

4.6 (continued)

$$\vec{x}^{(k)} = G \vec{x}^{(k-1)} + \vec{c} \quad \text{converges}$$

\Leftrightarrow you can find sub. matrix norm s.t. $\|G\| < 1$

$$\Leftrightarrow \rho(G) < 1$$

Thm If A is row or column diagonally dominant, then

Gauss-Seidel method converges.

$$Q \vec{x} = (Q - A) \vec{x} + \vec{b} \quad Q = \text{lower-triangular part of } A$$

$$G = I - Q^{-1}A.$$

Proof It suffices to show $\rho(I - Q^{-1}A) < 1$.

Let λ be an eigenvalue of $I - Q^{-1}A$, w/ eigenvector $\vec{x} \neq \vec{0}$

$$(I - Q^{-1}A) \vec{x} = \lambda \vec{x}$$

$$\vec{x} - Q^{-1}A \vec{x} = \lambda \vec{x}$$

$$Q^{-1}A \vec{x} = \vec{x} - \lambda \vec{x}$$

$$A \vec{x} = Q \vec{x} - \lambda Q \vec{x}$$

$$\underbrace{(Q - A)} \vec{x} = \lambda Q \vec{x}$$

- str. upper-tri.
part of A

$$- \sum_{j=i+1}^n a_{ij} x_j = \lambda \sum_{j=1}^{i-1} a_{ij} x_j + \lambda a_{ii} x_i \quad i=1, \dots, n$$

Suppose $|\lambda| \geq 1$. Take i such that $|x_i|$ is largest.

$$\text{Then } |\lambda a_{ii} x_i| = |\lambda| \cdot |a_{ii}| \cdot |x_i|$$

$$\begin{aligned}
& \left| - \sum_{j=i+1}^n a_{ij} x_j - \lambda \sum_{j=1}^{i-1} a_{ij} x_j \right| \\
& \leq \sum_{j=i+1}^n |a_{ij}| \cdot |x_j| + |\lambda| \sum_{j=1}^{i-1} |a_{ij}| \cdot |x_j| \\
& \leq |\lambda| \sum_{j=i+1}^n |a_{ij}| \cdot |x_i| + |\lambda| \sum_{j=1}^{i-1} |a_{ij}| \cdot |x_i| \\
& = |\lambda| \cdot |x_i| \cdot \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}| < |\lambda| \cdot |x_i| \cdot |a_{ii}| \quad \text{Contradiction!}
\end{aligned}$$

This gives $|\lambda| < 1 \Rightarrow \rho(I - Q^{-1}A) < 1$.

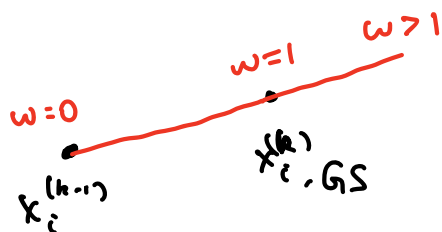
Successive over-relaxation method (SOR)

Gauss-Seidel:
$$x_i^{(k)} = \frac{1}{a_{ii}} \left(- \sum_{j=1}^{i-1} a_{ij} x_j^{(k)} - \sum_{j=i+1}^n a_{ij} x_j^{(k-1)} + b_i \right)$$



SOR:
$$x_i^{(k)} = (1-\omega)x_i^{(k-1)} + \omega \frac{1}{a_{ii}} \left(- \sum_{j=1}^{i-1} a_{ij} x_j^{(k)} - \sum_{j=i+1}^n a_{ij} x_j^{(k-1)} + b_i \right)$$

$$0 < \omega < 2$$



$$Q \bar{x}^{(k)} = (Q - A) \bar{x}^{(k-1)} + \bar{b}$$

$$A = D - C_L - C_U$$

$$\bar{x}^{(k)} = (1-\omega) \bar{x}^{(k-1)} + \omega D^{-1} (C_L \bar{x}^{(k)} + C_U \bar{x}^{(k-1)} + \bar{b})$$

$$\omega^{-1} D \bar{x}^{(k)} = \omega^{-1} (1-\omega) D \bar{x}^{(k-1)} + C_L \bar{x}^{(k)} + C_U \bar{x}^{(k-1)} + \bar{b}$$

$$(\omega^{-1} D - C_L) \bar{x}^{(k)} = (\omega^{-1} (1-\omega) D + C_U) \bar{x}^{(k-1)} + \bar{b}$$

$$Q = \omega^{-1} D - C_L \quad \begin{matrix} \uparrow \\ Q-A \end{matrix}$$

Thm If A is symmetric and positive definite, and $0 < \omega < 2$, then SOR converges.

Proof It suffices to prove $\rho(G) < 1$, where

$$G = I - Q^{-1}A = I - (\omega^{-1}D - C_L)^{-1}A$$

Let λ be an eigenvalue of G , w/ eigenvector \vec{x}

$$(I - (\omega^{-1}D - C_L)^{-1}A) \vec{x} = \lambda \vec{x}$$

$$\vec{x} - (\omega^{-1}D - C_L)^{-1}A \vec{x} = \lambda \vec{x}$$

$$A = D - C_L - C_L^T$$

$$(\omega^{-1}D - C_L)^{-1}A \vec{x} = (1 - \lambda) \vec{x}$$

$$A \vec{x} = (1 - \lambda) (\omega^{-1}D - C_L) \vec{x}$$

$$\vec{x}^* A \vec{x} = (1 - \lambda) \vec{x}^* (\omega^{-1}D - C_L) \vec{x}$$

\vec{x}^* : transpose conjugate of \vec{x}

$$\overline{\vec{x}^* C_L \vec{x}}$$

$$= (\vec{x}^* C_L \vec{x})^*$$

$$= \vec{x}^* C_L^T \vec{x}$$

Suppose $\lambda \in \mathbb{R}$, $\vec{x} \in \mathbb{R}^n$

$$\vec{x}^T A \vec{x} = (1 - \lambda) \vec{x}^T (\omega^{-1}D - \frac{1}{2}C_L - \frac{1}{2}C_L^T) \vec{x}$$

$$= (1 - \lambda) \vec{x}^T ((\omega^{-1} - \frac{1}{2})D + \frac{1}{2}A) \vec{x}$$

$$\left(\underbrace{1 - \frac{1}{2}(1 - \lambda)}_{= \frac{1}{2}(1 + \lambda)} \right) \underbrace{\vec{x}^T A \vec{x}}_{> 0} = (1 - \lambda) \underbrace{(\omega^{-1} - \frac{1}{2})}_{> 0} \underbrace{\vec{x}^T D \vec{x}}_{> 0}$$

$$\Rightarrow (1 + \lambda)(1 - \lambda) > 0 \quad \Rightarrow -1 < \lambda < 1$$

• When A is sym. posdef. and tri-diagonal, the optimal ω is

$$\omega_0 = \frac{2}{1 + \sqrt{1 - (\rho(J))^2}}$$

where $J = I - D^{-1}A$ is the "G" matrix for Jacobi.

4.7 Steepest descent and conjugate gradient methods

To solve $A\bar{x} = \bar{b}$ where A is sym. posdef.

Lemma The unique sol'n to $A\bar{x} = \bar{b}$ is the unique minimizer of

the quadratic form

$$\langle \bar{x}, \bar{y} \rangle := \bar{x}^T \bar{y}$$

$$q(\bar{x}) = \langle \bar{x}, A\bar{x} \rangle - 2\langle \bar{x}, \bar{b} \rangle$$

$$\nabla q(\bar{x}) = 2A\bar{x} - 2\bar{b}$$

Proof $q(\bar{x} + t\bar{v}) = \langle \bar{x} + t\bar{v}, A\bar{x} + tA\bar{v} \rangle - 2\langle \bar{x} + t\bar{v}, \bar{b} \rangle$

$$= \langle \bar{x}, A\bar{x} \rangle - 2\langle \bar{x}, \bar{b} \rangle$$

$$ax^2 + bx + c \quad a > 0$$

$$+ 2t \langle \bar{v}, A\bar{x} - \bar{b} \rangle$$

$$x = -\frac{b}{2a}$$

$$+ t^2 \langle \bar{v}, A\bar{v} \rangle \quad (\text{taking } \bar{v} \neq \bar{0})$$

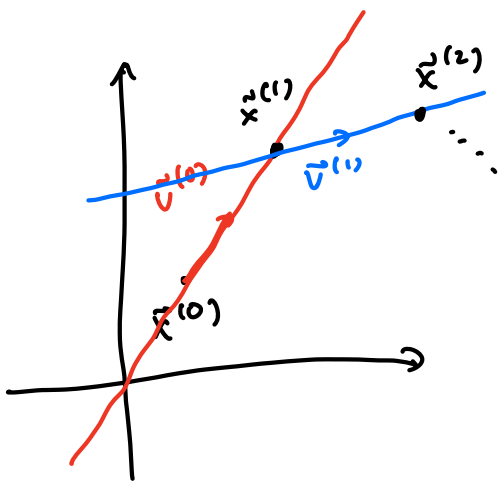
① If $A\bar{x} = \bar{b}$, then $q(\bar{x} + t\bar{v}) > q(\bar{x}) \quad \forall t \neq 0$.

$\Rightarrow \bar{x}$ is the unique minimizer of q .

② If $A\bar{x} \neq \bar{b}$, then $\min_{t \in \mathbb{R}} q(\bar{x} + t\bar{v})$ is achieved when

$$t = \frac{\langle \bar{v}, \bar{b} - A\bar{x} \rangle}{\langle \bar{v}, A\bar{v} \rangle}$$

• This gives a general iterative algorithm to find minimizer of $q(\bar{x})$.



At k -th iteration, choose a search direction

$\bar{v}^{(k)} \neq \bar{0}$, then let

$$\bar{x}^{(k+1)} = \bar{x}^{(k)} + t_k \bar{v}^{(k)} \quad \text{where}$$

$$t_k = \frac{\langle \bar{v}^{(k)}, \bar{b} - A\bar{x}^{(k)} \rangle}{\langle \bar{v}^{(k)}, A\bar{v}^{(k)} \rangle}$$

Steepest descent

$$\text{Choose } \vec{v}^{(k)} = \nabla q(\vec{x}^{(k)}) \parallel \vec{b} - A\vec{x}^{(k)} = \vec{r}^{(k)} \\ 2(A\vec{x} - \vec{b})$$

Proof of convergence of SDR, continued

$$\frac{1}{1-\lambda} \vec{x}^* A \vec{x} = \vec{x}^* (\omega^{-1} D - C_L) \vec{x}$$

$$\text{Re} \frac{1}{1-\lambda} \vec{x}^* A \vec{x} = \vec{x}^* \left((\omega^{-1} - \frac{1}{2}) D + \frac{1}{2} A \right) \vec{x}$$

$$\left(\text{Re} \frac{1}{1-\lambda} - \frac{1}{2} \right) \underbrace{\vec{x}^* A \vec{x}}_{>0} = \underbrace{(\omega^{-1} - \frac{1}{2}) \vec{x}^* D \vec{x}}_{>0}$$

$$\Rightarrow \text{Re} \frac{1}{1-\lambda} - \frac{1}{2} > 0$$

$$\lambda = a + bi \quad \frac{1}{1-a-bi} = \frac{1-a+bi}{(1-a)^2+b^2} \Rightarrow \frac{1-a}{(1-a)^2+b^2} > \frac{1}{2}$$

$$2-2a > 1-2a+a^2+b^2$$

$$a^2+b^2 < 1 \Rightarrow |\lambda| < 1$$