

Numerical Linear Algebra

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LU factorization, pivoting and stability of Gaussian elimination

- ► Recap of Previous Lecture
- ► Examples of LU factorization
- Existence of LU factorization
- ► Gaussian elimination(GE) and LU factorization
- Pivoting
- Stability of GE
- ► Q & A

Recap of Previous Lecture

- Perturbations in right hand side and coefficients
- Round-of errors
- How to avoid cancellation and recursion errors
- Computational template for numerical linear algebra
- ► Thomas algorithm

Example 8.1

General LU decomposition

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} =$$

$$\begin{pmatrix} l_{11} & 0 & \dots & 0 \\ l_{21} & l_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \end{pmatrix}$$

$$\begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix}$$

Example 8.1

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{11} & a_{12} & \dots & a_{1n} \end{pmatrix}$$

$$\begin{pmatrix} l_{11} & 0 & \dots & 0 \\ l_{21} & l_{22} & \dots & 0 \\ \dots & \dots & \dots & \dots \end{pmatrix}$$

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$$\begin{pmatrix} 1 & 0 & \dots & 0 \\ l_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ l_{n1} & l_{n2} & \dots & 1 \end{pmatrix}$$

$$\begin{vmatrix}
u_{11} & u_{12} & \dots & u_{1n} \\
0 & u_{22} & \dots & u_{2n} \\
\dots & \dots & \dots & \dots \\
0 & 0 & \dots & u_{nn}
\end{vmatrix}$$

 a_{1n}

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Example 8.2

$$\begin{vmatrix} a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{2n} & a_{2n} & a_{2n} \end{vmatrix}$$

$$\begin{pmatrix} 1 & 0 & \dots & 0 \\ I_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ I_{n1} & I_{n2} & \dots & 1 \end{pmatrix}$$

$$\begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix}$$

Crout
$$LU$$
 decomposition $\begin{pmatrix} l_{11} & 0 & \dots & 0 \\ l_{21} & l_{22} & \dots & 0 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

$$\begin{bmatrix} a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$$

$$I_{n1} \quad I_{n2} \quad ... \quad I_{nn}$$

$$\begin{pmatrix} 1 & u_{12} & \dots & u_{1n} \\ 0 & 1 & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{pmatrix}$$

Example 8.5

▶ Doolittle decomposition $A = LDU \Rightarrow A = (LD)U$

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- ▶ Crout decomposition $A = LDU \Rightarrow A = L(DU)$
- Exchanging rows or columns may be needed for implementation

$$\blacktriangleright \ B = \begin{pmatrix} 1 & 2 \\ 1 & 2 \end{pmatrix}, det(B) = 0, det(B_1) = 1 \neq 0$$

Example 8.6

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Example 8.7

$$D = \begin{pmatrix} 0 & 1 \\ 0 & 2 \end{pmatrix}, det(D) = 0, det(D_1) = 0$$

► Infinitely many *LU* factorizations exist

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$$D = L_{\beta}U_{\beta} = \begin{pmatrix} 1 & 0 \\ \beta & 1 \end{pmatrix} \cdot \begin{pmatrix} 0 & 1 \\ 0 & 2 - \beta \end{pmatrix}$$

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$$B = \begin{pmatrix} 1 & 2 \\ 1 & 2 \end{pmatrix}, det(B) = 0, det(B_1) = 1 \neq 0$$

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► Infinitely many LU factorizations exist

$$ightharpoonup C = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, det(C) = -1, det(C_1) = 0$$
: no LU factorization exists

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Example 8.8

$$ightharpoonup C = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, det(C) = -1, det(C_1) = 0$$
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Ramaz Botchorishvili (KIU)

Theorem 8.9

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Proof.

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Proof for sufficient condition, p1

proof by mathematical induction

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- $i = 1, A_1 = a_{11}, det(A_1) \neq 0 \Rightarrow A_1 = L_1 U_1 = 1 \cdot a_{11}$

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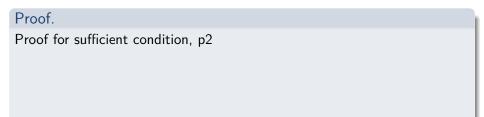
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- Assume $A_{i-1} = L_{i-1}U_{i-1}$
- ▶ Denote $A_i = \begin{pmatrix} A_{i-1} & c_i \\ d_i & a_{ii} \end{pmatrix}$, $c_i = \begin{pmatrix} a_{1i} \\ ... \\ a_{i-1i} \end{pmatrix}$, $d_i = \begin{pmatrix} a_{i1} & ... & a_{ii-1} \end{pmatrix}$

$$L_{i} = \begin{pmatrix} L_{i-1} & 0 \\ l_{i} & 1 \end{pmatrix}, l_{i} = \begin{pmatrix} l_{i1} & \dots & l_{ii-1} \end{pmatrix}, U_{i} = \begin{pmatrix} U_{i-1} & u_{i} \\ 0 & u_{ii} \end{pmatrix}, u_{i} = \begin{pmatrix} u_{1i} \\ \dots \\ u_{i-1i} \end{pmatrix}$$



Proof for sufficient condition, p2

 $\blacktriangleright \mathsf{Assume} \ A_{i-1} = L_{i-1}U_{i-1}$

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$$L_{i} = \begin{pmatrix} L_{i-1} & 0 \\ I_{i} & 1 \end{pmatrix}, I_{i} = \begin{pmatrix} I_{i1} & \dots & I_{ii-1} \end{pmatrix}, U_{i} = \begin{pmatrix} U_{i-1} & u_{i} \\ 0 & u_{ii} \end{pmatrix}, u_{i} = \begin{pmatrix} u_{1i} \\ \dots \\ u_{i-1i} \end{pmatrix}$$

► Formula to prove: $A_i = L_i U_i$

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► Formula to prove: $A_i = L_i U_i$

$$\begin{pmatrix}
L_{i-1} & 0 \\
I_{i} & 1
\end{pmatrix}
\begin{pmatrix}
U_{i-1} & u_{i} \\
0 & u_{ii}
\end{pmatrix} = \begin{pmatrix}
A_{i-1} & c_{i} \\
d_{i} & a_{ii}
\end{pmatrix}
\Rightarrow
\begin{cases}
L_{i-1}U_{i-1} = A_{i-1} \\
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- ▶ Formula to prove: $A_i = L_i U_i$
- ▶ $det(L_{i-1}) \neq 0$, $det(U_{i-1}) \neq 0 \Rightarrow$ proof is complete

Theorem 8.10

Unique LU factorization(Doolittle) of $A \in \mathbb{R}^{n \times n}$ exists iff

- $ightharpoonup det(A_i) \neq 0, i = 1, 2, ..., n-1$
- $ightharpoonup A_i$ -main submatrices, $A \in \mathbb{R}^{i \times i}$

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Proof.

Proof for necessary condition, p3:

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Proof for necessary condition, p3:

If unique LU factorization exists then first n-1 main submatrices are not degenerated

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proof by contradiction

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If unique LU factorization exists then first n-1 main submatrices are not degenerated

- proof by contradiction
- Assume unique LU factorization exists and for some k < n main submatrix $A_k, 1 \le k < n$ is degenerated and $A_{k-1}, 2 \le k < n$ is not degenerated

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$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ l_{21} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & \dots & 1 \end{pmatrix} \begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix} \Rightarrow det(A) = \prod_{i=1}^{n} u_{ii}$$

Proof.

Proof for necessary condition, p4:

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$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ l_{21} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & \dots & 1 \end{pmatrix} \begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix} \Rightarrow det(A) = \prod_{i=1}^{n} u_{ii}$$

• $det(A_{n-1}) = 0, det(A_{n-2}) \neq 0 \Rightarrow u_{n-1,n-1} = 0$

Proof.

Proof for necessary condition, p4:

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ l_{21} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & \dots & 1 \end{pmatrix} \begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix} \Rightarrow det(A) = \prod_{i=1}^{n} u_{ii}$$

• $det(A_{n-1}) = 0, det(A_{n-2}) \neq 0 \Rightarrow u_{n-1,n-1} = 0$

$$\begin{array}{ccc}
 & \begin{pmatrix} L_{n-1} & 0 \\ I_n & 1 \end{pmatrix} \begin{pmatrix} U_{n-1} & u_n \\ 0 & u_{nn} \end{pmatrix} = \begin{pmatrix} A_{n-1} & c_n \\ d_n & a_{nn} \end{pmatrix} \Rightarrow \begin{cases} L_{n-1}U_{n-1} = A_{n-1} \\ L_{n-1}u_n = A_{n-1}c_n \\ I_nU_{n-1} = d_n \\ I_n \cdot u_n + u_{nn} = a_{nn} \end{cases}$$

Proof.

Proof for necessary condition, p4:

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ l_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ l_{n1} & l_{n2} & \dots & 1 \end{pmatrix} \begin{pmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ 0 & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & u_{nn} \end{pmatrix} \Rightarrow det(A) = \prod_{i=1}^{n} u_{ii}$$

• $det(A_{n-1}) = 0, det(A_{n-2}) \neq 0 \Rightarrow u_{n-1,n-1} = 0$

$$\begin{pmatrix}
L_{n-1} & 0 \\
I_n & 1
\end{pmatrix}
\begin{pmatrix}
U_{n-1} & u_n \\
0 & u_{nn}
\end{pmatrix} =
\begin{pmatrix}
A_{n-1} & c_n \\
d_n & a_{nn}
\end{pmatrix}
\Rightarrow
\begin{cases}
L_{n-1}U_{n-1} = A_{n-1} \\
L_{n-1}u_n = A_{n-1}c_n \\
I_nU_{n-1} = d_n \\
I_n \cdot u_n + u_{nn} = a_{nn}
\end{cases}$$

▶ $det(U_{n-1}) = 0 \Rightarrow I_n U_{n-1} = d_n$ has no unique solution \Rightarrow contradiction, proof is complete

$$\begin{array}{ccc}
 & \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}$$

$$\blacktriangleright \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}$$

$$\blacktriangleright \begin{pmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & x & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
y_0 \\
y_1 \\
y_2 \\
y_3 \\
y_4
\end{pmatrix} = \begin{pmatrix}
y_0 \\
y_1 \\
y_2 \\
xy_1 + y_3 \\
y_4
\end{pmatrix}$$

LU factorization from Gaussian elimination 3 \blacktriangleright $A \equiv A^{(0)}$

 $A \equiv A^{(0)}$

$$A = A^{(1)} = M_1 A^{(0)} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ -\frac{a_{21}}{a_{11}} & 1 & 0 & \dots & 0 \\ -\frac{a_{31}}{a_{11}} & 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ -\frac{a_{n1}}{a_{11}} & 0 & 0 & \dots & 1 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nn} \end{pmatrix}$$

$$A = A^{(0)}$$

$$A = A^{(1)} = M_1 A^{(0)} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ -\frac{a_{21}}{a_{11}} & 1 & 0 & \dots & 0 \\ -\frac{a_{31}}{a_{21}} & 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ -\frac{a_{n1}}{a_{11}} & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nn} \end{pmatrix}$$

$$A^{(1)} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ 0 & a_{12}^{(1)} & a_{13}^{(1)} & \dots & a_{2n}^{(1)} \\ 0 & a_{32}^{(1)} & a_{33}^{(1)} & \dots & a_{3n}^{(1)} \\ \dots & \dots & \dots & \dots & \dots \\ 0 & a_{n2}^{(1)} & a_{n3}^{(1)} & \dots & a_{nn}^{(1)} \end{pmatrix}, A^{(2)} = M_2 A^{(1)}$$

$$A^{(1)} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(1)} & \dots & a_{2n}^{(1)} \\ 0 & a_{32}^{(1)} & a_{33}^{(1)} & \dots & a_{3n}^{(1)} \\ \dots & \dots & \dots & \dots & \dots \\ 0 & a_{n2}^{(1)} & a_{n3}^{(1)} & \dots & a_{nn}^{(1)} \end{pmatrix}, A^{(2)} = M_2 A^{(1)}$$

$$A \equiv A^{(0)}$$

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$$A^$$

$$A^{(1)} = \begin{pmatrix} 0 & a_{22}^{(1)} & a_{23}^{(1)} & \dots & a_{2n}^{(1)} \\ 0 & a_{32}^{(1)} & a_{33}^{(1)} & \dots & a_{3n}^{(1)} \\ \dots & \dots & \dots & \dots & \dots \\ 0 & a_{n2}^{(1)} & a_{n3}^{(1)} & \dots & a_{nn}^{(1)} \end{pmatrix}, A^{(2)}$$

$$M_2 A^{(1)} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & -\frac{a_{32}^{(1)}}{a_{22}^{(1)}} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & -\frac{a_{2n}^{(1)}}{a_{21}^{(1)}} & 0 & \dots & 1 \end{bmatrix}$$

$$A^{(2)} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(2)} & \dots & a_{2n}^{(2)} \\ 0 & 0 & a_{33}^{(2)} & \dots & a_{3n}^{(2)} \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix}$$

$$A^{(k-1)} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(2)} & \dots & a_{2n}^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & a_{nk}^{(k-1)} & \dots & a_{nn}^{(k-1)} \end{pmatrix}$$

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LU factorization from Gaussian elimination 4
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$$multipliers: \ \left\{ egin{aligned} m_{k+1,k} &= -rac{a_{k+1k}^{(k-1)}}{a_{kk}^{(k-1)}}, \ .. \ m_{n,k} &= -rac{a_{nk}^{(k-1)}}{a_{kk}^{(k-1)}} \end{aligned}
ight.$$

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$$M_k = egin{pmatrix} 1 & 0 & 0 & ... & ... & 0 \ 0 & 1 & 0 & ... & ... & ... & 0 \ ... & ... & ... & ... & ... & ... & ... \ ... & ... & ... & ... & ... & ... & ... \ ... & ... & ... & ... & ... & ... & ... & ... \ ... & ... & ... & ... & ... & ... & ... & ... \ 0 & ... & ... & -rac{a_{k+1k}^{(k-1)}}{a_{kk}^{(k-1)}} & ... & ... & 1 \ \end{pmatrix}$$

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Explicit expression for L?

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 - ▶ store entries of *L* in lower triangular part of *A* excluding diagonal

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LU factorization from Gaussian elimination 11 1. Given input matrix A.

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Forsythe, Moler (1967)

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In three digit arithmetic with rounding

$$f(1-10^{-4}) = f(-9999) = f(-0.9999 \cdot 10^4) = -10^4 L = \begin{pmatrix} 1 & 0 \\ 10^4 & 1 \end{pmatrix},$$

$$U = A^{(1)} = \begin{pmatrix} 10^{-4} & 1 \\ 0 & -10^{4} \end{pmatrix}, LU = \begin{pmatrix} 10^{-4} & 1 \\ 1 & 0 \end{pmatrix} \neq A$$

Ramaz Botchorishvili (KIU)

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Forsythe, Moler (1967)

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P is permutation matrix if in each row and column exactly one entry is 1 and other entries are 0.

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▶ Unit vector $e_1, e_2, ...e_n$

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► General permutation matrix

$$P = \begin{pmatrix} e_{\alpha_1}^T \\ e_{\alpha_2}^T \\ \vdots \\ e_{\alpha_n}^T \end{pmatrix}, 1 \le i, \alpha_i \le n, PP^T = I, PA = \begin{pmatrix} \alpha_1 - \text{th row of } A \\ \alpha_2 - \text{th row of } A \\ \vdots \\ \alpha_n - \text{th row of } A \end{pmatrix}$$

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$$P_{\textit{left}}A = \begin{pmatrix} \alpha_1 - \text{th row of matrix } A \\ \alpha_2 - \text{th row of matrix } A \\ & \cdot \\ & \cdot \\ \alpha_n - \text{th row of matrix } A \end{pmatrix}$$

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- General permutation matrix P_{left}

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$$P_{left}A = \begin{pmatrix} \alpha_1 - \text{th row of matrix } A \\ \alpha_2 - \text{th row of matrix } A \\ & \cdot \\ & \cdot \\ \alpha_n - \text{th row of matrix } A \end{pmatrix}$$

lacktriangle General permutation matrix $P_{\textit{right}} = \left(\mathsf{e}_{lpha_1}, \mathsf{e}_{lpha_2}, ..., \mathsf{e}_{lpha_n}
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- ightharpoonup Premultiplication: $P_{left}A$
- ► Postmultiplication: *AP*_{right}
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► Gaussian Elimination with Partial Pivoting (GEPP)

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$$A^{(1)} = M_1 P_1 A$$

$$A^{(2)} = M_2 P_2 A^{(1)} = M_2 P_2 M_1 P_1 A$$
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$$A^{(n-1)} = M_{n-1}P_{n-1} \cdots M_2P_2M_1P_1A =$$

$$= M_{n-1}P_{n-1} \cdots M_2P_2M_1(P_2^T ... P_{n-1}^T P_{n-1} ... P_2)P_1A =$$

$$= M_{n-1}P_{n-1} \cdots M_2P_2M_1(P_2^T ... P_{n-1}^T)P_{n-1} ... P_2P_1A =$$

$$= M_{n-1}P_{n-1} \cdots M_2(P_3^T ... P_{n-1}^T P_{n-1} ... P_3)P_2M_1(P_2^T ... P_{n-1}^T)PA =$$

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$$A^{(n-1)} = M'_{n-1} \cdots M'_2 M'_1 P A$$

$$P = P_{n-1} ... P_2 P_1$$

$$M'_1 = P_{n-1} ... P_3 P_2 M_1 P_2^T ... P_{n-1}^T$$

$$M'_2 = P_{n-1} ... P_3 M_1 P_3^T ... P_{n-1}^T$$

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$$A^{(n-1)} = U$$

$$PA = LU$$

$$L = (M'_{n-1} \cdots M'_2 M'_1)^{-1}$$

$$A^{(k)} = M_k P_k A^{(k-1)} Q_k$$

Gaussian elimination with complete pivoting (GECP)

$$A^{(k)} = M_k P_k A^{(k-1)} Q_k$$

 \triangleright P_k - for row exchange

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- $ightharpoonup P_k$ for row exchange
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$$A^{(n-1)} = U$$

$$PAQ = LU$$

$$P = P_{n-1}...P_2P_1$$

$$Q = Q_1Q_2...Q_{n-1}$$

Definition 8.17

▶ The growth factor ρ

$$\begin{split} \rho &= \frac{\max\{\alpha_0,\alpha_1,...,\alpha_{n-1}\}}{\alpha_0} \\ \alpha_k &= \max_{i,j} |a_{ij}^{(k)}|, k = 0,1,..,n-1 \end{split}$$

 $lacktriangledown A^{(0)}=A$, $A^{(k)}$ - matrix obtained after k steps of Gaussian elimination

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- ► The textbook, chapter 5, pp.108,109

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- ▶ A posterior estimate: ||LU A|| extra FLOPS needed

▶ A posterior estimate: theorems 6.12 in the textbook

Theorem 8.19

$$ightharpoonup Ax = b$$
, $\tilde{r} = A\tilde{x} - b$

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$$\frac{\|\tilde{x} - x\|}{\|x\|} \le cond(A) \frac{\|\tilde{r}\|}{\|b\|}$$

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 - ► A big residual vector

Scaling

Definition 8.20

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 - ► Scaling example: textbook, chapter 6, p.135

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- Convergence depends on cond(A)

Q & A