

Mathematics, Pusan National University

NUMIRICAL LINEAR ALGEBRA

Lecture 10. Householder Triangularization

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Householder and Gram-Schmidt

Householder Reflectors

The Better of Two Reflectors

The Algorithm

Applying of Forming Q

Operation Count



In Lecture 8, by the Gram-Schmidt iteration,

$$A \underbrace{R_1 R_2 \cdots R_n}_{\hat{R}^{-1}} = \hat{Q}$$

where \hat{Q} is orthogonal and each R_k is upper triangular.

$$\begin{bmatrix} | & | & | & | \\ v_1 & v_2 & \cdots & v_n \\ | & | & | & | \end{bmatrix} \begin{bmatrix} \frac{1}{r_{11}} & \frac{-r_{12}}{r_{11}} & \frac{-r_{13}}{r_{11}} & \cdots \\ & 1 & & \\ & & 1 & \\ & & & \ddots \end{bmatrix} = \begin{bmatrix} | & | & | & | \\ q_1 & v_2^{(2)} & \cdots & v_n^{(2)} \\ | & | & | & | \end{bmatrix}$$



In contrast, the Householder method applies

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

where R is uppertriangular and each Q_k is unitrary matrix.

$$\begin{array}{c} \begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \\ A \end{array} \xrightarrow{Q_1} \begin{array}{c} \begin{bmatrix} \times & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \end{bmatrix} \\ Q_1 A \end{array} \xrightarrow{Q_2} \begin{array}{c} \begin{bmatrix} \times & \times & \times \\ & \times & \times \\ & 0 & \times \\ & 0 & \times \\ & 0 & \times \end{bmatrix} \\ Q_2 Q_1 A \end{array} \xrightarrow{Q_3} \begin{array}{c} \begin{bmatrix} \times & \times & \times \\ & \times & \times \\ & & \times \\ & & 0 \\ & & 0 \end{bmatrix} \\ Q_3 Q_2 Q_1 A \end{array}$$



The two methods can thus be summarized as follows:

Gram-Schmidt : triangular orthogonalization,
Householder : orthogonal Triangularization.

Householder Reflectors



$$\begin{array}{c}
 \begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \\
 A
 \end{array}
 \xrightarrow{Q_1}
 \begin{array}{c}
 \begin{bmatrix} \times & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \\ 0 & \times & \times \end{bmatrix} \\
 Q_1 A
 \end{array}
 \xrightarrow{Q_2}
 \begin{array}{c}
 \begin{bmatrix} \times & \times & \times \\ & \times & \times \\ & 0 & \times \\ & 0 & \times \\ & 0 & \times \end{bmatrix} \\
 Q_2 Q_1 A
 \end{array}
 \xrightarrow{Q_3}
 \begin{array}{c}
 \begin{bmatrix} \times & \times & \times \\ & \times & \times \\ & & \times \\ & & 0 \\ & & 0 \end{bmatrix} \\
 Q_3 Q_2 Q_1 A
 \end{array}$$

The standard approach is as follows.

$$Q_k = \begin{bmatrix} I & 0 \\ 0 & F \end{bmatrix} \quad \text{where } I : (k-1) \times (k-1) \text{ identity, } F : (m-k+1) \times (m-k+1) \text{ unitary matrix.}$$



The Householder algorithm chooses F to be a particular matrix called a *House holder reflector*.

$$x = \begin{bmatrix} \times \\ \times \\ \times \\ \vdots \\ \times \end{bmatrix} \xrightarrow{F} Fx = \begin{bmatrix} \|x\| \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \|x\|e_1$$

Householder Reflectors

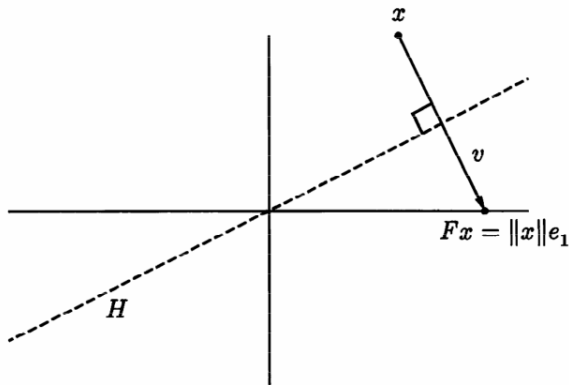
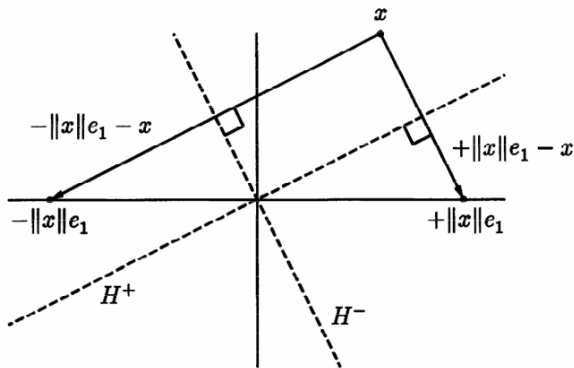


Figure: Householder reflection

The Better of Two Reflectors



For numerical stability, it is important to choose the one that moves x the larger distance.



Difference between Projector and Reflector

In section 6, we studied about projection with orthogonal basis and arbitrary nonzero vector. For arbitrary nonzero vector a , the formulas are

$$P_{\perp a} = I - \frac{aa^*}{a^*a}$$

The reflector Fy should therefore be

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

Hence the matrix F is

$$F = I - 2 \frac{vv^*}{v^*v}$$



Algorithm 1: Householder QR Factorization

Input: $A : m \times n$ matrix

for $k = 1$ **to** n **do**

$$x = A_{k:m,k}$$

$$v_k = \text{sign}(x_1) \|x\|_2 e_1 + x$$

$$x_k = v_k / \|v_k\|_2$$

$$A_{k:m,k:n} = A_{k:m,k:n} - 2v_k(v_k^* A_{k:m,k:n})$$

end



Calculate Q^*b where

$$Q^* = Q_n \cdots Q_2 Q_1$$

Algorithm 2: Implicit Calculation of a Product Q^*b

Input: $b : m \times 1$ vector

for $k = 1$ **to** n **do**

$b_{k:m} = b_{k:m} - 2v_k(v_k^* b_{k:m})$

end



Calculate Qx where

$$Q = Q_1 Q_2 \cdots Q_n$$

Algorithm 3: Implicit Calculation of a Product Qx

Input: $x : m \times 1$ vector

for $k = n$ **downto** 1 **do**

$x_{k:m} = x_{k:m} - 2v_k(v_k^* x_{k:m})$

end



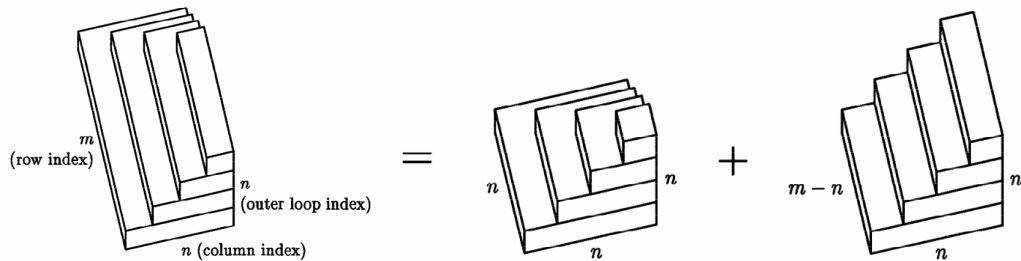
In $A_{k:m,k:n} = A_{k:m,k:n} - 2v_k(v_k^* A_{k:m,k:n})$, the FLOPS(FLOating point Operations Per Second) is

- ▶ $(2(m - k + 1) - 1)(n - k + 1)$ flops for product $v_k^*(A_{k:m,k:n})$
- ▶ $(m - k + 1)(n - k + 1)$ flops for outer product with v_k
- ▶ $(m - k + 1)(n - k + 1)$ flops for subtraction from $A_{k:m,k:n}$

sum is roughly $4(m - k + 1)(n - k + 1)$ flops.

$$\sum_{k=1}^n 4(m - k + 1)(n - k + 1)$$

Operation Count



Work for Householder orthogonalization $\sim 2mn^2 - \frac{2}{3}n^3$ flops



Thank you!