

## Lecture 17:

Another condition for the convergence (useful for analyzing SOR)

Let  $A = N - P$  ( $N$  is invertible)

Iterative scheme:  $N\vec{x}^{k+1} = P\vec{x}^k + \vec{b}$

Theorem: (Householder - John) Suppose  $A$  and  $(N^* + N - A)$  are self-adjoint positive-definite matrices, then the iterative scheme converges.

Proof: Consider  $M = N^{-1}P = N^{-1}(N-A) = I - N^{-1}A$ .

Suffice to show that all eigenvalues of  $M$  satisfy  $|\lambda| < 1$  ( $\lambda$  can be complex). Let  $\lambda$  be an eigenvalue associated to the eigenvector  $\vec{x}$ . Then:

$$\begin{aligned} M\vec{x} = \lambda\vec{x} &\Rightarrow (I - N^{-1}A)\vec{x} = \lambda\vec{x} \Rightarrow (N-A)\vec{x} = \lambda N\vec{x} \\ &\Rightarrow (1-\lambda)N\vec{x} = A\vec{x} \end{aligned}$$

Note that  $\lambda \neq 1$ . Otherwise 0 is an eigenvalue of  $A$ .  
Contradiction to the fact that  $A$  is positive definite.

Multiply  $\vec{x}^*$  on both sides:

$$(1-\lambda)\vec{x}^* N\vec{x} = \vec{x}^* A\vec{x} \Rightarrow \vec{x}^* N\vec{x} = \frac{1}{(1-\lambda)} \vec{x}^* A\vec{x} \quad (1)$$

Take conjugate transpose on both sides:

$$(1-\bar{\lambda}) \vec{x}^* N^* \vec{x} = \vec{x}^* A^* \vec{x} = \vec{x}^* A \vec{x}$$

$$\Rightarrow \vec{x}^* N^* \vec{x} = \frac{1}{(1-\bar{\lambda})} \vec{x}^* A \vec{x} \quad \text{--- (2)}$$

(1) + (2) -  $\vec{x}^* A \vec{x}$  on both sides:

$$\begin{aligned} \vec{x}^* (N + N^* - A) \vec{x} &= \left( \frac{1}{1-\lambda} + \frac{1}{1-\bar{\lambda}} - 1 \right) \vec{x}^* A \vec{x} \\ &= \frac{1-|\lambda|^2}{|1-\lambda|^2} \vec{x}^* A \vec{x} \end{aligned}$$

By assumption,  $A$  and  $N + N^* - A$  are both positive definite.

We have:  $\vec{x}^* A \vec{x} > 0$  and  $\vec{x}^* (N + N^* - A) \vec{x} > 0$

Hence,  $1-|\lambda|^2 > 0$  and  $|\lambda| < 1$ .

$\therefore \rho(CM) < 1$  and the iterative scheme converges.

Example: Let  $A = \begin{pmatrix} \alpha_1 & \beta_1 & & & \\ \beta_1 & \alpha_2 & \beta_2 & & \\ & \beta_2 & \ddots & \ddots & \\ & & & \alpha_{n-1} & \beta_{n-1} \\ & & & \beta_{n-1} & \alpha_n \end{pmatrix}$  be *real* symmetric tridiagonal matrix. Suppose  $A$  is positive-definite. Prove that the Gauss-Seidel method converges.

Solution: For Gauss-Seidel method,

$$N = \begin{pmatrix} \alpha_1 & & & & \\ \beta_1 & \alpha_2 & & & \\ & \beta_2 & \ddots & \ddots & \\ & & & \alpha_{n-1} & \\ & & & \beta_{n-1} & \alpha_n \end{pmatrix} \quad \text{and} \quad N^* + N - A = \begin{pmatrix} \alpha_1 & & & & \\ & \alpha_2 & & & \\ & & \ddots & & \\ & & & \alpha_{n-1} & \\ & & & & \alpha_n \end{pmatrix}$$

Then,  $N^* + N - A$  is symmetric.

Also,  $(0, \dots, \underset{\substack{\uparrow \\ i\text{th}}}{1}, 0, \dots, 0) A \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \leftarrow i\text{th} = \alpha_i > 0 \quad \therefore N + N^* - A$  is positive definite  
 ( $\because$  all eigenvalues are positive)

By Householder - John Theorem, Gauss-Seidel method converges.

Example: Suppose  $A$  is <sup>(real)</sup> self-adjoint positive-definite. Using Householder - John theorem, prove that SOR method converges if and only if  $0 < \omega < 2$ .

Solution: Note that  $N_{SOR} = L + \frac{1}{\omega} D$ . Now,  $L = U^*$

$$\therefore N_{SOR} + N_{SOR}^* - A = \left(\frac{2}{\omega} - 1\right) D$$

( $A$  is self-adjoint)

$\therefore N_{SOR} + N_{SOR}^* - A$  is also self-adjoint positive-definite if  $0 < \omega < 2$ .

$\therefore$  By Householder - John theorem, SOR converges.

## Eigenvalue Problem

Recall: Convergence of iterative scheme:

$N\vec{x}^{k+1} = P\vec{x}^k + \vec{f}$  depends on the spectral radius  $\rho(N^{-1}P)$ .

$\therefore$  Need: numerical method to compute eigenvalues.

## Computation of Spectral radius

Goal: Find eigenvalues with largest magnitude  $\leftarrow$  Spectral radius

Two methods =

1. Power method
2. QR method

## 1. Power method

Let  $A \in M_{n \times n}(\mathbb{C})$  with  $n$  eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$  with eigenvectors  $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n$ .

Let  $X = \begin{pmatrix} \frac{1}{|\vec{x}_1|} & \frac{1}{|\vec{x}_2|} & \dots & \frac{1}{|\vec{x}_n|} \\ | & | & & | \end{pmatrix} \in M_{n \times n}(\mathbb{C})$ . Then, we know:

$$AX = X \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \dots & \\ & & & \lambda_n \end{pmatrix}.$$

Assuming:  $|\lambda_1| > |\lambda_2| \geq |\lambda_3| \geq \dots \geq |\lambda_n|$

We'll use Power method to compute  $|\lambda_1|$ .

Observation: Start with an initial vector  $\vec{x}^{(0)}$ .

Consider the iterative scheme:  $\vec{x}^{(k+1)} = \frac{A \vec{x}^{(k)}}{\|A \vec{x}^{(k)}\|_\infty}$  for  $k=0, 1, \dots$

Suppose  $A$  is diagonalizable. That's, we can assume  $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n$  form a basis for  $\mathbb{C}^n$ .

Take  $\vec{x}^{(0)} = a_1 \vec{x}_1 + a_2 \vec{x}_2 + \dots + a_n \vec{x}_n$  (assuming  $a_1 \neq 0$ )

Note that  $A^k \vec{x}^{(0)} = a_1 \lambda_1^k \left[ \vec{x}_1 + \sum_{j=2}^n \frac{a_j}{a_1} \left( \frac{\lambda_j}{\lambda_1} \right)^k \vec{x}_j \right]$ .

$$\begin{aligned} \text{Hence, } \vec{x}^{(k)} &= \frac{A \vec{x}^{(k-1)}}{\|A \vec{x}^{(k-1)}\|_\infty} = \frac{A \left( A \vec{x}^{(k-2)} / \|A \vec{x}^{(k-2)}\|_\infty \right)}{\|A \left( A \vec{x}^{(k-2)} / \|A \vec{x}^{(k-2)}\|_\infty \right)\|_\infty} \\ &= \frac{A^2 \vec{x}^{(k-2)}}{\|A^2 \vec{x}^{(k-2)}\|_\infty} = \dots = \frac{A^k \vec{x}^{(0)}}{\|A^k \vec{x}^{(0)}\|_\infty} \end{aligned}$$



$$\vec{x}^{(k)} = \frac{a_1 \lambda_1^k [\vec{x}_1 + \sum_{j=2}^n \frac{a_j}{a_1} (\frac{\lambda_j}{\lambda_1})^k \vec{x}_j]}{\| a_1 \lambda_1^k [\vec{x}_1 + \sum_{j=2}^n \frac{a_j}{a_1} (\frac{\lambda_j}{\lambda_1})^k \vec{x}_j] \|_\infty} \approx \frac{a_1 \vec{x}_1 \lambda_1^k}{|a_1| \|\vec{x}_1\|_\infty |\lambda_1|^k}$$

Note:  $\vec{v}$  is an eigenvector associated to  $\lambda_1$ .

In fact,

$$\| A \vec{x}^{(k)} \|_\infty \rightarrow \| A \left( \frac{a_1 \vec{x}_1}{|a_1| \|\vec{x}_1\|_\infty} \right) \|_\infty = \left\| \frac{a_1}{|a_1|} \lambda_1 \frac{\vec{x}_1}{\|\vec{x}_1\|_\infty} \right\|_\infty = |\lambda_1|$$

$\frac{\lambda_1^k}{|\lambda_1|^k}$  can be removed  
under  $\|\cdot\|_\infty$

when  $k$  is big  
( $\because |\frac{\lambda_j}{\lambda_1}| < 1$  for  
 $j=2, \dots, n$ )

Example: Consider:  $A = \begin{pmatrix} 0 & 11 & -5 \\ -2 & 17 & -7 \\ -4 & 26 & 10 \end{pmatrix}$ . Using power method with  $\vec{x}^{(0)} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ , find the spectral radius of  $A$ .

Solution:  $\vec{x}^{(1)} = \frac{A\vec{x}^{(0)}}{\|A\vec{x}^{(0)}\|_\infty} = \frac{(6, 8, 12)^T}{\|(6, 8, 12)^T\|_\infty} = \begin{pmatrix} \frac{1}{2} \\ \frac{2}{3} \\ 1 \end{pmatrix}$ .

$\vec{x}^{(2)} = \frac{A\vec{x}^{(1)}}{\|A\vec{x}^{(1)}\|_\infty} = \frac{(\frac{7}{3}, \frac{10}{3}, \frac{16}{3})^T}{\|(\frac{7}{3}, \frac{10}{3}, \frac{16}{3})^T\|_\infty} = \begin{pmatrix} \frac{7}{16} \\ \frac{5}{8} \\ 1 \end{pmatrix}$ .

Compute  $\|A\vec{x}^{(k)}\|_\infty$ , we have:

$k$	6	8	10
$\ A\vec{x}^{(k)}\ _\infty$	4.02536	4.066270	4.001564

The dominant eigenvalue  $\approx 4$