Lecture 10 Householder Triangularization

NLA Reading Group Spring '13 by Onur Güngör

Householder and Gram-Schmidt

Gram-Schmidt: triangular orthogonalization

$$A\underbrace{R_1R_2\cdots R_n}_{\hat{R}^{-1}} = \hat{Q}$$

Householder: orthogonal triangularization

$$\underbrace{Q_n\cdots Q_2 Q_1}_{Q^*} A = R$$

Triangularization by Introducing Zeros

$$Q_{k} = \left[\begin{array}{cc} I & 0 \\ 0 & F \end{array} \right]$$

Householder Reflectors



Householder Reflectors



$$Py = \left(I - \frac{vv^*}{v^*v}\right)y = y - v\left(\frac{v^*y}{v^*v}\right)$$

P is the projector onto the space H

$$Fy = \left(I - 2\frac{vv^*}{v^*v}\right)y = y - 2v\left(\frac{v^*y}{v^*v}\right)$$

Householder Reflectors



Instead of $v = ||x||e_1 - x$.

We use $v = \operatorname{sign}(x_1) \|x\| e_1 + x$.

for numerical stability.

Householder Algorithm

Algorithm 10.1. Householder QR Factorization for k = 1 to n $x = A_{k:m,k}$ $v_k = \operatorname{sign}(x_1) ||x||_2 e_1 + x$ $v_k = v_k / ||v_k||_2$ $A_{k:m,k:n} = A_{k:m,k:n} - 2v_k (v_k^* A_{k:m,k:n})$

Applying Q

Algorithm 10.2. Implicit Calculation of a Product Q^*b for k = 1 to n $b_{k:m} = b_{k:m} - 2v_k(v_k^* b_{k:m})$

This will be employed while solving least squares problems using QR factorization.

Forming Q

Algorithm 10.3. Implicit Calculation of a Product
$$Qx$$

for $k = n$ downto 1
 $x_{k:m} = x_{k:m} - 2v_k(v_k^* x_{k:m})$

Q can be formed by calculating Qe_1 , Qe_2 , ... and Qe_m .

Operation Count

Algorithm 10.1. Householder QR Factorization for k = 1 to n $x = A_{k:m,k}$ $v_k = \operatorname{sign}(x_1) ||x||_2 e_1 + x$ $v_k = v_k / ||v_k||_2$ $A_{k:m,k:n} = A_{k:m,k:n} - 2v_k (v_k^* A_{k:m,k:n})$

$$A_{\boldsymbol{k}:\boldsymbol{m},\boldsymbol{j}} - 2v_{\boldsymbol{k}}(v_{\boldsymbol{k}}^*A_{\boldsymbol{k}:\boldsymbol{m},\boldsymbol{k}})$$

Let l = m - k + 1

Each vector requires $4l - 1 \sim 4l$ flops.

Operation Count





Operation Count



$$\sim 2mn^2 - rac{2}{3}n^3$$
 flops.

Lecture 11 Least Squares Problems

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Definition

Given $A \in \mathbb{C}^{m \times n}$, $m \ge n$, $b \in \mathbb{C}^m$, find $x \in \mathbb{C}^n$ such that $||b - Ax||_2$ is minimized.

Polynomial Interpolation



Polynomial Least Squares Fitting



Solve by minimizing

$$\sum_{i=1}^{m} |p(x_i) - y_i|^2$$



Orthogonal Projection



Theorem 11.1. Let $A \in \mathbb{C}^{m \times n}$ $(m \geq n)$ and $b \in \mathbb{C}^m$ be given. A vector $x \in \mathbb{C}^n$ minimizes the residual norm $||r||_2 = ||b - Ax||_2$, thereby solving the least squares problem (11.2), if and only if $r \perp \operatorname{range}(A)$, that is,

$$A^*r = 0, (11.8)$$

or equivalently,

$$A^*\!Ax = A^*b, \tag{11.9}$$

or again equivalently,

$$Pb = Ax, (11.10)$$

where $P \in \mathbb{C}^{m \times m}$ is the orthogonal projector onto range(A). The $n \times n$ system of equations (11.9), known as the normal equations, is nonsingular if and only if A has full rank. Consequently the solution x is unique if and only if A has full rank.

Pseudoinverse and Normal Equations

$$A^*Ax = A^*b,$$

 $A^+ = (A^*A)^{-1}A^* \in \mathbb{C}^{n,m}.$
 $x = A^+b,$

Least Squares via Normal Equations

 $A^*\!Ax = A^*b,$

 $R^*Rx = A^*b.$

Algorithm 11.1. Least Squares via Normal Equations

- 1. Form the matrix A^*A and the vector A^*b .
- 2. Compute the Cholesky factorization $A^*A = R^*R$.
- 3. Solve the lower-triangular system $R^*w = A^*b$ for w.
- 4. Solve the upper-triangular system Rx = w for x.

Work for Algorithm 11.1:
$$\sim mn^2 + \frac{1}{3}n^3$$
 flops.

Least Squares via QR Factorization

$$y = Pb = \hat{Q}\hat{Q}^*b.$$
 $\hat{Q}\hat{R}x = \hat{Q}\hat{Q}^*b,$ $\hat{R}x = \hat{Q}^*b.$

Algorithm 11.2. Least Squares via QR Factorization

- 1. Compute the reduced QR factorization $A = \hat{Q}\hat{R}$.
- 2. Compute the vector \hat{Q}^*b .
- 3. Solve the upper-triangular system $\hat{R}x = \hat{Q}^*b$ for x.

Work for Algorithm 11.2:
$$\sim 2mn^2 - \frac{2}{3}n^3$$
 flops.

Least Squares via SVD

$$y = Pb = \hat{U}\hat{U}^*b,$$
$$\hat{U}\hat{\Sigma}V^*x = \hat{U}\hat{U}^*b$$
$$\hat{\Sigma}V^*x = \hat{U}^*b.$$

Algorithm 11.3. Least Squares via SVD

- 1. Compute the reduced SVD $A = \hat{U}\hat{\Sigma}V^*$.
- 2. Compute the vector \hat{U}^*b .
- 3. Solve the diagonal system $\hat{\Sigma}w = \hat{U}^*b$ for w.

4. Set
$$x = Vw$$
.

Work for Algorithm 11.3: $\sim 2mn^2 + 11n^3$ flops,