

Poisson equations ($-u_{xx} - u_{yy} = f$)

Theorem: Let A be the 2D Laplacian matrix. The eigenvalues of A are given by:

$$\lambda_{ij} = \frac{4}{h^2} [\sin^2(\frac{i\pi h}{2}) + \sin^2(\frac{j\pi h}{2})] \quad 1 \leq i, j \leq m$$

- The smallest eigenvalue is attained with $i = j = 1$:

$$\lambda_{\min} = \frac{8}{h^2} \sin^2(\frac{\pi h}{2})$$

- The largest eigenvalue is attained with $i = j = m$:

$$\begin{aligned} \lambda_{\max} &= \frac{8}{h^2} \sin^2(\frac{m\pi h}{2}) \\ &= \frac{8}{h^2} \sin^2(\frac{\pi}{2}(1-h)) \quad (h = \frac{1}{m+1}, mh = 1-h) \\ &= \frac{8}{h^2} \cos^2(\frac{\pi h}{2}) \end{aligned}$$

- A is SPD and an M-matrix.

Richardson

$$\rho(I - \theta A) = \max\{|1 - \theta \frac{8}{h^2} \sin^2(\frac{\pi h}{2})|, |1 - \theta \frac{8}{h^2} \cos^2(\frac{\pi h}{2})|\}$$

Convergence holds for $0 < \theta < h^2/(4 \cos^2(\pi h/2))$ and

$$\theta_{opt} = \frac{2}{\lambda_{\min} + \lambda_{\max}} = \frac{h^2}{4} \quad \rho_{opt} = \frac{\lambda_{\min} - \lambda_{\max}}{\lambda_{\min} + \lambda_{\max}} = 1 - 2 \sin^2(\frac{\pi h}{2})$$

Jacobi

$D = 4/h^2 I = \theta_{opt}^{-1} I = \text{optimal Richardson}$

$$\therefore \rho(I - D^{-1}A) = \rho_{opt} = 1 - 2 \sin^2(\pi h/2) = \cos(\pi h)$$

By Taylor expansion,

$$\cos(x) = 1 - x^2/2 + x^4/4! + \dots$$

$$\therefore \rho(I - D^{-1}A) = \cos(\pi h) = 1 - \pi^2/2 h^2 + O(h^4)$$

For small mesh size h , $\rho(G^J) \approx 1 \rightarrow$ slow convergence

GS & SOR

$$\begin{aligned}\rho(I - M_{GS}^{-1}A) &= \rho(I - M_J^{-1}A)^2 = \cos^2(\pi h) \\ &= 1 - \sin^2(\pi h) \\ &= 1 - \pi^2 h^2 + O(h^4)\end{aligned}$$

- For small h , slow convergence for GS.
- Convergence rate = $2 \times$ convergence rate of Jacobi.
- For SOR,

$$\begin{aligned}\omega_{opt} &= \frac{2}{1 + \sin(\pi h)} \\ \rho_{opt}^{SOR} &= \omega_{opt} - 1 = \frac{1 - \sin(\pi h)}{1 + \sin(\pi h)} \\ &= 1 - 2\pi h + O(h^2)\end{aligned}$$

- Optimal SOR is an order of magnitude better than GS and Jacobi.

Convergence analysis for CG

$$\text{Recall: } F(x^k) = \min \left\{ F(x^0 + \sum_{i=0}^{k-1} \alpha_i p^i) : \alpha_0, \dots, \alpha_{k-1} \in R \right\}$$

$$\Rightarrow F(x^k) - F(x) = \min \left\{ F(x^0 + \sum_{i=0}^{k-1} \alpha_i p^i) - F(x) : \alpha_0, \dots, \alpha_{k-1} \in R \right\}$$

$$\begin{array}{c} : \\ \text{algebra} \quad (F(y) - F(x) = \frac{1}{2} \|y - x\|_A^2) \\ : \end{array}$$

$$\frac{1}{2} \|x^k - x\|_A^2 = \min \left\{ \frac{1}{2} \left\| e^0 + \sum_{i=0}^{k-1} \alpha_i p^i \right\|_A^2 : \alpha_0, \dots, \alpha_{k-1} \in R \right\}$$

Let $e^k = x^k - x$. Then

$$\begin{aligned} \|e^k\|_A &= \min \left\{ \left\| e^0 + \sum_{i=0}^{k-1} \alpha_i p^i \right\|_A : \alpha_0, \dots, \alpha_{k-1} \in R \right\} \\ &= \min \left\{ \left\| e^0 + \sum_{i=0}^{k-1} \gamma_i A^i r^0 \right\|_A : \alpha_0, \dots, \alpha_{k-1} \in R \right\} \end{aligned}$$

(since $\text{span} \{ p^0, \dots, p^{k-1} \} = \text{span} \{ r^0, \dots, A^{k-1} r^0 \}$)

Let $Q_{k-1}(x) = \gamma_0 + \gamma_1 x + \dots + \gamma_{k-1} x^{k-1}$. Then

$$Q_{k-1}(A) = \gamma_0 I + \gamma_1 A + \dots + \gamma_{k-1} A^{k-1} = \sum \gamma_i A^i$$

$$\begin{aligned} \therefore e^0 + \sum_{i=0}^{k-1} \gamma_i A^i r^0 &= e^0 + Q_{k-1}(A) r^0 \\ &= e^0 + Q_{k-1}(A) A e^0 \quad (r^0 = A(x - x^0) = A e^0) \\ &= (I + Q_{k-1}(A) A) e^0 \end{aligned}$$

Let $P_k(x) = 1 + Q_{k-1}(x)x$. Then $\deg(P_k) \leq k$, $P_k(0) = 1$, and

$$e^0 + \sum_{i=0}^{k-1} \gamma_i A^i r^0 = P_k(A) e^0$$

$\therefore \|e^k\|_A = \min \{ \|P_k(A)e^0\|_A : P_k(x) = \text{poly. of deg} \leq k, P_k(0) = 1 \}$

In other words, let $\tilde{P}_k(x)$ be a poly. of $\deg \leq k$, $\tilde{P}_k(0) = 1$. Then

$$\|e^k\|_A \leq \|\tilde{P}_k(A)e^0\|_A$$

\therefore CG finds the optimal poly. P_k to min the error in the A-norm.

By choosing $P_k(x)$ appropriately, one can show:

Theorem:

$$\|x^k - x\|_A^2 \leq 2 \left(\frac{\sqrt{\kappa(A)} - 1}{\sqrt{\kappa(A)} + 1} \right)^k \|x^0 - x\|_A^2$$

where $\kappa(A) = \lambda_{\max} / \lambda_{\min}$.

Notes

- 1) This is upper bound only. CG convergence is usually better.
- 2) CG convergence depends only all $\{\lambda_j\}$, not just $\lambda_{\min}, \lambda_{\max}$.

E.g. A has 3 distinct eigenvalues: $\lambda_1 < \lambda_2 < \lambda_3$

Define Lagrange poly. $P_3(x)$ of $\deg \leq 3$ such that

$$P_3(0) = 1, P_3(\lambda_j) = 0 \quad j = 1, 2, 3.$$

$$\text{Then } \|e^3\|_A^2 \leq \|P_3(A)e^0\|_A^2 = \sum_{j=1}^3 \xi_j^2 P_3^2(\lambda_j) \lambda_j = 0$$

\Rightarrow CG converges in 3 iterations, independent of $\kappa(A)$.

- 3) For Poisson equation, the asymptotic convergence rates for SOR and CG are the same. However, no optimal parameter needed for CG.