

# MA423 Matrix Computations

## Lecture 8: System of Linear Equations-II

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# Outline

- Gaussian elimination with pivoting
- Permuted LU decomposition

## Pivoting

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**Theorem (GEPP):** Let  $A$  be an  $n \times n$  matrix. Then there is a permutation matrix  $P$  such that

$$PA = LU$$

where  $L$  is unit lower triangular and  $U$  is upper triangular.

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$$L_1^{-1} P_1 A = \left[ \begin{array}{c|ccc} a_{11} & a_{12} & \cdots & a_{1n} \\ \hline 0 & a_{22}^{(1)} & \cdots & a_{2n}^{(1)} \\ \vdots & \vdots & & \vdots \\ 0 & a_{n2}^{(1)} & \cdots & a_{nn}^{(1)} \end{array} \right], \text{ where } a_{ij}^{(1)} = a_{ij} - \ell_{i1} a_{1j}. \text{ Cost: } 2(n-1)^2 \text{ flops.}$$

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Here  $P_2$  is the permutation matrix that interchanges second row with  $n$ -th row of  $L_1^{-1} A$ .

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$$PA = \underbrace{\hat{L}_1 \hat{L}_2 \cdots \hat{L}_{n-2} L_{n-1}}_L U = LU,$$

where  $L$  is unit lower triangular,  $\hat{L}_j$ 's are obtained from  $L_j$ 's by permutating their multipliers and  $P := P_{n-1} P_{n-2} \cdots P_2 P_1$ .

## Gaussian Elimination with Partial Pivoting (GEPP):

```
function [L, U, p] = GEPP(A);  
% [L U, p] = GEPP(A) produces a unit  
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```
[n, n] = size(A);  
p = (1:n)';  
for k = 1:n-1  
    % find largest element in A(k:n,k)  
    [r, m] = max( abs( A(k:n,k) ) );  
    m = m+k-1;  
    if (m ~= k) % swap rows  
        A([k m], :) = A([m k], :);  
        p([k m]) = p([m k]);  
    end
```

## GEPP (cont.)

```
if (A(k,k) ~= 0)
    % compute multipliers for k-th step
    A(k+1:n,k) = A(k+1:n,k)/A(k,k);
    % update A(k+1:n,k+1:n)
    j = k+1:n;
    A(j,j) = A(j,j)-A(j,k)*A(k,j);
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% strict lower triangle of A, plus I
L = eye(n,n)+ tril(A,-1);
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The search for the **largest entry in each column** guarantees that the denominator  $A(k,k)$  in the entries  $L(k+1:n,k) = A(k+1:n,k)/A(k,k)$  is at least as large as the numerators.

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This ensures that  $|L(i,j)| \leq 1$  for all  $i,j$ . This is crucial for **stability**.

## Example

Consider

$$\underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{P_1} \underbrace{\begin{bmatrix} 2 & 4 & -2 \\ 4 & 9 & -3 \\ -2 & -3 & 7 \end{bmatrix}}_A = \begin{bmatrix} 4 & 9 & -3 \\ 2 & 4 & -2 \\ -2 & -3 & 7 \end{bmatrix}.$$

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$$\text{Then } L_1 = I + \begin{bmatrix} 0 \\ \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix} e_1^\top, \quad L_1^{-1}A = \begin{bmatrix} 4 & 9 & -3 \\ 0 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{3}{2} & \frac{11}{2} \end{bmatrix}.$$

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Then  $L_2 = I + \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{3} \end{bmatrix} e_2^\top$ ,  $L_2^{-1}P_2L_1^{-1}P_1A = \begin{bmatrix} 4 & 9 & -3 \\ 0 & \frac{3}{2} & \frac{11}{2} \\ 0 & 0 & \frac{4}{3} \end{bmatrix}$

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Now

$$\begin{aligned}P_1L_1 &= P_1 \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & 1 & 0 \\ 1 & 0 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix} \\P_2L_2 &= P_2 \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -\frac{1}{3} & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -\frac{1}{3} & 1 \\ 0 & 1 & 0 \end{bmatrix}\end{aligned}$$

shows that  $M$  is not lower triangular.

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Thus we have  $L_2^{-1}P_2L_1^{-1}P_1A = U \implies A = MU$ , where  $M := (L_2^{-1}P_2L_1^{-1}P_1)^{-1} = P_1L_1P_2L_2$ .

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## Permutated LU decomposition ( $PA = LU$ )

By GEPP we have  $L_{n-1}^{-1}P_{n-1} \cdots L_2^{-1}P_2L_1^{-1}P_1A = U$ , where  $P_k$  is the permutation matrix and  $L_k := I + \ell_k e_k^\top$  is the elimination matrix at the  $k$ -th step.

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**Proof:** Note that the first  $m - 1$  rows of  $P_m$  ( $P_m$  is used at the  $m$ -th step of elimination) are the same as the first  $m - 1$  rows of  $I_n$ . Hence  $e_k^\top P_m = e_k^\top$  for  $k = 1 : m - 1$ .

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Now

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Continuing this process, we have

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Hence the results follow. ■

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GEPP is the standard method used in practice for solving a linear system. GEPP is a default method in MATLAB for solution of a linear system. The command  $x = A \backslash b$  solves  $Ax = b$  using GEPP. The command  $[L, U, P] = \text{lu}(A)$  computes  $PA = LU$ .

## Gaussian elimination with complete pivoting

Gaussian elimination with complete pivoting (GECP) is a variant of GE. At the  $k$ -step, GECP searches not just column  $A(k:n, k)$  but the entire submatrix  $A(k:n, k:n)$  for the largest entry and then swaps rows and columns to put that entry into  $A(k, k)$ .

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**Cost:**  $2n^3/3 + n^3/3 = n^3$  flops. Additional  $n^3/3$  flops is due to finding maximum element at each step.

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- Sparsity of  $A$  can be exploited by clever choice of row and column interchanges (at possible detriment to stability).
- We still do not fully understand why GEPP and GECP work so well in the presence of roundoff.

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