

October 8, 2013

Arnoldi:

$$AQ_k = Q_{k+1} H_{k+1,k}$$

$$Q_k^T A Q_k = H_{k,k}$$

"truncated
similarity
transformation"

upper Hessenberg:

$$\begin{array}{cccc} x & x & x & x \\ x & x & x & x \\ & x & x & x \\ & & x & x \\ \hline & & & x \end{array} \left. \begin{array}{l} H_{k,k} \\ H_{k+1,k} \end{array} \right\} H_{k+1,k}$$

Why is this correct?

$$\begin{array}{|c|c|} \hline n & k \\ \hline \end{array} \begin{array}{|c|} \hline n \\ \hline \end{array} = \begin{array}{|c|} \hline k+1 \\ \hline \end{array} \begin{array}{|c|} \hline n \\ \hline \end{array} \begin{array}{|c|} \hline 0 \\ \hline \end{array}$$

$A \quad Q_k$

$\hookrightarrow Q_k$ is orthogonal

$$Q_k^T Q_k = I_k$$

$$Q_k Q_k^T \neq I_n$$

projection matrix

Krylov subspace solvers:

① orthogonal projection: ($k=L$)

$$Q_k^T (b - A x_k) = 0$$

$$Q_k^T b = Q_k^T A x_k$$

we know

$$x_k \in x_0 + K^k(A; r_0) \Rightarrow x_k = x_0 + Q_k z$$

$$\Rightarrow Q_k^T b = \underbrace{Q_k^T A Q_k}_{H_{k,k}} z + Q_k^T A x_0$$

$$\Rightarrow Q_k^T r_0 = H_{k,k} z$$

recall: $q_1 = \frac{r_0}{\|r_0\|} \Rightarrow \|q_1\| = 1$

and $K^k(A; r_0) = \text{span}\{r_0, A r_0, \dots, A^{k-1} r_0\}$

$$\text{so } \begin{pmatrix} -q_1^T \\ -q_2^T \\ \vdots \\ -q_k^T \end{pmatrix} \bigg| r_0 = \begin{pmatrix} \frac{r_0^T r_0}{\|r_0\|} \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \beta e_1 \quad \text{where } \beta = \|r_0\|$$

FOM: Full Orthogonalization Method. : $H_{kk} z = p e_1$

Algorithm:

• Arnoldi $\rightarrow \{q_i\}, H_{k,k}$

• $x_r = x_0 + H_{kk}^{-1} p e_1$ where $p = \|r\|$

If A is SPD

$H_{kk} \rightarrow T_{kk}$ Lanczos

$x_k = x_0 + T_{kk}^{-1} p e_1$ • a fancy implementation of this gives CG

At least two nice ways to derive CG:

1. optimization-like

$$x_{k+1} = x_k + \alpha_k p_k$$

where $p_k^T A p_j = 0 \quad j \neq k$; A-conjugate direction

$\min \phi(x)$ is equivalent to $\min \|e_k\|_A$ over some space

$$\begin{aligned} \|e_k\|_A^2 &= e_k^T A e_k \\ &= (x - x_k)^T A (x - x_k) \\ &= \underbrace{x^T A x}_{\text{some fixed number}} - 2 \underbrace{x_k^T A x}_{\triangle} + x_k^T A x_k \\ &\quad \underbrace{\hspace{10em}}_{2\phi(x_k)} \end{aligned}$$

2. Linear algebra-type way:

$$T_{kk} = L_k D_k L_k^T$$

and find recurrence relations among the $\{k\}$ -related and $\{k+1\}$ -related quantities

② Minimum Residual Methods

$$\min \|b - Ax_k\|_2$$

$$x_k = x_0 + Q_k z$$

$$\|b - Ax_k\|_2 = \|b - A(x_0 + Q_k z)\|_2$$

$$= \|r_0 - A Q_k z\|_2 \quad \text{Least Squares Problem}$$

$$\min \|p e_i - H_{k+1,k} z\|$$

$$\text{use } A Q_k = Q_{k+1} H_{k+1,k}$$

and orthogonality of Q_k

Important property of orthogonal transformations: preserve norm

$$b - A x_k = b - A(x_0 + Q_k z)$$

$$= r_0 - A Q_k z$$

$$= p e_i - Q_{k+1} H_{k+1,k} z$$

$$= Q_{k+1} (p e_i - H_{k+1,k} z)$$

Subtlety! \rightarrow can now multiply by Q_{k+1}^T

This is Arnoldi method $\xrightarrow{\text{fancy implementation}} \text{GMRES}$

Algorithm: $\xrightarrow{\text{if } A \text{ sym (not nec. PD)}} \text{MINRES}$

$$\text{Arnoldi: } \rightarrow A Q_k = Q_{k+1} H_{k+1,k}$$

$$\min_z \|p e_i - H_{k+1,k} z\|_2$$

$$x_k = x_0 + Q_k z$$

Caveats:

• for A nonsymmetric: long recurrence relations, accumulating cost & storage

\hookrightarrow Remedy: restarted GMRES

- after k iterations, refer to r_k as r_0 and start from scratch

- effective if we have a memory restriction

- but: we lose optimality

• Nonsym systems: either optimality or modest memory requirements, but not both