

# EE636: Matrix Computations

## Lecture 4

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- How a computer solves

$$Ax = b, \quad \min \|Ax - b\|, \quad Ax = \lambda x, \quad Av = \sigma u$$

where  $\sigma \geq 0$ ,  $\{u_1, u_2, \dots, u_m\} \subseteq \mathbb{R}^m$ ,  $\{v_1, v_2, \dots, v_n\} \subseteq \mathbb{R}^n$  are orthonormal.

- The effect of **round off error**.
- When a solution can be trusted.
- FLOPS** to measure computation time.
- Counted the FLOPS for basic matrix multiplication:  $2mn$  for a matrix of size  $m \times n$  and a vector of size  $n$ .
- How to solve linear systems of equations: triangular systems.
- The (almost) general case: Gaussian elimination.
- Gaussian elimination (without pivoting) is possible if and only if the **leading principal minors** of  $A$  are non-zero.
- Gaussian elimination without pivoting results in the **LU decomposition** of  $A$ : that is  $A = LU$ , where  $U$  is an **upper triangular matrix** and  $L$  is a **unity lower triangular matrix**.
- The  $L$  and  $U$  in the LU decomposition is unique.
- LU requires  $(O)(n^3)$  FLOPs.
- Inversion of a matrix that admits LU requires  $(O)(n^3)$  FLOPs.
- Symmetric positive definite matrices.

## Special case: symmetric positive definite matrices

### Theorem

$A = A^T$  is PD if and only if every eigenvalue of  $A$  is positive.

$A \exists Q$  orthogonal matrix ( $Q^T Q = Q Q^T = I$ )

$$Q^T A Q = \Lambda \rightarrow \text{real entries.}$$

$$\Rightarrow A = Q \Lambda Q^T$$

$$\Rightarrow A \text{ is PD} \Leftrightarrow \lambda_1, \dots, \lambda_n > 0.$$

$$\text{PSD} \Leftrightarrow \lambda_1, \dots, \lambda_n \geq 0.$$

|| by for ND/NSD.

PSD: All leading principal minors  $\geq 0$   
 is necessary for PSD but NOT sufficient.

$$e_1^T \begin{bmatrix} \boxed{0} & 0 & 0 \\ 0 & \boxed{0} & 1 \\ 0 & 1 & \boxed{0} \end{bmatrix} e_2^T A e_2 = 0$$

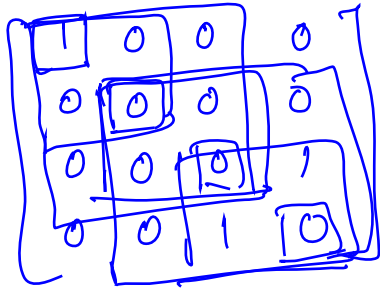
$A$

$$e_1 = 0, \quad e_2^T A e_2 = 0$$

$$\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}^T A \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = 2 > 0$$

$$\begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix}^T A \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} = (0 \ 1 \ -1) \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = -2 < 0$$

## Special case: symmetric positive definite matrices



is indefinite

All leading principal  
minors  $> 0$

But  $A$  is indefinite

All principal minors  $\geq 0 \Leftrightarrow$  APSD

## Special case: symmetric positive definite matrices

### Theorem

$A = A^T$  is PD if and only if every leading principal submatrix of  $A$  is PD. ✓

THM 1  $\Leftrightarrow$  leading principal minors are (+)ve numbers.

$$(PD \Rightarrow \det > 0) \equiv (\det \neq 0 \Rightarrow \cancel{PD})$$

$\Rightarrow$  ✓

$\Leftarrow$  use induction.

## Special case: symmetric positive definite matrices

Lemma

If  $A = A^T$  is PD then  $\det A > 0$ . ✓✓

$$Q^T A Q = \Lambda$$

$$\det Q = \pm 1$$

$$\Rightarrow \det(Q^T A Q) = \det \Lambda = \prod_{i=1}^n \lambda_i$$

$$\Rightarrow (\det Q)^2 \det A > 0 \Rightarrow \det A > 0$$

$$Q^T Q = I$$

$$\det(Q^T Q) = \det I = 1$$

$$\Rightarrow \det Q^T \cdot \det Q = 1$$

$$\Rightarrow (\det Q)^2 = 1$$

## The Schur complement

Suppose a symmetric matrix is given in block form as

$$M = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}.$$

Further, suppose  $A$  is invertible. Then  $M$  is invertible iff the Schur complement of  $A$  is invertible.

$$C - B^T A^{-1} B.$$



# The Schur complement

$$\begin{bmatrix} I & 0 \\ -B^T A^{-1} & I \end{bmatrix} \begin{bmatrix} \boxed{A} & \boxed{B} \\ \boxed{B^T} & \boxed{C} \end{bmatrix} \begin{bmatrix} I & -A^{-1} B \\ 0 & I \end{bmatrix} = \begin{bmatrix} I & 0 \\ -B^T A^{-1} & I \end{bmatrix} \begin{bmatrix} A & 0 \\ B^T & C - B^T A^{-1} B \end{bmatrix}$$

$$\begin{bmatrix} x^T & y^T \end{bmatrix} \begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x^T & y^T \end{bmatrix} P^{-T} S \begin{bmatrix} P x \\ y \end{bmatrix}$$

$$= \begin{bmatrix} x^T & y^T \end{bmatrix} S \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\begin{bmatrix} A & 0 \\ 0 & C - B^T A^{-1} B \end{bmatrix}$$

SPECIAL CASE:

$$\det \begin{bmatrix} \boxed{A} & \boxed{b} \\ \boxed{b^T} & \boxed{c} \end{bmatrix} = \det \begin{bmatrix} A & 0 \\ 0 & C - b^T A^{-1} b \end{bmatrix} = \det A \cdot (C - b^T A^{-1} b)$$

## Special case: symmetric positive definite matrices

HW: Using Schur complement, and induction on the size of  $A$  prove lemma 1.

### Theorem

Let  $A = A^T$  be PD, then  $A$  admits an LU factorization. ✓✓

=====

$$A = L \tilde{U} = L \underbrace{(D)}_{\text{diagonal}} U$$

Annotations for  $L$  and  $\tilde{U}$ :

- $L$ : unit lower  $\Delta^r$
- $\tilde{U}$ : unit upper  $\Delta^r$

Annotations for  $D$  and  $U$ :

- $D$ : diagonal
- $U$ : unit upper  $\Delta^r$

Annotation for the final  $L$  in the second decomposition:

- $L$ : unit lower  $\Delta^r$

## LU decomposition of symmetric PD matrices: Cholesky factorization

Suppose  $A = A^T$  (suppose  $A$  admits LU)

$$A = LDU \Rightarrow A^T = \underbrace{U^T}_{\parallel A} \underbrace{D}_{=} \underbrace{L^T}_{=} \checkmark$$
$$= LDU$$

By uniqueness of  
LDU decomposition.

$$A = LDL^T$$

Assume  $A$  is PD  $\Rightarrow A = L D L^T \Rightarrow$  all the diagonal entries in  $D$  are  $> 0$ .

$$x^T A x = x^T L D \underline{\underline{L^T x}} \quad \xi := L^T x$$

$$= \xi^T D \xi$$

Since  $L^T$  is invertible,  $x^T A x > 0 \quad \forall x \neq 0$

$$\Leftrightarrow \xi^T D \xi > 0 \quad \forall \underline{\xi \neq 0}.$$

$$\Leftrightarrow d_{ii} > 0.$$

$$A = L D L^T = L \begin{bmatrix} \sqrt{d_{11}} & & \\ & \sqrt{d_{22}} & \\ & & \ddots \\ & & & \sqrt{d_{nn}} \end{bmatrix} \begin{bmatrix} \sqrt{d} \\ \sqrt{d} \\ \sqrt{d} \\ \sqrt{d} \end{bmatrix} L^T$$

$\sqrt{D}$

$$F^T := \sqrt{D} L^T$$

$$\Rightarrow \boxed{A = F F^T} \text{ where } F \text{ is Lower } \Delta^n.$$

$\in \mathbb{R}^{n \times n}$

We assume that all leading principal minors  $> 0$ , TST  $A$  is PD.

Use induction on the size of  $A$ .

Base case  $n=1$   $A \in \mathbb{R}$   $A > 0 \Rightarrow A$  is PD.

Inductive step: Suppose the result holds true for matrices of size  $(n-1)$  (or less). TST the result must hold for size  $n$ .

$$A = \begin{bmatrix} A_{11} & a_{12} \\ a_{12}^T & a_{22} \end{bmatrix} \quad A_{11} \in \mathbb{R}^{(n-1) \times (n-1)}$$

$$a_{12} \in \mathbb{R}^{(n-1)}, \quad a_{22} \in \mathbb{R}.$$

All leading principal minors of  $A > 0 \Rightarrow$

$$\gamma \quad \gamma \quad \gamma \quad \gamma \quad \gamma \quad A_{11} > 0$$

By inductive hypothesis  $\Rightarrow A_{11}$  is PD.

$$\begin{bmatrix} A_{11} & a_{12} \\ a_{12}^T & a_{22} \end{bmatrix} = \begin{bmatrix} I & 0 \\ a_{12}^T A_{11}^{-1} & I \end{bmatrix} \begin{bmatrix} \underline{A_{11}} & 0 \\ 0 & \underline{a_{22} - a_{12}^T A_{11}^{-1} a_{12}} \end{bmatrix}$$

$$\det A > 0 \Rightarrow a_{22} - a_{12}^T A_{11}^{-1} a_{12} > 0$$

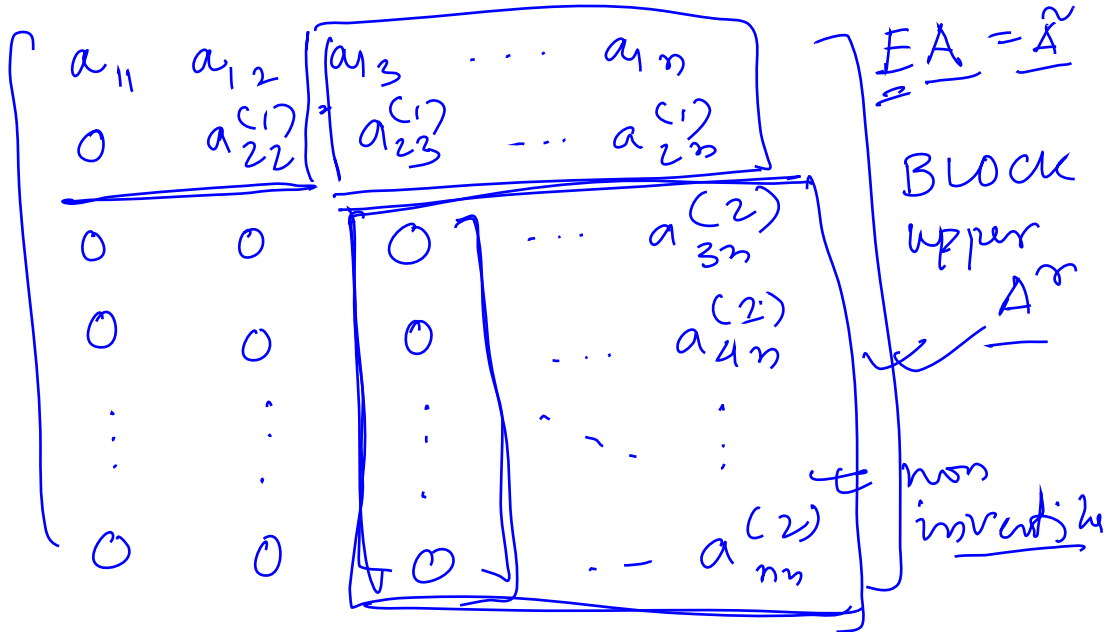
$$\Rightarrow \underline{\underline{\begin{pmatrix} x \\ y \end{pmatrix}^T A \begin{pmatrix} x \\ y \end{pmatrix}}} = \xi^T A_{11} \xi + \eta \left( \underline{a_{22} - a_{12}^T A_{11}^{-1} a_{12}} \right) \eta > 0$$

$$\therefore \quad \forall \begin{pmatrix} x \\ y \end{pmatrix} \in \mathbb{R}^n \quad \forall \xi \in \mathbb{R}^m, \eta \in \mathbb{R}.$$

$$\Rightarrow \underline{\underline{A \text{ is PD.}}}$$



# LU decomposition with partial pivoting



## ~~• Orthogonal.~~

If  $A$  is invertible and  $a_{kk}^{(k-1)}$  is zero

$\Rightarrow \exists l = k+1, \dots, n$  s.t.

$$a_{l,k}^{(k-1)} \neq 0$$

## ~~• Permutation involving only one swap is idempotent.~~

This idea of pivoting misses the LU structure.

# How the permutation matrix pervades through a chain of elementary row operation matrices

$$\pi_{35} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix}$$

# How the permutation matrix pervades through a chain of elementary row operation matrices

$$\begin{aligned}
 \pi_{35} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} \\
 \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 1 & 0 & 0 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 0 & 0 & 1 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} \pi_{35}
 \end{aligned}$$

# How the permutation matrix pervades through a chain of elementary row operation matrices

$$\pi_{35} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 0 & 0 & 1 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 1 & 0 & 0 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -m_{52} & 1 & 0 & 0 & 0 \\ 0 & -m_{42} & 0 & 1 & 0 & 0 \\ 0 & -m_{32} & 0 & 0 & 1 & 0 \\ 0 & -m_{62} & 0 & 0 & 0 & 1 \end{bmatrix} \pi_{35}$$

$$\pi_{35} E_2 E_1 A = \pi_{35} A^{(2)}$$

$$\hat{E}_2 \pi_{35} E_1 A = \hat{A}^{(2)}$$

$$\hat{E}_2 \hat{E}_1 \pi_{35} A = \hat{A}^{(2)}$$

# Back to LU decomposition with partial pivoting

Thank you