# Lecture 04

**Chapter 2 Matrix Algebra** 

- 2.3. Partitioned Matrices
- 2.4. Elementary Matrices

# 2.3. Partitioned Matrices

It is useful to think of a matrix as being composed of a number of sub-matrices. These smaller sub-matrices are called as blocks.

#### **Partitioned Matrices**

For a given matrix, it is useful to rewrite it into sub-matrices [子矩阵].

For example, let

$$C = \begin{pmatrix} 1 & -2 & 4 & 1 & 3 \\ 2 & 1 & 1 & 1 & 1 \\ 3 & 3 & 2 & -1 & 2 \\ 4 & 6 & 2 & 2 & 4 \end{pmatrix}$$

can be rewrite as

$$\begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix} = \begin{pmatrix} 1 & -2 & 4 & 1 & 3 \\ 2 & 1 & 1 & 1 & 1 \\ \hline 3 & 3 & 2 & -1 & 2 \\ 4 & 6 & 2 & 2 & 4 \end{pmatrix}.$$

The smaller matrices are often referred to as blocks [块].

#### **Partitioned Matrices**

**Definition 1.** (Partitioned Matrix) A partitioned matrix [分块矩阵] is a matrix broken into blocks.

$$C = \begin{pmatrix} 1 & -2 & 4 & 1 & 3 \\ 2 & 1 & 1 & 1 & 1 \\ 3 & 3 & 2 & -1 & 2 \\ 4 & 6 & 2 & 2 & 4 \end{pmatrix} \qquad \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix} = \begin{pmatrix} 1 & -2 & 4 & 1 & 3 \\ 2 & 1 & 1 & 1 & 1 \\ \hline 3 & 3 & 2 & -1 & 2 \\ 4 & 6 & 2 & 2 & 4 \end{pmatrix}$$

$$\begin{pmatrix} C_{11} \\ C_{21} \\ C_{31} \\ C_{41} \end{pmatrix} = \begin{pmatrix} 1 & -2 & 4 & 1 & 3 \\ 2 & 1 & 1 & 1 & 1 \\ \hline 3 & 3 & 2 & -1 & 2 \\ \hline 4 & 6 & 2 & 2 & 4 \end{pmatrix}$$

$$\begin{pmatrix} 1 & -2 & | 4 & | 1 & | 3 \\ 2 & 1 & | 1 & | 1 & | 1 \\ 3 & 3 & | 2 & | -1 & | 2 \\ 4 & | 6 & | 2 & | 2 & | 4 \end{pmatrix}$$
$$= (C_{11}, C_{12}, C_{13}, C_{14}, C_{15})$$

#### Block addition and scalar multiplication

Suppose that matrices A and B are two  $m \times n$  matrices and are partitioned in the same way. That is,

$$A = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1r} \\ A_{21} & A_{22} & \cdots & A_{2r} \\ \vdots & \vdots & & \vdots \\ A_{s1} & A_{s2} & \cdots & A_{sr} \end{pmatrix}, \qquad B = \begin{pmatrix} B_{11} & B_{12} & \cdots & B_{1r} \\ B_{21} & B_{22} & \cdots & B_{2r} \\ \vdots & \vdots & & \vdots \\ B_{s1} & B_{s2} & \cdots & B_{sr} \end{pmatrix}$$

where  $A_{ij}$ ,  $B_{ij}$  are submatrices of order  $p_i \times q_j$ , i = 1, 2, ..., s, j = 1, 2, ..., r. Then the block addition of these two matrices is given by

$$A + B = \begin{pmatrix} A_{11} + B_{11} & A_{12} + B_{12} & \cdots & A_{1r} + B_{1r} \\ A_{21} + B_{21} & A_{22} + B_{22} & \cdots & A_{2r} + B_{2r} \\ \vdots & \vdots & & \cdots \\ A_{s1} + B_{s1} & A_{s2} + B_{s2} & \cdots & A_{sr} + B_{sr} \end{pmatrix}, \ \alpha A = \begin{pmatrix} \alpha A_{11} & \alpha A_{12} & \cdots & \alpha A_{1r} \\ \alpha A_{21} & \alpha A_{22} & \cdots & \alpha A_{2r} \\ \vdots & \vdots & & \cdots \\ \alpha A_{s1} & \alpha A_{s2} & \cdots & \alpha A_{sr} \end{pmatrix}.$$

#### Block Addition and Scalar Multiplication

Example. If 
$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} 1 & 2 & 2 & 1 \\ 2 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ \hline 1 & 1 & 2 & 1 \end{pmatrix}$$

$$B = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} = \begin{pmatrix} 0 & 3 & 2 & 1 \\ 3 & 0 & 2 & 2 \\ 1 & 2 & 1 & 1 \\ 2 & 2 & 2 & 3 \end{pmatrix}$$

perform block addition for A + B.

Solution.

Solution.
$$A + B = \begin{pmatrix} A_{11} + B_{11} & A_{12} + B_{12} \\ A_{21} + B_{21} & A_{22} + B_{22} \end{pmatrix} = \begin{pmatrix} 1 & 5 & 4 & 2 \\ 5 & 1 & 3 & 3 \\ 1 & 3 & 1 & 1 \\ \hline 3 & 3 & 4 & 4 \end{pmatrix}.$$

One useful way of partitioning a matrix is into columns. For example,

let

$$B = \begin{pmatrix} -1 & 2 & 1 \\ 2 & 3 & 1 \\ 1 & 4 & 1 \end{pmatrix}$$

We can partition B into three column submatrices:

$$B = (\boldsymbol{b}_1, \boldsymbol{b}_2, \boldsymbol{b}_3) = \begin{pmatrix} -1 & 2 & 1 \\ 2 & 3 & 1 \\ 1 & 4 & 1 \end{pmatrix}$$

Then the multiplication of matrix can be represented as

$$AB = A(b_1, b_2, b_3) = (Ab_1, Ab_2, Ab_3).$$

**Example 1.** Check the above equality for  $A = \begin{pmatrix} 1 & 3 & 1 \\ 2 & 1 & -1 \end{pmatrix}$ .

In general, if A is an  $m \times n$  matrix and B is an  $n \times r$  matrix that has been partitioned into columns  $(\boldsymbol{b}_1, \boldsymbol{b}_2, ..., \boldsymbol{b}_r)$ , then the block multiplication of A times B is given by

$$AB = (A\boldsymbol{b}_1, A\boldsymbol{b}_2, \dots, A\boldsymbol{b}_r).$$

In particular,

$$(a_1, a_2, ..., a_n) = A = AI = (Ae_1, Ae_2, ..., Ae_n).$$

The columns of AB are linear combinations of columns of A.

A matrix can also be partitioned into rows.

For example, 
$$A = \begin{pmatrix} \boldsymbol{a}(1,:) \\ \boldsymbol{a}(2,:) \\ \vdots \\ \boldsymbol{a}(m,:) \end{pmatrix}$$
, then  $AB = \begin{pmatrix} \boldsymbol{a}(1,:)B \\ \boldsymbol{a}(2,:)B \\ \vdots \\ \boldsymbol{a}(m,:)B \end{pmatrix}$ .

**Example 2.** Check the above equality for  $A = \begin{pmatrix} 2 & 5 \\ 3 & 4 \\ 1 & 7 \end{pmatrix}$ ,  $B = \begin{pmatrix} 3 & 2 & -3 \\ -1 & 1 & 1 \end{pmatrix}$ .

The rows of AB are linear combinations of rows of B.

Let A be an  $m \times n$  matrix and B be an  $n \times r$  matrix. Four steps.

t columns

Case 1.  $B = (B_1 \ B_2)$ , where  $B_1$  is an  $n \times t$  matrix and  $B_2$  is an  $n \times (r - t)$ matrix. Then  $AB = (AB_1 \ AB_2)$ .

k rows Case 2.  $A = \begin{pmatrix} A_1 \\ A_2 \end{pmatrix}$ , where  $A_1$  is a  $k \times n$  matrix and  $A_2$  is an  $(m - k) \times n$  matrix. Then  $AB = \begin{pmatrix} A_1B \\ A_2B \end{pmatrix}$ . (m - k) rows Case 3. If  $A = (A_1 \ A_2)$ , where  $A_1$  is a  $m \times s$  matrix and  $A_2$  is an  $m \times (n - s)$  matrix,  $B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}$  where  $B_1$  is an  $S \times r$  matrix and  $B_2$  is an  $(n - s) \times r$  matrix, then

$$AB = (A_1 \quad A_2) \begin{pmatrix} B_1 \\ B_2 \end{pmatrix} = A_1 B_1 + A_2 B_2.$$
s columns
$$(n - s) \text{ columns}$$

In general, if the blocks have the proper dimensions, the block multiplication can be carried out in the same manner as ordinary matrix multiplication. If

$$A = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1t} \\ A_{21} & A_{22} & \cdots & A_{2t} \\ \vdots & \vdots & & \vdots \\ A_{s1} & A_{s2} & \cdots & A_{st} \end{pmatrix}, \qquad B = \begin{pmatrix} B_{11} & B_{12} & \cdots & B_{1r} \\ B_{21} & B_{22} & \cdots & B_{2r} \\ \vdots & \vdots & & \vdots \\ B_{t1} & B_{t2} & \cdots & B_{tr} \end{pmatrix},$$

then

$$AB = \begin{pmatrix} C_{11} & C_{12} & \cdots & C_{1r} \\ C_{21} & C_{22} & \cdots & C_{2r} \\ \vdots & \vdots & & \vdots \\ C_{c1} & C_{c2} & \cdots & C_{cr} \end{pmatrix}, \quad \text{where } C_{ij} = \sum_{k=1}^{t} A_{ik} B_{kj}.$$

**Example 3.** Let 
$$A = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ 3 & 3 & 2 & 2 \end{pmatrix}$$
 and  $B = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ \hline 3 & 1 & 1 & 1 \\ \hline 3 & 2 & 1 & 2 \end{pmatrix}$ .

There are many ways to partition A into blocks and perform block multiplication.

(i) 
$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ 3 & 3 & 2 & 2 \end{pmatrix}$$

Then

$$AB = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ 3 & 3 & 2 & 2 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ \hline 3 & 1 & 1 & 1 \\ \hline 3 & 2 & 1 & 2 \end{pmatrix} = \begin{pmatrix} 8 & 6 & 4 & 5 \\ 10 & 9 & 6 & 7 \\ 18 & 15 & 10 & 12 \end{pmatrix}.$$

#### Example 3. (continue)

(ii) 
$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ \hline 3 & 3 & 2 & 2 \end{pmatrix}$$

$$AB = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ \hline 3 & 3 & 2 & 2 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ \hline 3 & 1 & 1 & 1 \\ \hline 3 & 2 & 1 & 2 \end{pmatrix} = \begin{pmatrix} 8 & 6 & 4 & 5 \\ 10 & 9 & 6 & 7 \\ \hline 18 & 15 & 10 & 12 \end{pmatrix}.$$

**Remark.** Although matrices can be partitioned in different ways, the products of block multiplication are the same.

Review of **matrix multiplication**: 
$$A_{m \times n}$$
,  $B_{n \times r}$ 

(i)  $A = \begin{pmatrix} a(1,:) \\ a(2,:) \\ \vdots \\ a(m,:) \end{pmatrix}$ ,  $B = (\boldsymbol{b}_1, \boldsymbol{b}_2, ..., \boldsymbol{b}_r)$ ,
$$AB = \begin{pmatrix} a(1,:)\boldsymbol{b}_1 & a(1,:)\boldsymbol{b}_2 & \cdots & a(1,:)\boldsymbol{b}_r \\ a(2,:)\boldsymbol{b}_1 & a(2,:)\boldsymbol{b}_2 & \cdots & a(2,:)\boldsymbol{b}_r \\ \vdots & \vdots & \vdots & \vdots \\ a(m,:)\boldsymbol{b}_1 & a(m,:)\boldsymbol{b}_2 & \cdots & a(m,:)\boldsymbol{b}_r \end{pmatrix}$$

(ii)  $A = (\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_r)$ ,  $B = (\boldsymbol{b}_1, \boldsymbol{b}_2, \ldots, \boldsymbol{b}_r)$ ,  $B = (\boldsymbol{b}$ 

$$(ii) A = (\boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_n), B = \begin{pmatrix} \boldsymbol{b}(1, :) \\ \boldsymbol{b}(2, :) \\ \vdots \\ \boldsymbol{b}(n, :) \end{pmatrix},$$

$$AB = a_1b(1,:) + a_2b(2,:) + \cdots + a_nb(n,:)$$

## Quasi Triangular Matrices

**Definition.** (Quasi Triangular Matrices) A partitioned matrix has the form

$$M = \begin{pmatrix} M_{11} & M_{12} & \cdots & M_{1r} \\ O & M_{22} & \cdots & M_{2r} \\ \vdots & \vdots & & \vdots \\ O & O & \cdots & M_{rr} \end{pmatrix}$$

where  $M_{ij}$  (i, j = 1, 2, ..., r) are blocks, called **quasi-upper triangular matrix** [淮上三角矩阵] and a partitioned matrix in the form of

$$M = \begin{pmatrix} M_{11} & O & \cdots & O \\ M_{21} & M_{22} & \cdots & O \\ \vdots & \vdots & & \vdots \\ M_{S1} & M_{S2} & \cdots & M_{SS} \end{pmatrix}$$

is called **quasi-lower triangular matrix** [准下三角矩阵]. Both of them are called **quasi triangular matrix** [准三角矩阵].

We will review the process of solving linear systems in terms of matrix multiplications, rather than row operations. These special matrices which will be used are called elementary matrices.

## **Equivalent Systems**

Recall that two linear systems are equivalent, if they have the same solution set.

Given an  $m \times n$  linear system Ax = b, we can obtain an equivalent system by multiplying both sides of the equation by a nonsingular  $m \times m$  matrix M

$$Ax = b \Leftrightarrow MAx = Mb$$

since these two systems have the same solution set.

## **Equivalent Systems**

To obtain an equivalent system that is easy to solve, we can apply a sequence of nonsingular matrices  $E_1, E_2, ..., E_k$  to both sides of the equation  $A\mathbf{x} = \mathbf{b}$  and obtain

$$Ux = c$$

where  $U = E_k \dots E_2 E_1 A$  and  $\boldsymbol{c} = E_k \dots E_2 E_1 \boldsymbol{b}$ . The new system will be equivalent to the original one provided that  $M = E_k \dots E_2 E_1$  is nonsingular.

**Theorem.** If A and B are nonsingular  $n \times n$  matrices, then AB is nonsingular and  $(AB)^{-1} = B^{-1}A^{-1}$ . Moreover, if  $E_1, E_2, ..., E_k$  are all nonsingular, then the product  $E_1E_2...E_k$  is nonsingular and

$$(E_1 E_2 \dots E_k)^{-1} = E_k^{-1} \dots E_2^{-1} E_1^{-1}.$$

**Type I. Type I** elementary matrices are obtained by interchanging two rows of *I*.

**Example.** 
$$E_1 = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$
 is an elementary matrix of **type I**.

Let A be a  $3 \times 3$  matrix. Then

$$E_{1}A = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} = \begin{pmatrix} a_{21} & a_{22} & a_{23} \\ a_{11} & a_{12} & a_{13} \\ a_{31} & a_{32} & a_{33} \end{pmatrix},$$

$$AE_{1} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} a_{12} & a_{11} & a_{13} \\ a_{22} & a_{21} & a_{23} \\ a_{32} & a_{31} & a_{33} \end{pmatrix}.$$

**Type I. Type I** elementary matrices are obtained by interchanging two rows of *I*.

In general, we can interchange two **rows** of matrix A by multiplying a **type I** elementary matrix E on the **left** side of A.

This corresponds to the **first type** of elementary row operations.

(We can interchange two columns of matrix A by multiplying a **type I** elementary matrix E on the **right** side of A.)

Type II: Type II elementary matrices are obtained by multiplying a row of I by a nonzero constant.

**Example.** 
$$E_2 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$
 is an elementary matrix of **type II**. Then

$$E_{2}A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 3a_{31} & 3a_{32} & 3a_{33} \end{pmatrix},$$

$$AE_2 = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & 3a_{13} \\ a_{21} & a_{22} & 3a_{23} \\ a_{31} & a_{32} & 3a_{33} \end{pmatrix}.$$

**Type II: Type II** elementary matrices are obtained by multiplying a row of *I* by a nonzero constant.

In general, we can multiply a **row** of matrix A by a nonzero constant, by multiplying a **type II** elementary matrix  $E_2$  on the **left** side of matrix A.

This corresponds to the **second type** of elementary row operations.

(We can multiply a **column** of matrix A by a nonzero constant, by multiplying a **type II** elementary matrix  $E_2$  on the **right** side of matrix A.)

**Type III: Type III** elementary matrices are obtained from *I* by adding a multiple of one row to another row.

**Example.** 
$$E_3 = \begin{pmatrix} 1 & 0 & 3 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$
 is an elementary matrix of **type III**. Then

Example. 
$$E_3 = \begin{pmatrix} 1 & 0 & 3 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$
 is an elementary matrix of **type III**. Then
$$E_3 A = \begin{pmatrix} 1 & 0 & 3 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} = \begin{pmatrix} a_{11} + 3a_{31} & a_{12} + 3a_{32} & a_{13} + 3a_{33} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix},$$

$$AE_{3} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} 1 & 0 & 3 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & 3a_{11} + a_{13} \\ a_{21} & a_{22} & 3a_{21} + a_{23} \\ a_{31} & a_{32} & 3a_{31} + a_{33} \end{pmatrix}$$

**Type III: Type III** elementary matrices are obtained from *I* by adding a multiple of one row to another row.

In general, we can add a multiple of one **row** to another **row** of a matrix A by multiplying a **type III** elementary matrix  $E_3$  on the **left** side of A.

This corresponds to the **third type** of elementary row operations.

(We can add a multiple of one **column** to another **column** of a matrix A by multiplying a **type III** elementary matrix  $E_3$  on the **right** side of A.)

In previous examples, we see that each type of these matrices can be associated with one elementary row operations. All row operations are invertible, it is natural to have the following theorem.

Theorem 1. (The Inverse Matrix of Elementary Matrices) Let E be an elementary matrix, then E is nonsingular and  $E^{-1}$  is an elementary matrix of the same type.

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#### Proof.

(1) If *E* is the elementary matrix of type I formed from *I* by interchanging the *i*th and *j*th rows, then *E* can be transformed back into *I* by interchanging the same rows again. Thus

$$EE = I$$

and hence E is its own inverse.

Theorem 1. (The Inverse Matrix of Elementary Matrices) Let E be an elementary matrix, then E is nonsingular and  $E^{-1}$  is an elementary matrix of the same type.

#### Proof.

(2) If  $E_{\alpha}$  is the elementary matrix of type II formed by multiplying the *i*th row of *I* by a nonzero scalar  $\alpha$ , then  $E_{\alpha}$  can be transformed into the identity by multiplying either its *i*th row or *i*th column by  $1/\alpha$ .

Theorem 1. (The Inverse Matrix of Elementary Matrices) Let E be an elementary matrix, then E is nonsingular and  $E^{-1}$  is an elementary matrix of the same type.

#### Proof.

(3) If *E* is the elementary matrix of type III formed by *I* by adding *m* times of the *i*th row to the *j*th row, then *E* can be transformed back into *I* by subtracting *m* times the *i*th row from the *j*th row or by subtracting *m* times the *j*th column from the *i*th column.

**Definition 2.** (Row Equivalent Matrices) Let A and B be two matrices. B is said to be row equivalent [行等价] to A if there exists a finite sequence  $E_1, E_2, ..., E_k$  of elementary matrices such that

$$B = E_k E_{k-1} \dots E_1 A.$$

**Property 1. (Row Equivalent Matrices)** Let A, B, C be matrices, then

- (1) If A is row equivalent to B, then B is row equivalent to A;
- (2) If A is row equivalent to B, and B is row equivalent to C, then A is row equivalent to C.

Theorem 2. (Equivalent Conditions for Nonsingularity) Let A be an  $n \times n$  matrix. The following are equivalent:

- (a) A is nonsingular;
- (b) Ax = 0 has only the trivial solution 0;
- (c) A is row equivalent to I.

**Proof.** (a) $\Rightarrow$ (b). If A is nonsingular and  $\widehat{x}$  is a solution to  $Ax = \mathbf{0}$ , then  $\widehat{x} = I\widehat{x} = (A^{-1}A)\widehat{x} = A^{-1}(A\widehat{x}) = A^{-1}\mathbf{0} = \mathbf{0}$ .

Thus Ax = 0 has only the trivial solution.

Theorem 2. (Equivalent Conditions for Nonsingularity) Let A be an  $n \times n$  matrix. The following are equivalent:

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**Proof.** (b) $\Rightarrow$ (c). By elementary row operations, the system can be transformed into the form Ux = 0, where U is in row echelon form. If one of the diagonal elements of U were 0, the last row of U would consist entirely of 0's. But then Ax = 0 will have infinite nontrivial solutions. Thus U must be a triangular matrix with diagonal elements all equal to 1. Then I is the reduced row echelon form of A.

Theorem 2. (Equivalent Conditions for Nonsingularity) Let A be an  $n \times n$  matrix. The following are equivalent:

- (a) A is nonsingular;
- (b) Ax = 0 has only the trivial solution 0;
- (c) A is row equivalent to I.

**Proof.** (c) $\Rightarrow$ (a). If A is row equivalent to I, there exist elementary matrices  $E_1, E_2, \dots, E_k$  such that

$$A = E_k E_{k-1} \dots E_1 I = E_k E_{k-1} \dots E_1$$

Since  $E_1, E_2 \dots, E_k$  are nonsingular, the product  $E_k E_{k-1} \dots E_k$  is also invertible. Hence A is nonsingular. Finish.

Theorem 2. (Equivalent Conditions for Nonsingularity) Let A be an  $n \times n$  matrix. The following are equivalent:

- (a) A is nonsingular;
- (b) Ax = 0 has only the trivial solution 0;
- (c) A is row equivalent to I.

**Remark.** An  $n \times n$  matrix A is singular if and only if Ax = 0 has nontrivial solutions.

Corollary. The system of n linear equations in n unknowns Ax = b has a unique solution if and only if A is nonsingular.

**Proof.** If A is nonsingular, then  $A^{-1}b$  is the only solution to Ax = b.

Conversely, suppose that Ax = b has a unique solution  $\hat{x}$ . If A is singular, Ax = 0 has a solution  $z \neq 0$  by the Theorem. Let  $y = \hat{x} + z$ . Clearly,  $y \neq \hat{x}$  and  $Ay = A(\hat{x} + z) = A\hat{x} + Az = b + 0 = b$ .

Thus y is also a solution to Ax = b, which is a contradiction.

If A is **nonsingular**, then A is row equivalent to I, so there exist elementary matrices  $E_1, E_2, ..., E_k$  such that

$$E_k E_{k-1} \dots E_1 A = I.$$

Multiplying both sides of this equation on the right by  $A^{-1}$ , we obtain

$$E_k E_{k-1} \dots E_1 I = A^{-1}.$$

Thus the same series of elementary row operations that transform the nonsingular matrix A into I will transform I into  $A^{-1}$ .

This gives us a practical method for computing  $A^{-1}$ .

$$E_k E_{k-1} \dots E_1 A = I.$$

$$E_k E_{k-1} \dots E_1 I = A^{-1}$$
.

If we augment A by I, and perform the elementary row operations that transform A into I on the augmented matrix, then I will be transformed into  $A^{-1}$ .

That is, the reduced row echelon form of the augmented matrix (A|I) will be  $(I|A^{-1})$ .

**Example.** Compute 
$$A^{-1}$$
 for  $A = \begin{pmatrix} 1 & 4 & 3 \\ -1 & -2 & 0 \\ 2 & 2 & 3 \end{pmatrix}$ .

Solution.

$$\begin{pmatrix} 1 & 4 & 3 & 1 & 0 & 0 \\ -1 & -2 & 0 & 0 & 1 & 0 \\ 2 & 2 & 3 & 0 & 0 & 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 4 & 3 & 1 & 0 & 0 \\ 0 & 2 & 3 & 1 & 1 & 0 \\ 0 & -6 & -3 & -2 & 0 & 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 4 & 3 & 1 & 0 & 0 \\ 0 & 2 & 3 & 1 & 1 & 0 \\ 0 & 0 & 6 & 1 & 3 & 1 \end{pmatrix}$$

$$\rightarrow \begin{pmatrix} 1 & 0 & 0 & -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & 2 & 0 & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 0 & 0 & 6 & 1 & 3 & 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 0 & 0 & -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & 1 & 0 & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\ 0 & 0 & 1 & \frac{1}{6} & \frac{1}{2} & \frac{1}{6} \end{pmatrix}.$$

**Example.** Solve the system

$$x_1 + 4x_2 + 3x_3 = 12,$$
  
 $-x_1 - 2x_2 = -12,$   
 $2x_1 + 2x_2 + 3x_3 = 8.$ 

**Solution.** The solution to the system is

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 1 & 4 & 3 \\ -1 & -2 & 0 \\ 2 & 2 & 3 \end{pmatrix}^{-1} \begin{pmatrix} 12 \\ -12 \\ 8 \end{pmatrix} = \begin{pmatrix} -\frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & -\frac{1}{4} & -\frac{1}{4} \\ \frac{1}{6} & \frac{1}{2} & \frac{1}{6} \end{pmatrix} \begin{pmatrix} 12 \\ -12 \\ 8 \end{pmatrix} = \begin{pmatrix} 4 \\ 4 \\ 8 \\ -\frac{8}{3} \end{pmatrix}.$$

#### **LU** Factorization

If an  $n \times n$  matrix A can be reduced to strict upper triangular form using only row operation III, then the reduction process can be represented in terms of a matrix factorization.

**Example.** 
$$A = \begin{pmatrix} 2 & 4 & 2 \\ 1 & 5 & 2 \\ 4 & -1 & 9 \end{pmatrix}$$
. Using only row operation III, the matrix A can be

transformed into 
$$U = \begin{pmatrix} 2 & 4 & 2 \\ 0 & 3 & 1 \\ 0 & 0 & 8 \end{pmatrix}$$
. Unit lower triangular

$$A = LU = \begin{pmatrix} 1 & 0 & 0 \\ \frac{1}{2} & 1 & 0 \\ 2 & -2 & 1 \end{pmatrix} \begin{pmatrix} 2 & 4 & 2 \\ 0 & 3 & 1 \\ 0 & 0 & 8 \end{pmatrix}.$$
 Strict upper triangular strict

Strict upper triangular

#### Review

- Partitioned matrices; block multiplication
- Elementary matrices; representing elementary row operations in terms of matrix multiplication; the method of finding inverse of a matrix

#### Preview

The determinant of a matrix