_{k+1} &= [-wU + (1-w)D]x_k + wb \\ &= -[L(w-1)D + wU]x_k + wb \end{aligned}$$

which is  $(\#1)$ .



Next: write RHS of (DQ) in terms of  $(D+WL)x_k$ :

$$\text{RHS} = (D+WL)x_k - \left[ \begin{array}{c} (w-1)D + wL \\ D + WL \end{array} \right] x_k + wb$$

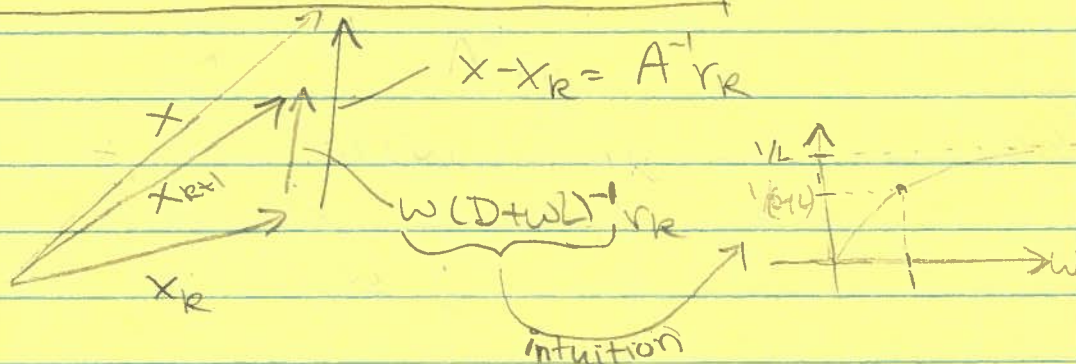
$$= (D+WL)x_k - [wD + wL + wL]x_k + wb$$

$$= (D+WL)x_k + w[b - Ax_k]$$

$r_k$  = residual @  $k^{\text{th}}$  step  
( $= A(x - x_k)$ )

Then:

$$(*) \Rightarrow \boxed{x_{k+1} = x_k + w(D+WL)^{-1}r_k} \quad (***)$$



We say that  $x_k$  is "relaxing" towards  $x$  and that when  $w > 1$ ,  $x_k$  "over-relaxes" to  $x$ , i.e. relaxes faster than for  $w=1$  (Gauss-Seidel). Thus ~~(\*)~~ is a way to accelerate convergence relative to Gauss-Seidel. The method is called "Successive Over-Relaxation (SOR)".

COMPONENT

Recall  $(*)$ :

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$$(D + wL)x_{k+1} = -[(w-1)D + wU]x_k + wb$$

Given  $x_k$ , we want to compute  $x_{k+1}$ .  
This can be done by using forward substitution to solve the system of eqns above, ie

$$\hat{A}x_{k+1} = \hat{b} \quad (\Delta)$$

where

$$\hat{A} = D + wL = \text{lower triangular}$$

$$\hat{b} = -[(w-1)D + wU]x_k + wb$$

Forward subst. applied to  $(\Delta)$  yields:

$$\hat{a}_{ii}^{(k+1)} x_i^{(k+1)} = - \sum_{j=1}^{i-1} \hat{a}_{ij}^{(k+1)} x_j^{(k+1)} + \hat{b}_i$$

In terms of  $D, L, U$ , we have:

$$\begin{aligned} a_{ii} x_i^{(k+1)} &= - \sum_{j=1}^{i-1} w a_{ij} x_j^{(k+1)} \\ &\quad - \sum_{j=1}^n [(w-1)D_{ij} + wU_{ij}] x_j^{(k)} + w b_i. \end{aligned} \quad (\Delta\Delta)$$



But:

$$D_{ij} = a_{ii} \delta_{ij}$$

$$\Rightarrow \sum_{j=1}^n (w-1) D_{ij} x_j^{(k)} = (w-1) a_{ii} x_i^{(k)}$$

Similarly:

$$U_{ij} = \begin{cases} a_{ij} & j > i \\ 0 & j \leq i \end{cases}$$

$$\Rightarrow \sum_{j=1}^n w U_{ij} x_j^{(k)} = \sum_{j=i+1}^n w a_{ij} x_j^{(k)}$$

Thus:  $(A\Delta) \Rightarrow$

$$a_{ii} x_i^{(k+1)} = - \sum_{j=1}^{i-1} w a_{ij} x_j^{(k+1)}$$

$$- (w-1) a_{ii} x_i^{(k)}$$

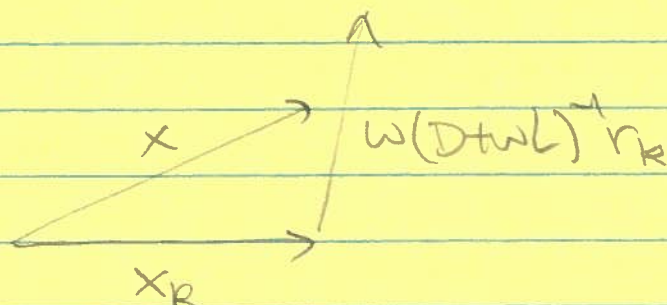
$$- \sum_{j=i+1}^n w a_{ij} x_j^{(k)}$$

$$+ w b_i$$

or:

$$\text{SOR} \quad x_i^{(k+1)} = (1-w) x_i^{(k)} + \frac{w}{a_{ii}} \left[ b_i - \sum_{j < i} a_{ij} x_j^{(k+1)} - \sum_{j > i} a_{ij} x_j^{(k)} \right]$$

One could imagine that for large  $w$ , the vector  $w(D+L)^{-1}r_k$  might "over-shoot" the exact solution.



which could destroy the convergence.

In 1947, Ostrowski proved:

Thm 1 If  $A$  is positive definite and  $0 < w < 2$ , then SOR converges for any starting point  $x_0$ .



But which value of  $w$  in that range yields fastest convergence?

Thm 2 If  $A$  is positive definite and tridiagonal, then  $\rho_{GS} = \rho_J^2 < 1$  and the optimal value of  $w$  is

$$w^* = \frac{2}{1 + \sqrt{1 - \rho_J^2}}$$

for which

$$\rho_{w^*} = w^* - 1.$$

Example  $A = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$

Evidently,  $A$  is tridiagonal.



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A is positive definite:

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$= \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2x - y \\ -x + 2y \end{bmatrix}$$

$$= x(2x - y) + y(-x + 2y)$$

$$= 2x^2 - xy - xy + 2y^2$$

$$= x^2 + y^2 + [x^2 - 2xy + y^2]$$

$$= x^2 + y^2 + (x - y)^2$$

$$\geq 0 \quad \forall x, y$$

Thus, the assumptions of Thm 2 hold

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$$x_{k+1} = Bx_k + c \quad \text{where}$$

$$\text{Jacobi: } B = S^{-1}T = -D^{-1}(L+U)$$

$$= - \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & \frac{1}{2} \end{bmatrix} \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$$

$$= - \begin{bmatrix} 0 & -\frac{1}{2} \\ -\frac{1}{2} & 0 \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{2} \\ \frac{1}{2} & 0 \end{bmatrix}$$

$$\det(B - \lambda I) = 0 \Rightarrow \det \begin{pmatrix} -\lambda & \frac{1}{2} \\ \frac{1}{2} & -\lambda \end{pmatrix} = 0.$$

$$\Rightarrow \lambda^2 - \left(\frac{1}{2}\right)^2 = 0 \Rightarrow \lambda = \pm \frac{1}{2} \Rightarrow \rho_J = \frac{1}{2}.$$



Gauss-

$$B = S^{-1}T = -(L+D)^{-1}u$$

Seidel:

$$\text{Now: } L+D = \begin{bmatrix} 2 & 0 \\ -1 & 2 \end{bmatrix}$$

$$\Rightarrow (L+D)^{-1} = \begin{bmatrix} \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{1}{2} \end{bmatrix}$$

$$\therefore B = - \begin{bmatrix} \frac{1}{2} & 0 \\ \frac{1}{4} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} = - \begin{bmatrix} 0 & -\frac{1}{2} \\ 0 & -\frac{1}{4} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{2} \\ 0 & \frac{1}{4} \end{bmatrix}$$

$$\therefore \det(B - \lambda I) = \begin{vmatrix} -\lambda & \frac{1}{2} \\ 0 & \frac{1}{4} - \lambda \end{vmatrix}$$

$$\Rightarrow -\lambda(\frac{1}{4} - \lambda) = 0$$

$$\Rightarrow \lambda = 0 \text{ or } \frac{1}{4} \Rightarrow \rho_{GS} = \frac{1}{4}.$$

Note:  $\rho_{GS} = \rho_J^2$ , as promised by Thm 2.

Thm 2  $\Rightarrow$  Optimal  $w$  is:

$$w^* = \frac{2}{1 + \sqrt{1 - \rho_J^2}}$$

$$= \frac{2}{1 + \sqrt{1 - (\frac{1}{2})^2}}$$

$$= \frac{2}{1 + \sqrt{3/4}}$$

$$= \frac{2}{1 + \sqrt{3}/2} = \frac{4}{2 + \sqrt{3}}$$

$$= \frac{4}{2 + \sqrt{3}} \cdot \frac{2 - \sqrt{3}}{2 - \sqrt{3}} = \frac{8 - 4\sqrt{3}}{4 - 3}$$

$$= 8 - 4\sqrt{3}$$

Thm 2  $\Rightarrow$   $\rho_{w^*} = w^* - 1 = 7 - 4\sqrt{3} \approx 0.08$



Thus for the positive definite, tridiagonal matrix

$$A = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

we have:

$$\rho_{\text{w}} = 0.08 \ll \rho_{\text{GS}} = 0.25 < \rho_{\text{J}} = \frac{1}{2} < 1.$$

All three methods converge, but SOR is by far the fastest.