

# Important Matrix Factorizations

LU

Choleski

QR

LU Factorization

Choleski Factorization

The QR Factorization

# LU Factorization: Gaussian Elimination Matrices

Gaussian elimination transforms vectors of the form

$$\begin{bmatrix} a \\ \alpha \\ b \end{bmatrix},$$

where  $a \in \mathbb{R}^k$ ,  $0 \neq \alpha \in \mathbb{R}$ , and  $b \in \mathbb{R}^{n-k-1}$ , to those of the form

$$\begin{bmatrix} a \\ \alpha \\ 0 \end{bmatrix}.$$

This is accomplished by left matrix multiplication as follows:

$$\begin{bmatrix} I_{k \times k} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -\alpha^{-1}b & I_{(n-k-1) \times (n-k-1)} \end{bmatrix} \begin{bmatrix} a \\ \alpha \\ b \end{bmatrix} = \begin{bmatrix} a \\ \alpha \\ 0 \end{bmatrix}.$$

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The matrix on the left is called a Gaussian elimination matrix.

# Gaussian Elimination Matrices

The matrix

$$\begin{bmatrix} I_{k \times k} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -\alpha^{-1}b & I_{(n-k-1) \times (n-k-1)} \end{bmatrix}$$

has ones on the diagonal and so is invertible. Indeed,

$$\begin{bmatrix} I_{k \times k} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -\alpha^{-1}b & I_{(n-k-1) \times (n-k-1)} \end{bmatrix}^{-1} = \begin{bmatrix} I_{k \times k} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \alpha^{-1}b & I_{(n-k-1) \times (n-k-1)} \end{bmatrix}.$$

Also note that

$$\begin{bmatrix} I_{k \times k} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -\alpha^{-1}b & I_{(n-k-1) \times (n-k-1)} \end{bmatrix} \begin{bmatrix} x \\ 0 \\ y \end{bmatrix} = \begin{bmatrix} x \\ 0 \\ y \end{bmatrix}.$$

# LU Factorization

Suppose

$$A = \begin{bmatrix} a_1 & v_1^T \\ u_1 & \tilde{A}_1 \end{bmatrix} \in \mathbb{C}^{n \times m},$$

with  $0 \neq a_1 \in \mathbb{C}$ ,  $u_1 \in \mathbb{C}^{m-1}$ ,  $v_1 \in \mathbb{C}^{n-1}$ , and  $\tilde{A}_1 \in \mathbb{C}^{(m-1) \times (n-1)}$ .

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Then

$$\begin{bmatrix} 1 & 0 \\ -\frac{u_1}{a_1} & I \end{bmatrix} \begin{bmatrix} a_1 & v_1^T \\ u_1 & \tilde{A}_1 \end{bmatrix} \in \mathbb{C}^{n \times m} = \begin{bmatrix} a_1 & v_1^T \\ 0 & A_1 \end{bmatrix}, \quad (*)$$

where  $A_1 = \tilde{A}_1 - u_1 v_1^T / a_1$ .

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where  $A_1 = \tilde{A}_1 - u_1 v_1^T / a_1$ .

Repeat  $m$  times to get  $L_{\tilde{m}-1}^{-1} \cdots L_2^{-1} L_1^{-1} A = U_{\tilde{m}-1} = U$  is upper triangular, so

$$A = LU$$

where  $L$  is lower triangular with ones on the diagonal.



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This is called the Cholesky Factorization of  $M$ .



# The QR Factorization: Householder Reflections

Given  $w \in \mathbb{R}^n$  we can associate the matrix

$$U = I - 2 \frac{ww^T}{w^T w}$$

which reflects  $\mathbb{R}^n$  across the hyperplane  $\text{Span}\{w\}^\perp$ . The matrix  $U$  is called the Householder reflection across this hyperplane.

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Given a pair of vectors  $x$  and  $y$  with

$$\|x\|_2 = \|y\|_2, \quad \text{and} \quad x \neq y,$$

there is a Householder reflection such that  $y = Ux$ :

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Householder reflections are symmetric unitary tranformations:

$$U^{-1} = U^T = U.$$





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Given  $A \in \mathbb{R}^{m \times n}$  write

$$A_0 = \begin{bmatrix} \alpha_0 & a_0^T \\ b_0 & A_0 \end{bmatrix} \quad \text{and} \quad \nu_0 = \left\| \begin{pmatrix} \alpha_0 \\ b_0 \end{pmatrix} \right\|_2.$$

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Set

$$H_0 = I - 2 \frac{ww^T}{w^T w} \quad \text{where} \quad w = \begin{pmatrix} \alpha_0 \\ b_0 \end{pmatrix} - \nu_0 e_1 = \begin{pmatrix} \alpha_0 - \nu_0 \\ b_0 \end{pmatrix}.$$

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Repeat to get

$$Q^T A = H_{n-1} H_{n-2} \dots H_0 A = R,$$

where  $R$  is upper triangular and  $Q$  is unitary.

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Suppose  $A \in \mathbb{R}^{m \times n}$  with  $m > n$ , then  $A =$



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$$A = [Q_1, Q_2] \begin{bmatrix} R \\ 0 \end{bmatrix} = Q_1 R$$

where the columns of  $Q_1$  and  $Q_2$  form an orthonormal basis for  $\mathbb{R}^m$ .



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The columns of  $Q_1$  form an orthonormal basis for the range of  $A$  with

$$Q_1 Q_1^T = \text{the orthogonal projector onto } \text{Ran}(A)$$

and


$$I - Q_1 Q_1^T = Q_2 Q_2^T = \text{the orthogonal projector onto } \text{Ran}(A)^\perp$$

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