

Lecture 14:

Note: Previous example requires that $M = N^{-1}P$ is diagonalizable.
 What if $N^{-1}P$ is NOT diagonalizable?

Theorem: Let $A \in M_{n \times n}(\mathbb{C})$ be a complex-valued matrix.

Then: $\lim_{k \rightarrow \infty} A^k = 0$ if and only if $\rho(A) < 1$.

Simple consequence:

Corollary: The iterative scheme $\vec{x}^{k+1} = M\vec{x}^k + \vec{b}$ converges if and only if $\rho(M) < 1$.

Proof: Consider $\vec{x}^{k+1} = M\vec{x}^k + \vec{b}$
 $\vec{x}^* = M\vec{x}^* + \vec{b}$ $\vec{x}^* = \text{sol of } A\vec{x} = \vec{f}$.
 $\therefore \vec{e}^{k+1} = M\vec{e}^k \Rightarrow \vec{e}^k = M^k \vec{e}^0$
 $\vec{e}^k \rightarrow \vec{0}$ iff $M^k \rightarrow 0$ iff $\rho(M) < 1$.

Lecture 16:

Recall:

Theorem: Let $A \in M_{n \times n}(\mathbb{C})$ be a complex-valued matrix.

Then: $\lim_{k \rightarrow \infty} A^k = 0$ if and only if $\rho(A) < 1$.

Simple consequence:

Corollary: The iterative scheme $\vec{x}^{k+1} = M\vec{x}^k + \vec{b}$ converges if and only if $\rho(M) < 1$.

Proof of Theorem

(\Rightarrow) Let λ be an eigenvalue of A with eigenvector \vec{v} .

Then: $A^k \vec{v} = \lambda^k \vec{v}$. Thus, $\lim_{k \rightarrow \infty} A^k \vec{v} = \lim_{k \rightarrow \infty} \lambda^k \vec{v}$

$\stackrel{0}{\vec{0}} = (\lim_{k \rightarrow \infty} \lambda^k) \vec{v} \stackrel{0}{\vec{0}}$

$\therefore |\lambda| < 1$ (for all eigenvalue λ)

$$\therefore \rho(A) < 1$$

$$\max_j \{ |\lambda_j| : \lambda_j \text{ is eigenvalue} \}$$

(\Leftarrow) Let $\lambda_1, \lambda_2, \dots, \lambda_n$ be eigenvalues of A (can be repeated)

We apply the idea of Jordan Canonical Form



Find the invertible Q such that $Q^{-1}AQ$ becomes

Simple



ALMOST looks like a diagonal matrix.

Useful Fact: (Can be used without proof)

For any $A \in M_{n \times n}(\mathbb{C})$, there exists an invertible $Q \in M_{n \times n}(\mathbb{C})$ such that $A = QJQ^{-1}$ where J is the Jordan Canonical Form of A . Actually,

$$J = \begin{pmatrix} J_{m_1}(\lambda_{i_1}) & & & & \\ & J_{m_2}(\lambda_{i_2}) & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & J_{m_s}(\lambda_{i_s}) \end{pmatrix} \quad (\lambda_{i_j} \text{ are eigenvalues of } A)$$

Where $\underbrace{J_{m_j}(\lambda_{i_j})}_{\{ } = \begin{pmatrix} \lambda_{i_j} & & & & \\ & \lambda_{i_j} & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \lambda_{i_j} \end{pmatrix} \in M_{m_j \times m_j}(\mathbb{C})$

is called Jordan block with λ_{i_j}

e.g.

$$\bar{J} = \begin{pmatrix} \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix} & \begin{pmatrix} 0 & 0 \end{pmatrix} \\ \begin{pmatrix} 0 \end{pmatrix} & \begin{pmatrix} 2 & 1 \\ 0 & 2 \end{pmatrix} & \begin{pmatrix} 0 \end{pmatrix} \\ \begin{pmatrix} 0 \end{pmatrix} & \begin{pmatrix} 0 \end{pmatrix} & \begin{pmatrix} 5 & 1 & 0 \\ 0 & 5 & 1 \\ 0 & 0 & 5 \end{pmatrix} \end{pmatrix}$$

Now, $A^k = Q J^k Q^{-1}$ and

$$J^k = \begin{pmatrix} J_{m_1}^k(\lambda_{i_1}) & & & \\ & \ddots & & \\ & & \ddots & \\ & & & J_{m_s}^k(\lambda_{i_s}) \end{pmatrix}$$

For $k \geq m_j - 1$

$$J_{m_j}^k(\lambda_{ij}) = \begin{pmatrix} \lambda_{ij}^k & C_1^k \lambda_{ij}^{k-1} & C_2^k \lambda_{ij}^{k-2} & \cdots & C_{m_j-1}^k \lambda_{ij}^{k-m_j+1} \\ \lambda_{ij}^k & C_1^k \lambda_{ij}^{k-1} & \cdots & \cdots & C_{m_j-2}^k \lambda_{ij}^{k-m_j+2} \\ \vdots & & & & \vdots \\ C_1^k \lambda_{ij}^{k-1} & \lambda_{ij}^k & \cdots & \cdots & C_{m_j-2}^k \lambda_{ij}^{k-m_j+2} \end{pmatrix} \quad (\text{By M.I.})$$

$\therefore p(A) < 1 \quad \therefore |\lambda_{ij}| < 1 \text{ for all } j.$

$$\therefore \lim_{k \rightarrow \infty} J_{m_j}^k(\lambda_{ij}) = 0 \text{ for all } j$$

and $\lim_{k \rightarrow \infty} J^k = 0$

$$\therefore \lim_{k \rightarrow \infty} A^k = \lim_{k \rightarrow \infty} Q J^k Q^{-1} = 0$$

Splitting choice 3: Successive overrelaxation method (SOR)

Consider the iterative scheme =

(Suppose $A = L + D + U$)

$$L \vec{x}^{k+1} + D \vec{y}^{k+1} + U \vec{x}^k = \vec{b} \quad (*)$$

$$\vec{x}^{k+1} = \vec{x}^k + \omega (\vec{y}^{k+1} - \vec{x}^k) \quad (**)$$

$$\Leftrightarrow \vec{y}^{k+1} = \frac{1}{\omega} (\vec{x}^{k+1} + (\omega-1) \vec{x}^k)$$

Putting (**) into (*):

$$(L + \frac{1}{\omega} D) \vec{x}^{k+1} + \frac{1}{\omega} (\omega U + (\omega-1) D) \vec{x}^k = \vec{b}$$

or $\underbrace{(L + \frac{1}{\omega} D)}_N \vec{x}^{k+1} = \underbrace{\left(\frac{1}{\omega} D - (D+U) \right)}_P \vec{x}^k + \vec{b}$

Remark: • SOR is equivalent to:

$$A = N - P = \underbrace{\left(L + \frac{1}{\omega} D \right)}_{\text{Matrix}} - \underbrace{\left(\frac{1}{\omega} D - (D + U) \right)}_{\text{Vector}}$$

$$N \vec{x}^{k+1} = P \vec{x}^k + \vec{b} \Leftrightarrow \vec{x}^{k+1} = \underbrace{N^{-1}P}_{P} \vec{x}^k + \underbrace{N^{-1}\vec{b}}_{P}$$

• $P(N^{-1}P) = P \left(\underbrace{\left(L + \frac{1}{\omega} D \right)^{-1}}_{H} \left(\frac{1}{\omega} D - (D + U) \right) \right)$

has to be strictly less than M_w

and it has to be small in order to converge fast.

• If $\omega = 1$, SOR = Gauss-Seidel