

Dec 7, 2020

$Ax = b \quad K_r(A, b) = \{b, Ab, \dots, A^{r-1}b\}$

MINRES
 $A = A^T$

opt problem
 $\min \|Ax - b\|_2$
s.t. $x \in K_r$

GMRES

$\min \|Ax - b\|_2$
s.t. $x \in K_r$

subproblems

$y_k = \operatorname{argmin} \|\bar{T}_k y - \beta_0 e_1\|_2$
 $x_k = Q_k y_k$

$y_k = \operatorname{argmin} \|\bar{H}_k y - \beta_0 e_1\|_2$
 $x_k = Q_k y_k$

$AQ_k = Q_{k+1} \bar{A}_k$
 $\bar{T}_k = \begin{pmatrix} \beta_0 & & & \\ & \beta_1 & & \\ & & \ddots & \\ & & & \beta_{k-1} \\ & & & & \beta_k \end{pmatrix}$ Lanczos

$AQ_k = Q_{k+1} \bar{H}_k$ $q_i = b / \|b\|$
 $\bar{H}_k = \begin{pmatrix} \beta_0 & & & \\ & \beta_1 & & \\ & & \ddots & \\ & & & \beta_k \\ & & & & 0 \end{pmatrix}$

$x = Q_k y$

$\|AQ_k y - b\|_2$
 $\stackrel{Q_{k+1}^T}{=} \|Q_{k+1}^T \bar{H}_k y - \beta_0 e_1\|_2$
 $= \left\| \begin{pmatrix} I \\ 0 \end{pmatrix} \bar{H}_k y - \begin{pmatrix} \beta_0 \\ 0 \end{pmatrix} \right\|_2$
 $= \|\bar{H}_k y - \beta_0 e_1\|_2$

$\|G_k^T \bar{H}_k y - G_k^T \beta_0 e_1\|_2$
 $= \left\| \begin{pmatrix} R_k \\ 0 \end{pmatrix} y - \begin{pmatrix} z_k \\ \bar{\tau}_{k+1} \end{pmatrix} \right\|_2$

$\tilde{G}_k^T \dots \tilde{G}_1^T \bar{H}_k = \begin{pmatrix} R_k \\ 0 \end{pmatrix}$
 $\tilde{G}_k^T \dots \tilde{G}_1^T \beta_0 e_1 = \begin{pmatrix} z_k \\ \bar{\tau}_{k+1} \end{pmatrix}$

$R_k y_k = z_k$
residual = $\bar{\tau}_{k+1}$

$\tilde{G}_{k+1}^T \tilde{G}_k^T \dots \tilde{G}_1^T \bar{H}_{k+1} = \begin{pmatrix} R_{k+1} & \times \\ 0 & \times \end{pmatrix}$

$\bar{H}_k = \begin{matrix} G_k^R \\ \text{---} \\ G_k^R \end{matrix} \begin{pmatrix} R_k \\ 0 \end{pmatrix}$
 $G_k^T G_k = I$

$\bar{H}_{k+1} = \begin{pmatrix} \bar{H}_k & h_{k+1} \\ 0 & h_{k+1, k+1} \end{pmatrix}$

$\tilde{G}_{k+1}^T \begin{pmatrix} z_k \\ \bar{\tau}_{k+1} \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} z_{k+1} \\ \bar{\tau}_{k+2} \end{pmatrix}$

Problem: no short recurrence

Partial solution: restarted GMRES

① Run m steps of GMRES $\rightarrow x_m$

② $r = b - Ax_m$

③ Run m steps of GMRES

$$Az = r \Rightarrow z_m$$

④ $x_{m+1} = x_m + z_m$

⑤ Repeat 2, 3, 4

$$A(x_m + z_m) = b - r + Az_m$$

Error analysis

$$\min \|Ax - b\| \text{ s.t. } x \in \mathbb{R}^k$$

$$\rightarrow \min \|A p(A) b - b\|_2 \text{ s.t. } p \in \mathcal{P}_{k-1}$$

$$A = V \Lambda V^{-1}$$

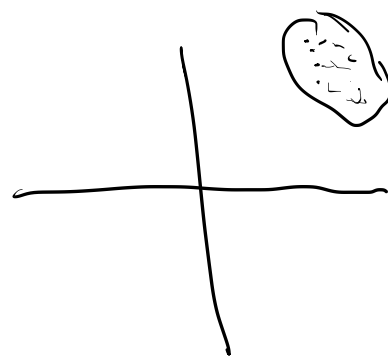
$$\rightarrow \|V \Lambda V^{-1} V p(\Lambda) V^{-1} b - V V^{-1} b\|_2$$

$$\leq \|V\| \|(I - \Lambda p(\Lambda)) V^{-1} b\|_2$$

$$\leq \|V\| \|V^{-1}\| \|b\| \|q(\Lambda)\|$$

$$= \kappa_2(V) \|r_0\| \min_{q \in \mathcal{P}_k} \max_i |q(\lambda_i)|$$

s.t. $q(0) = 1$



$$q(z) = (1 - z/c)^k$$

$$q(0) = 1$$

Choose c so that

λ_i/c is small for all i

dependence $k_2(A)$, $k_2(V)$, distribution of evals, etc..

pre-conditioning: transform system for better properties

$$Ax = b \Rightarrow M^{-1}Ax = M^{-1}b$$

$$M = I$$



$$M = A \quad A^{-1}Ax = A^{-1}b \quad Ix = A^{-1}b$$

some pre-computation
much better system

$$C_L, C_R \quad C_L C_R \approx A \quad C_L^{-1} A C_R^{-1} y = C_L^{-1} b \quad C_L^{-1} A \approx C_L^{-1} b$$

$$C_R z = y$$

$$D_r = \text{row sums} = A \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \left. \vphantom{\begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}} \right\} \text{two mat-vecs}$$

$$D_c = \text{col sums} = A^T \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

$$D_r^{-1} A D_c^{-1} y = b$$

$$A \begin{pmatrix} e_1 \\ \vdots \\ e_i \\ \vdots \\ e_n \end{pmatrix} = Ae_i \rightarrow v \rightarrow e_i^T v = e_i^T Ae_i = A_{ii}$$

$$Ax = b \Rightarrow D^{-1}Ax = D^{-1}b$$

$$A = M - N \quad M^{-1}(M - N)x = b$$

$$Mx_{k+1} = Nx_k + b$$

$$\underline{(I - M^{-1}N)x = M^{-1}b}$$

$$x_{k+1} = M^{-1}Nx_k + M^{-1}b$$

$$\boxed{A} = \boxed{D} - \boxed{L} - \boxed{U}$$

A
 D
 L
 U

Jacobi: $M = D, N = L + U \Rightarrow$ diagonal scaling

Gauss-Seidel: $M = D - L, N = U$

sparse direct $Ax = b$

$$P^T A Q = LU$$

$$\begin{pmatrix} x & x & \dots \\ \vdots & \vdots & \ddots \\ x & \dots & x \end{pmatrix} \begin{pmatrix} 0 \\ \vdots \\ x \end{pmatrix} (0 \dots 0 x) = \begin{pmatrix} \vdots \\ x \end{pmatrix}$$

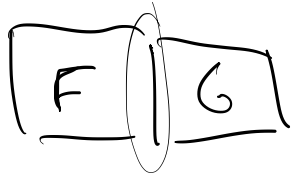
$$\begin{pmatrix} x & xxx & x \\ x & \cancel{0} & \vdots \\ x & \cancel{0} & \vdots \\ x & \dots & x \end{pmatrix} \begin{pmatrix} x \\ \vdots \\ x \end{pmatrix} (x+x \dots x) = \begin{pmatrix} x & x & x \\ x & x & \cancel{x} & 0 \\ x & \cancel{x} & x & 0 \\ x & \dots & x \end{pmatrix} \begin{pmatrix} \vdots \\ x \end{pmatrix}$$

$$M = LU \quad M^{-1} \overset{P^T A Q}{A} x = M^{-1} b$$

Incomplete LU: only fill in where $P^T A Q$ has non-zeros

~ Same storage cost, can work extremely well
(2x)

Physics-based problems

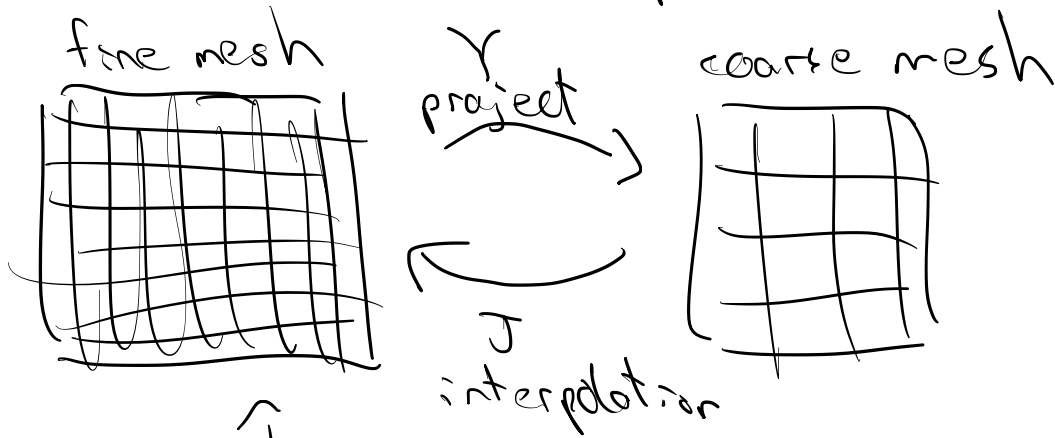


$$A = \begin{pmatrix} A_{FF} & A_{FG} \\ A_{GF} & A_{GG} \end{pmatrix}$$

$$\Rightarrow \begin{pmatrix} A_{FF} & 0 \\ 0 & A_{GG} \end{pmatrix}$$

block Jacobi

"Domain decomposition"



$$M \approx A_f$$

$$M \approx J A_c Y$$

- ① projects
- ② solve on coarse mesh
- ③ interpolates to fine mesh

"multigrid"