

# Iterative Methods - May 12, 2006

Note Title

5/12/2006

$$\| \underset{\sim}{b} - A \underset{\sim}{x} \|_2 = \min.$$

$A$ : sparse

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LSQR: Paige - Saunders

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$$A^T A \underset{\sim}{x} = A^T \underset{\sim}{b}$$

"NEVER" form normal, especially for

sparse problems. because

$$\kappa(A^T A) = \kappa^2(A)$$

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$$A = P J Q^T \quad P^T P = I_n$$

$$Q^T Q = I_n$$

This decomposition can be computed via

Householder transformations. Jan Duff

$$J = \begin{pmatrix} \alpha_1 & p_1 & & 0 \\ & & \beta_{n-1} & \\ & 0 & & \alpha_n \end{pmatrix}$$

Upper bi-diagonal

$$B = \begin{pmatrix} \alpha_1 & & & 0 \\ p_2 & & & \\ & & & \\ 0 & & \beta_n & \alpha_n \end{pmatrix}$$

$$A = P J Q^T \quad (2n-1) \text{ elements}$$

$m \times n$                    $m \times n$

$$J = \begin{pmatrix} // & \\ & // \\ & & 0 \end{pmatrix}$$

$$Q^T \begin{bmatrix} \phantom{R} \\ \phantom{O} \end{bmatrix} = \begin{bmatrix} R \\ O \end{bmatrix} \quad R := \nabla$$

$m \times n$   
 $m \geq n$

$$X^T R Y = J$$

$$P^T A = B Q^T$$

$$P P^T = I$$

$$A Q = P B$$

$$P^T P = I$$

$$P = \begin{pmatrix} p_1^T \\ \vdots \\ p_n^T \end{pmatrix}$$

~~$$P = [p_1, \dots, p_n]$$~~

$$B = \begin{pmatrix} \alpha_1 & & \\ & \ddots & \\ & & \alpha_n \end{pmatrix}$$

$$p_i^T A = \alpha_i q_i^T,$$

$$\|q_i\|_2 = 1$$

$$\|p_i^T A\|_2 = |\alpha_i| \|q_i^T\|_2 = |\alpha_i|; \quad q_i^T = \frac{1}{\alpha_i} p_i^T A$$

$$A [g_1, \dots, g_n] = [p_1, \dots, p_n] B$$

$$A \check{g}_1 = \alpha_1 \check{p}_1 + \beta_2 \check{p}_2$$

$$\beta_2 \check{p}_2 = A \check{g}_1 - \alpha_1 \check{p}_1$$

$$|\beta_2| \|\check{p}_2\|_2 = \|A \check{g}_1 - \alpha_1 \check{p}_1\|_2$$

$$\beta_2 = \pm \|A \check{g}_1 - \alpha_1 \check{p}_1\|_2$$

$$\check{p}_2 = \frac{1}{\beta_2} (A \check{g}_1 - \alpha_1 \check{p}_1)$$

Algorithm:

Begin  $p_1$

$\alpha_1, g_1, \beta_2, p_2, \alpha_2, g_2, \dots$

After  $k$  iterations

$$\bar{B}_k = \begin{pmatrix} \alpha_1 & & & & & \\ & \beta_2 & & & & \\ & & \alpha_2 & & & \\ & & & \ddots & & \\ & & & & \beta_m & \\ & & & & & \alpha_k \\ & & & & & & \beta_{k+1} \end{pmatrix} (k+1 \times k)$$

$$\| \underset{\sim}{b} - A \underset{\sim}{x} \|_2$$

$$\| \underset{\sim}{b} - P B Q^T \underset{\sim}{x} \|_2$$

$$= \| P^T \underset{\sim}{b} - B \underset{\sim}{Q}^T \underset{\sim}{x} \|_2$$

$$p_1^T = \underset{\sim}{b}^T \cdot \frac{1}{\| \underset{\sim}{b} \|_2} \quad \underset{\sim}{p}_2^T \underset{\sim}{p}_1 = 0 \Rightarrow \underset{\sim}{p}_2^T \underset{\sim}{b} = 0$$

$$p_1^T \underset{\sim}{b} = \| \underset{\sim}{b} \|_2 \underset{\sim}{e}_1$$



$$A Q = P B$$

$$A \underline{q}_1 = \alpha_1 \underline{p}_1 + \beta_2 \underline{p}_2$$

$$A \underline{q}_j = \alpha_j \underline{p}_j + \beta_{j+1} \underline{p}_{j+1}$$

We are given  $\underline{p}_1$ ,

$$\alpha_1 = \pm \| \underline{p}_1^T A \|_2, \quad \underline{q}_1^T = \frac{1}{\alpha_1} \underline{p}_1^T A$$

$$\beta_2 = \pm \| A \underline{q}_1 - \alpha_1 \underline{p}_1 \|_2$$

$$\underline{p}_2 = \frac{1}{\beta_2} (A \underline{q}_1 - \alpha_1 \underline{p}_1)$$

$$\hat{q}_2^T = \frac{1}{\alpha_2} (\hat{p}_2^T A - \beta_2 \hat{q}_1^T)$$

$$A = P B Q^T$$

$$A Q = P B$$

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$$\| \hat{b}_k \hat{e}_k - B_k \hat{y}_k \|$$

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$$\| \hat{b}_k - P B Q^T \hat{x} \|_2$$

$$= \| \hat{b}_k \hat{e}_k - B \hat{y} \|_2 \approx$$

$$\approx \| \hat{b}_k \hat{e}_k - B_k \hat{y}_k \|_2 = \text{min.}$$

~~fact~~

$$A \approx A_k = P_k B_k Q_k^T$$

rhs  $\|e_i\| \approx 1$ ,  $B_k = \begin{pmatrix} \alpha_1 & & & 0 \\ \beta_1 & & & \\ & \ddots & & \\ & & \alpha_k & \\ 0 & & & \beta_k \end{pmatrix} \begin{matrix} \\ \\ \\ \\ \end{matrix} \begin{matrix} \\ \\ \\ \\ \end{matrix}$   $\mathbb{R}^+(k \times k)$   
 $\text{eigenvalues}$

$$Z_1 = \begin{pmatrix} \cos \theta & \sin \theta & & \\ -\sin \theta & \cos \theta & & \\ & & \ddots & \\ & & & 1 \end{pmatrix}$$

$$Z_1 B_k = \begin{pmatrix} \alpha'_1 & \beta'_1 & 0 & \dots & 0 \\ 0 & \alpha'_2 & 0 & \dots & \cdot \end{pmatrix}$$

$$\alpha'_i = \sqrt{\alpha_i^2 + \beta_i^2}$$

$$Z_{k+1} \dots Z_2 Z_1 B_k = \begin{pmatrix} d_1' & \beta_1' & & & \\ & d_2' & \beta_2' & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & d_n' \end{pmatrix}$$

$$Z_k z_i \| e_i = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_k \end{pmatrix}$$

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$$Q^T A Q = T := \begin{pmatrix} \diagup & & \\ & \diagdown & \\ & & 0 \end{pmatrix}$$

$$Q^T \begin{pmatrix} 0 & A \\ A^T & 0 \end{pmatrix} Q = \begin{pmatrix} \diagup & & 0 \\ & \diagdown & \\ 0 & & \diagup \end{pmatrix}$$

$$= \begin{pmatrix} x_1 & x_2 & \dots & x_n \\ & & & \\ & & & \\ & & & x_n \end{pmatrix} \sim$$

$$= \left( \begin{array}{c|c} 0 & B \\ \hline B^T & 0 \end{array} \right)$$

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$$P^T A Q = B$$

$$\| \tilde{b} - A \tilde{x} \|_2 \approx \| \| \tilde{b} \| \cdot \tilde{e}_i - B_k^T \tilde{y}_k \|$$

$$A \approx P_k B_k Q_k^T$$

$$\tilde{y}_k \approx Q_k^T \tilde{x}_k$$

$$Z_k \dots Z_1 B_k = R_k; \quad Z_k \dots Z_1 \tilde{y}_k = \tilde{f}_k$$

$$Q_k^T B_k = \begin{pmatrix} \sigma_1 & & & & 0 \\ & \ddots & & & \\ & & \sigma_r & & \\ & & & \ddots & \\ 0 & & & & 0 \end{pmatrix} \begin{pmatrix} \tilde{y}_1 \\ \vdots \\ \tilde{y}_r \\ \vdots \\ \tilde{y}_{k+1} \end{pmatrix}$$

$$\tilde{d}_k = \frac{1}{\rho_k} (\mathcal{L}_k - \Theta_k \tilde{d}_{k-1})$$

$$\tilde{x}_k = \tilde{x}_{k-1} + \rho_k \tilde{d}_k$$

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Paige & Saunders LSQR (1982)

$$\min_x \| \tilde{b} - Ax \|^2 + \lambda^2 \|x\|^2$$

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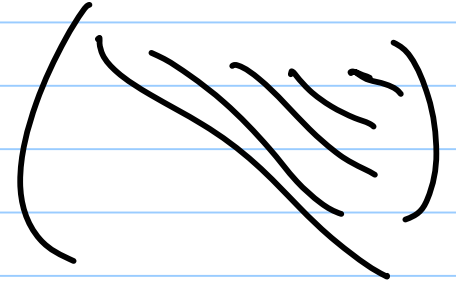
To Chan & many others

$$Q^T \begin{bmatrix} A \end{bmatrix} = \begin{bmatrix} R \\ 0 \end{bmatrix}$$

Chem:  $R \rightarrow X^T B y$ ,  $B = \begin{pmatrix} \cancel{0} \\ 0 \end{pmatrix}$



x x x ~~x~~ ~~x~~  
     x   x x x  
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No benefit

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