

# Linear Algebra

Department of Mathematics  
Indian Institute of Technology Guwahati

January – May 2019

MA 102 (RA, RKS, MGPP, KVK)

# System of Linear Equations

## Topics:

- Matrices
- Gaussian elimination
- Row echelon form (ref)
- Gauss-Jordan elimination and reduced row echelon form (rref)
- Rank of a matrix

# Matrices

**Definition:** A **matrix** is an array of numbers called **entries** or **elements** of the matrix. The **size** of a matrix  $A$  is a description of the number of **rows** and **columns** of the matrix  $A$ . An  $m \times n$  **matrix**  $A$  has  $m$  **rows** and  $n$  **columns** and is of the form

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}.$$

# Matrices

**Definition:** A **matrix** is an array of numbers called **entries** or **elements** of the matrix. The **size** of a matrix  $A$  is a description of the number of **rows** and **columns** of the matrix  $A$ . An  $m \times n$  **matrix**  $A$  has  $m$  **rows** and  $n$  **columns** and is of the form

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}.$$

Let  $\mathbf{a}_j := [a_{1j}, \dots, a_{mj}]^\top$  be the  $j$ -th column of  $A$  for  $j = 1 : n$ . Then we represent  $A$  as  $A = \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_n \end{bmatrix}$ .

# Matrices

**Definition:** A **matrix** is an array of numbers called **entries** or **elements** of the matrix. The **size** of a matrix  $A$  is a description of the number of **rows** and **columns** of the matrix  $A$ . An  $m \times n$  **matrix**  $A$  has  **$m$  rows** and  **$n$  columns** and is of the form

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}.$$

Let  $\mathbf{a}_j := [a_{1j}, \dots, a_{mj}]^\top$  be the  $j$ -th column of  $A$  for  $j = 1 : n$ .

Then we represent  $A$  as  $A = \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_n \end{bmatrix}$ .

Let  $\mathbf{A}_i := [a_{i1}, a_{i2}, \dots, a_{in}]$  be the  $i$ -th row of  $A$  for  $i = 1 : m$ . Then

we represent  $A$  as  $A = \begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_m \end{bmatrix}$ .

# Special matrices

Let  $A$  be an  $m \times n$  matrix with  $(i, j)$ -th entry  $a_{ij}$ . Set  $p := \min(m, n)$ . Then

- $a_{ii}$  for  $i = 1 : p$  are called the **diagonal entries** of  $A$ ;
- $A$  is said to be a **diagonal matrix** if  $a_{ij} = 0$  for all  $i \neq j$ ;

# Special matrices

Let  $A$  be an  $m \times n$  matrix with  $(i, j)$ -th entry  $a_{ij}$ . Set  $p := \min(m, n)$ . Then

- $a_{ii}$  for  $i = 1 : p$  are called the **diagonal entries** of  $A$ ;
- $A$  is said to be a **diagonal matrix** if  $a_{ij} = 0$  for all  $i \neq j$ ;
- $A$  is said to be an **upper triangular** if  $a_{ij} = 0$  for all  $i > j$ ;
- $A$  is said to be a **lower triangular** if  $a_{ij} = 0$  for all  $i < j$ ;
- $A$  is said to be a **square matrix** if  $m = n$ .

# Special matrices

Let  $A$  be an  $m \times n$  matrix with  $(i, j)$ -th entry  $a_{ij}$ . Set  $p := \min(m, n)$ . Then

- $a_{ii}$  for  $i = 1 : p$  are called the **diagonal entries** of  $A$ ;
- $A$  is said to be a **diagonal matrix** if  $a_{ij} = 0$  for all  $i \neq j$ ;
- $A$  is said to be an **upper triangular** if  $a_{ij} = 0$  for all  $i > j$ ;
- $A$  is said to be a **lower triangular** if  $a_{ij} = 0$  for all  $i < j$ ;
- $A$  is said to be a **square matrix** if  $m = n$ .

**Identity matrix:** An  $n \times n$  diagonal matrix with all diagonal entries equal to 1 is called the **identity matrix** and is denoted by  $I_n$  or  $I$ .

**Zero matrix:** An  $m \times n$  matrix with all entries 0 is called the **zero matrix** and is denoted by  $\mathbf{O}_{m \times n}$  or simply by  $\mathbf{O}$ .



# Special matrices

Let  $A$  be an  $m \times n$  matrix with  $(i, j)$ -th entry  $a_{ij}$ . Set  $p := \min(m, n)$ . Then

- $a_{ii}$  for  $i = 1 : p$  are called the **diagonal entries** of  $A$ ;
- $A$  is said to be a **diagonal matrix** if  $a_{ij} = 0$  for all  $i \neq j$ ;
- $A$  is said to be an **upper triangular** if  $a_{ij} = 0$  for all  $i > j$ ;
- $A$  is said to be a **lower triangular** if  $a_{ij} = 0$  for all  $i < j$ ;
- $A$  is said to be a **square matrix** if  $m = n$ .

**Identity matrix:** An  $n \times n$  diagonal matrix with all diagonal entries equal to 1 is called the **identity matrix** and is denoted by  $I_n$  or  $I$ .

**Zero matrix:** An  $m \times n$  matrix with all entries 0 is called the **zero matrix** and is denoted by  $\mathbf{O}_{m \times n}$  or simply by  $\mathbf{O}$ .

# Linear combination

Let  $\mathbf{u}$  and  $\mathbf{v}$  be vectors in  $\mathbb{R}^n$ . Let  $\alpha$  and  $\beta$  be scalars. Adding  $\alpha\mathbf{u}$  and  $\beta\mathbf{v}$  gives the **linear combination**  $\alpha\mathbf{u} + \beta\mathbf{v}$ .

**Example:** Let  $\mathbf{u} := [1, 1, -1]^\top$ ,  $\mathbf{v} := [2, 3, 4]^\top$  and  $\mathbf{w} := [4, 5, 2]^\top$ . Then  $\mathbf{w} = 2\mathbf{u} + \mathbf{v}$ . Thus  $\mathbf{w}$  is a **linear combination** of  $\mathbf{u}$  and  $\mathbf{v}$ .

# Linear combination

Let  $\mathbf{u}$  and  $\mathbf{v}$  be vectors in  $\mathbb{R}^n$ . Let  $\alpha$  and  $\beta$  be scalars. Adding  $\alpha\mathbf{u}$  and  $\beta\mathbf{v}$  gives the **linear combination**  $\alpha\mathbf{u} + \beta\mathbf{v}$ .

**Example:** Let  $\mathbf{u} := [1, 1, -1]^\top$ ,  $\mathbf{v} := [2, 3, 4]^\top$  and  $\mathbf{w} := [4, 5, 2]^\top$ . Then  $\mathbf{w} = 2\mathbf{u} + \mathbf{v}$ . Thus  $\mathbf{w}$  is a **linear combination** of  $\mathbf{u}$  and  $\mathbf{v}$ .

**Definition:** Let  $\mathbf{v}_1, \dots, \mathbf{v}_m$  be vectors in  $\mathbb{R}^n$  and let  $\alpha_1, \dots, \alpha_m$  be scalars. Then the vector  $\mathbf{u} := \alpha_1\mathbf{v}_1 + \dots + \alpha_m\mathbf{v}_m$  is called a **linear combination** of  $\mathbf{v}_1, \dots, \mathbf{v}_m$ .

# Linear combination

Let  $\mathbf{u}$  and  $\mathbf{v}$  be vectors in  $\mathbb{R}^n$ . Let  $\alpha$  and  $\beta$  be scalars. Adding  $\alpha\mathbf{u}$  and  $\beta\mathbf{v}$  gives the **linear combination**  $\alpha\mathbf{u} + \beta\mathbf{v}$ .

**Example:** Let  $\mathbf{u} := [1, 1, -1]^\top$ ,  $\mathbf{v} := [2, 3, 4]^\top$  and  $\mathbf{w} := [4, 5, 2]^\top$ . Then  $\mathbf{w} = 2\mathbf{u} + \mathbf{v}$ . Thus  $\mathbf{w}$  is a **linear combination** of  $\mathbf{u}$  and  $\mathbf{v}$ .

**Definition:** Let  $\mathbf{v}_1, \dots, \mathbf{v}_m$  be vectors in  $\mathbb{R}^n$  and let  $\alpha_1, \dots, \alpha_m$  be scalars. Then the vector  $\mathbf{u} := \alpha_1\mathbf{v}_1 + \dots + \alpha_m\mathbf{v}_m$  is called a **linear combination** of  $\mathbf{v}_1, \dots, \mathbf{v}_m$ .

**Problem:** Let  $\mathbf{a}_1, \dots, \mathbf{a}_n$  and  $\mathbf{b}$  be vectors in  $\mathbb{R}^m$ . Find scalars  $x_1, \dots, x_n$ , if exist, such that  $x_1\mathbf{a}_1 + \dots + x_n\mathbf{a}_n = \mathbf{b}$ .

**Example:** Vector equation

$$x_1 \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} + x_3 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix}.$$

## Matrix times vector

We rewrite the linear combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$  using a matrix. Set  $A := [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n]$  and  $\mathbf{x} := [x_1, \dots, x_n]^\top$ . We define the **matrix  $A$  times the vector  $\mathbf{x}$**  to be the same as the combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$ .

## Matrix times vector

We rewrite the linear combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$  using a matrix. Set  $A := [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n]$  and  $\mathbf{x} := [x_1, \dots, x_n]^\top$ . We define the **matrix  $A$  times the vector  $\mathbf{x}$**  to be the same as the combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$ .

**Definition:** Matrix-vector multiplication

$$A\mathbf{x} = [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n] \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n.$$

The matrix  $A$  **acts** on the vector  $\mathbf{x}$  and the result  $A\mathbf{x}$  is a linear combination of the columns of  $A$ .

## Matrix times vector

We rewrite the linear combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$  using a matrix. Set  $A := [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n]$  and  $\mathbf{x} := [x_1, \dots, x_n]^\top$ . We define the **matrix  $A$  times the vector  $\mathbf{x}$**  to be the same as the combination  $x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n$ .

**Definition:** Matrix-vector multiplication

$$A\mathbf{x} = [\mathbf{a}_1 \ \cdots \ \mathbf{a}_n] \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n.$$

The matrix  $A$  **acts** on the vector  $\mathbf{x}$  and the result  $A\mathbf{x}$  is a linear combination of the columns of  $A$ .

**Example:** Compact notation for vector equation

$$\begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} + x_3 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix}.$$

## Matrix times vector

A row vector  $\begin{bmatrix} a_{i1} & \cdots & a_{in} \end{bmatrix}$  is a  $1 \times n$  matrix. Therefore

$$\begin{bmatrix} a_{i1} & \cdots & a_{in} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = a_{i1}x_1 + \cdots + a_{in}x_n.$$



## Matrix times vector

A row vector  $\begin{bmatrix} a_{i1} & \cdots & a_{in} \end{bmatrix}$  is a  $1 \times n$  matrix. Therefore

$$\begin{bmatrix} a_{i1} & \cdots & a_{in} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = a_{i1}x_1 + \cdots + a_{in}x_n.$$

**Example:** Matrix-vector multiplication in two ways

$$\begin{aligned} \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} &= x_1 \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} + x_3 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\ &= \begin{bmatrix} x_1 \\ x_1 + x_2 \\ x_2 + x_3 \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \mathbf{x} \\ \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \mathbf{x} \\ \begin{bmatrix} 0 & 1 & 1 \end{bmatrix} \mathbf{x} \end{bmatrix} \end{aligned}$$

# Matrix-vector multiplication

More generally

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \cdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x_1 \begin{bmatrix} a_{11} \\ \vdots \\ a_{m1} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ \vdots \\ a_{mn} \end{bmatrix}$$
$$= \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n \\ \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n \end{bmatrix} = \begin{bmatrix} [a_{11} \ \cdots \ a_{1n}] \mathbf{x} \\ \vdots \\ [a_{m1} \ \cdots \ a_{mn}] \mathbf{x} \end{bmatrix}.$$

# Matrix-vector multiplication

More generally

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \cdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x_1 \begin{bmatrix} a_{11} \\ \vdots \\ a_{m1} \end{bmatrix} + \cdots + x_n \begin{bmatrix} a_{1n} \\ \vdots \\ a_{mn} \end{bmatrix} \\ = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n \\ \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} a_{11} & \cdots & a_{1n} \end{bmatrix} \mathbf{x} \\ \vdots \\ \begin{bmatrix} a_{m1} & \cdots & a_{mn} \end{bmatrix} \mathbf{x} \end{bmatrix}.$$

Now represent  $A := \begin{bmatrix} \mathbf{a}_1 & \cdots & \mathbf{a}_n \end{bmatrix}$  by its rows:  $A = \begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_m \end{bmatrix}$ .

Then we have

$$\mathbf{A}\mathbf{x} = x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n \\ \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n \end{bmatrix} = \begin{bmatrix} \mathbf{A}_1\mathbf{x} \\ \vdots \\ \mathbf{A}_m\mathbf{x} \end{bmatrix}.$$

# Linear equations

**Definition:** A **linear equation** in the  $n$  variables  $x_1, \dots, x_n$  is an equation of the form

$$a_1x_1 + \cdots + a_nx_n = b \quad (1)$$

where the **coefficients**  $a_1, \dots, a_n$  and the **constant term**  $b$  are constants.

# Linear equations

**Definition:** A **linear equation** in the  $n$  variables  $x_1, \dots, x_n$  is an equation of the form

$$a_1x_1 + \cdots + a_nx_n = b \quad (1)$$

where the **coefficients**  $a_1, \dots, a_n$  and the **constant term**  $b$  are constants.

The equation (1) can be rewritten as

$$\begin{bmatrix} a_1 & \cdots & a_n \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = b. \quad (2)$$

# Linear equations

**Definition:** A **linear equation** in the  $n$  variables  $x_1, \dots, x_n$  is an equation of the form

$$a_1x_1 + \dots + a_nx_n = b \quad (1)$$

where the **coefficients**  $a_1, \dots, a_n$  and the **constant term**  $b$  are constants.

The equation (1) can be rewritten as

$$\begin{bmatrix} a_1 & \dots & a_n \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = b. \quad (2)$$

A vector  $\mathbf{s} := [s_1, \dots, s_n]^\top$  is said to be a **solution** of the linear equation (1) if it satisfies the equation (2).

# System of linear equations

An  $m \times n$  **system of linear equations** is a set of  $m$  equations in the  $n$  variables  $x_1, \dots, x_n$  of the form

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ & \vdots & \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array} \quad (3)$$

where  $a_{ij}$  and  $b_i$  are constants for  $i = 1 : m$  and  $j = 1 : n$ .

# System of linear equations

An  $m \times n$  **system of linear equations** is a set of  $m$  equations in the  $n$  variables  $x_1, \dots, x_n$  of the form

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array} \quad (3)$$

where  $a_{ij}$  and  $b_i$  are constants for  $i = 1 : m$  and  $j = 1 : n$ .  
The system of equations in (3) can be rewritten as matrix equation

$$A\mathbf{x} = \mathbf{b} \quad \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (4)$$

where  $A$  is called the **coefficient matrix** and  $\mathbf{b}$  is called the **constant vector**.



# System of linear equations

An  $m \times n$  **system of linear equations** is a set of  $m$  equations in the  $n$  variables  $x_1, \dots, x_n$  of the form

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array} \quad (3)$$

where  $a_{ij}$  and  $b_i$  are constants for  $i = 1 : m$  and  $j = 1 : n$ .  
The system of equations in (3) can be rewritten as matrix equation

$$\mathbf{Ax} = \mathbf{b} \quad \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (4)$$

where  $A$  is called the **coefficient matrix** and  $\mathbf{b}$  is called the **constant vector**. A vector  $\mathbf{s} := [s_1, \dots, s_n]^\top$  is said to be a **solution** of (3) if it satisfies (4).

# System of linear equations

An  $m \times n$  **system of linear equations** is a set of  $m$  equations in the  $n$  variables  $x_1, \dots, x_n$  of the form

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array} \quad (3)$$

where  $a_{ij}$  and  $b_i$  are constants for  $i = 1 : m$  and  $j = 1 : n$ .  
The system of equations in (3) can be rewritten as matrix equation

$$\mathbf{Ax} = \mathbf{b} \quad \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (4)$$

where  $A$  is called the **coefficient matrix** and  $\mathbf{b}$  is called the **constant vector**. A vector  $\mathbf{s} := [s_1, \dots, s_n]^T$  is said to be a **solution** of (3) if it satisfies (4). We refer to  $\mathbf{Ax} = \mathbf{b}$  as a **linear system**.

## Augmented system

The system of equations in (3) can also be rewritten as a vector equation

$$x_1 \begin{bmatrix} a_{11} \\ \vdots \\ a_{m1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{1n} \\ \vdots \\ a_{mn} \end{bmatrix} x_n - \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} = \mathbf{0} \quad (5)$$

which shows that solving the system amounts to expressing  $\mathbf{b}$  as a **linear combination** of the columns of  $A$ . Rewriting (5) as a matrix equation yields the **augmented system**

## Augmented system

The system of equations in (3) can also be rewritten as a vector equation

$$x_1 \begin{bmatrix} a_{11} \\ \vdots \\ a_{m1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{1n} \\ \vdots \\ a_{mn} \end{bmatrix} x_n - \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} = \mathbf{0} \quad (5)$$

which shows that solving the system amounts to expressing  $\mathbf{b}$  as a **linear combination** of the columns of  $A$ . Rewriting (5) as a matrix equation yields the **augmented system**

$$\underbrace{\begin{bmatrix} a_{11} & \cdots & a_{1n} & | & b_1 \\ \vdots & \vdots & \vdots & & \vdots \\ a_{m1} & \cdots & a_{mn} & | & b_m \end{bmatrix}}_{\text{augmented matrix}} \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

where  $[A \mid \mathbf{b}]$  is called the **augmented matrix**.

## Augmented system

Note that  $\mathbf{x} := [x_1, \dots, x_n]^\top$  is a solution of

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array}$$

if and only if  $\mathbf{x}$  satisfies the **augmented system**

$$\left[ \begin{array}{ccc|c} a_{11} & \cdots & a_{1n} & b_1 \\ \vdots & \vdots & \vdots & \\ a_{m1} & \cdots & a_{mn} & b_m \end{array} \right] \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

## Augmented system

Note that  $\mathbf{x} := [x_1, \dots, x_n]^\top$  is a solution of

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array}$$

if and only if  $\mathbf{x}$  satisfies the **augmented system**

$$\left[ \begin{array}{ccc|c} a_{11} & \cdots & a_{1n} & b_1 \\ \vdots & \vdots & \vdots & \\ a_{m1} & \cdots & a_{mn} & b_m \end{array} \right] \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

**Strategy:** We solve the augmented system by reducing the augmented matrix  $[A \mid \mathbf{b}]$  to **row echelon form**.

## Augmented system

Note that  $\mathbf{x} := [x_1, \dots, x_n]^\top$  is a solution of

$$\begin{array}{rcl} a_{11}x_1 + \cdots + a_{1n}x_n & = & b_1 \\ \vdots & & \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n & = & b_m \end{array}$$

if and only if  $\mathbf{x}$  satisfies the **augmented system**

$$\left[ \begin{array}{ccc|c} a_{11} & \cdots & a_{1n} & b_1 \\ \vdots & \vdots & \vdots & \\ a_{m1} & \cdots & a_{mn} & b_m \end{array} \right] \begin{bmatrix} x_1 \\ \vdots \\ x_n \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

**Strategy:** We solve the augmented system by reducing the augmented matrix  $[A \mid \mathbf{b}]$  to **row echelon form**.

**Remark:** There are **two matrices** associated with a linear system  $A\mathbf{x} = \mathbf{b}$ , namely, the **coefficient matrix**  $A$  and the **augmented matrix**  $[A \mid \mathbf{b}]$ .

# Equivalent systems

**Definition:** Two linear systems  $A\mathbf{x} = \mathbf{b}$  and  $U\mathbf{y} = \mathbf{d}$  are said to be **equivalent** if they have the **same solution**, where the matrices  $A$  and  $U$  have the same size.



# Equivalent systems

**Definition:** Two linear systems  $A\mathbf{x} = \mathbf{b}$  and  $U\mathbf{y} = \mathbf{d}$  are said to be **equivalent** if they have the **same solution**, where the matrices  $A$  and  $U$  have the same size.

**Strategy:** **Transform** a given linear system to an **equivalent linear system** that is easier to solve.

# Equivalent systems

**Definition:** Two linear systems  $Ax = b$  and  $Uy = d$  are said to be **equivalent** if they have the **same solution**, where the matrices  $A$  and  $U$  have the same size.

**Strategy:** **Transform** a given linear system to an **equivalent linear system that is easier to solve**.

**Example:** Gaussian (forward) elimination

$$\begin{array}{rcl} x - y - z & = & 2 \\ 3x - 3y + 2z & = & 16 \\ 2x - y + z & = & 9 \end{array} \iff \underbrace{\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 3 & -3 & 2 & 16 \\ 2 & -1 & 1 & 9 \end{array} \right]}_{\text{augmented matrix}}$$

## Equivalent systems

**Definition:** Two linear systems  $Ax = b$  and  $Uy = d$  are said to be **equivalent** if they have the **same solution**, where the matrices  $A$  and  $U$  have the same size.

**Strategy:** **Transform** a given linear system to an **equivalent linear system that is easier to solve**.

**Example:** Gaussian (forward) elimination

$$\begin{array}{rcl} x - y - z & = & 2 \\ 3x - 3y + 2z & = & 16 \\ 2x - y + z & = & 9 \end{array} \iff \underbrace{\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 3 & -3 & 2 & 16 \\ 2 & -1 & 1 & 9 \end{array} \right]}_{\text{augmented matrix}}$$

Use first equation to eliminating  $x$  from 2nd and 3rd equation

$$\begin{array}{rcl} x - y - z & = & 2 \\ 5z & = & 10 \\ y + 3z & = & 5 \end{array} \iff \left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 0 & 5 & 10 \\ 0 & 1 & 3 & 5 \end{array} \right].$$

## Example (cont.)

Now interchange 2nd and 3rd equations

$$\begin{array}{rcl} x - y - z & = & 2 \\ y + 3z & = & 5 \\ 5z & = & 10 \end{array} \iff \left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 1 & 3 & 5 \\ 0 & 0 & 5 & 10 \end{array} \right].$$

Solving equivalent **upper triangular system** (back substitution), we have the solution  $[x, y, z]^T = [3, -1, 2]^T$ .

## Example (cont.)

Now interchange 2nd and 3rd equations

$$\begin{array}{rcl} x - y - z & = & 2 \\ y + 3z & = & 5 \\ 5z & = & 10 \end{array} \iff \left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 1 & 3 & 5 \\ 0 & 0 & 5 & 10 \end{array} \right].$$

Solving equivalent **upper triangular system** (back substitution), we have the solution  $[x, y, z]^T = [3, -1, 2]^T$ .

**Observation:** Elementary operations (**scalar multiplication, addition, interchange**) on equations correspond to **elementary row operations** on the augmented matrix.

## Row echelon form (ref)

**Pivot:** First nonzero entry in a row is called a **pivot** (leading entry).

**Pivot column:** A column containing a pivot (leading entry) is called a **pivot column**.

## Row echelon form (ref)

**Pivot:** First nonzero entry in a row is called a **pivot** (leading entry).

**Pivot column:** A column containing a pivot (leading entry) is called a **pivot column**.

**Definition:** An  $m \times n$  matrix  $A$  is in **row echelon form** provided:

## Row echelon form (ref)

**Pivot:** First nonzero entry in a row is called a **pivot** (leading entry).

**Pivot column:** A column containing a pivot (leading entry) is called a **pivot column**.

**Definition:** An  $m \times n$  matrix  $A$  is in **row echelon form** provided:

- All zero rows appear at the bottom.



# Row echelon form (ref)

**Pivot:** First nonzero entry in a row is called a **pivot** (leading entry).

**Pivot column:** A column containing a pivot (leading entry) is called a **pivot column**.

**Definition:** An  $m \times n$  matrix  $A$  is in **row echelon form** provided:

- All zero rows appear at the bottom.
- The **pivot** (leading entry) in a row is always to the right of the pivot of the row above it.

**Notation:**  $\text{ref}(A)$  = row echelon form of  $A$ .

**Remark:** Row echelon form of a matrix is not unique.

# Row echelon form (ref)

**Pivot:** First nonzero entry in a row is called a **pivot** (leading entry).

**Pivot column:** A column containing a pivot (leading entry) is called a **pivot column**.

**Definition:** An  $m \times n$  matrix  $A$  is in **row echelon form** provided:

- All zero rows appear at the bottom.
- The **pivot** (leading entry) in a row is always to the right of the pivot of the row above it.

**Notation:**  $\text{ref}(A)$  = row echelon form of  $A$ .

**Remark:** Row echelon form of a matrix is not unique.

**Convention:** We refer to **row echelon form** simply by **echelon form**.

# Examples

## Matrices in echelon form:

$$\begin{bmatrix} p & * & * & * & * & * & * & * \\ 0 & 0 & p & * & * & * & * & * \\ 0 & 0 & 0 & p & * & * & * & * \\ 0 & 0 & 0 & 0 & 0 & 0 & p & * \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} p & * & * & * & * \\ 0 & 0 & p & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} p & * & * \\ 0 & p & * \\ 0 & 0 & p \end{bmatrix}.$$

Here  $p$  stands for **pivot** and  $*$  stands for arbitrary (zero or nonzero) entry.

## Matrices not in echelon form:

$$\begin{bmatrix} 2 & 3 & 4 & 2 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 2 \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 2 \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 2 \\ 0 & 2 & 3 \\ 0 & 0 & 0 \end{bmatrix}.$$

# Elementary row operations

- Multiply a row by nonzero scalar:  $\text{row}_i(A) \longrightarrow \alpha \text{row}_i(A)$ .
- Add a row with another row:  $\text{row}_i(A) + \text{row}_j(A) \longrightarrow \text{row}_j(A)$ .
- Interchange rows:  $\text{row}_i(A) \leftrightarrow \text{row}_j(A)$

**Exercise:** Describe the inverse operations.

# Elementary row operations

- Multiply a row by nonzero scalar:  $\text{row}_i(A) \longrightarrow \alpha \text{row}_i(A)$ .
- Add a row with another row:  $\text{row}_i(A) + \text{row}_j(A) \longrightarrow \text{row}_j(A)$ .
- Interchange rows:  $\text{row}_i(A) \leftrightarrow \text{row}_j(A)$

**Exercise:** Describe the inverse operations.

The process of applying elementary row operations to reduce a matrix to row echelon form is called row reduction.

**Definition:** Matrices  $A$  and  $B$  are said to be row equivalent if there is a sequence of elementary row operations that converts  $A$  into  $B$ .

# Elementary row operations

- Multiply a row by nonzero scalar:  $\text{row}_i(A) \longrightarrow \alpha \text{row}_i(A)$ .
- Add a row with another row:  $\text{row}_i(A) + \text{row}_j(A) \longrightarrow \text{row}_j(A)$ .
- Interchange rows:  $\text{row}_i(A) \leftrightarrow \text{row}_j(A)$

**Exercise:** Describe the inverse operations.

The process of applying elementary row operations to reduce a matrix to row echelon form is called row reduction.

**Definition:** Matrices  $A$  and  $B$  are said to be row equivalent if there is a sequence of elementary row operations that converts  $A$  into  $B$ .

**Example:** The augmented matrices (from the previous example)

$$\left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 3 & -3 & 2 & 16 \\ 2 & -1 & 1 & 9 \end{array} \right] \quad \text{and} \quad \left[ \begin{array}{ccc|c} 1 & -1 & -1 & 2 \\ 0 & 1 & 3 & 5 \\ 0 & 0 & 5 & 10 \end{array} \right]$$

are row equivalent.

## Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

## Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

- 1 **Search the first column** of  $A$  to find a **nonzero entry** and interchange rows to bring the **nonzero entry** to **(1, 1) position**. Use (1, 1) entry as the **pivot** and perform elementary row operations to introduce **zeros** in the **first column below the (1, 1) entry**.



# Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

- 1 Search the first column of  $A$  to find a **nonzero entry** and interchange rows to bring the **nonzero entry** to **(1, 1) position**. Use (1, 1) entry as the **pivot** and perform elementary row operations to introduce **zeros** in the **first column below the (1, 1) entry**. The **reduced matrix** would be of the form

$$\left[ \begin{array}{c|ccc} p_{11} & p_{12} & \cdots & p_{1n} \\ \hline 0 & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & p_{m2} & \cdots & p_{mn} \end{array} \right]$$

## Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

- 1 Search the **first column** of  $A$  to find a **nonzero entry** and interchange rows to bring the **nonzero entry** to **(1, 1) position**. Use (1, 1) entry as the **pivot** and perform elementary row operations to introduce **zeros** in the **first column below the (1, 1) entry**. The **reduced matrix** would be of the form

$$\left[ \begin{array}{c|ccc} p_{11} & p_{12} & \cdots & p_{1n} \\ \hline 0 & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & p_{m2} & \cdots & p_{mn} \end{array} \right]$$

- 2 Repeat step 1 to the  $(m - 1) \times (n - 1)$  submatrix **until the matrix is reduced to upper triangular form**.

## Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

- 1 Search the **first column** of  $A$  to find a **nonzero entry** and interchange rows to bring the **nonzero entry** to **(1, 1) position**. Use (1, 1) entry as the **pivot** and perform elementary row operations to introduce **zeros** in the **first column below the (1, 1) entry**. The **reduced matrix** would be of the form

$$\left[ \begin{array}{c|ccc} p_{11} & p_{12} & \cdots & p_{1n} \\ \hline 0 & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & p_{m2} & \cdots & p_{mn} \end{array} \right]$$

- 2 Repeat step 1 to the  $(m - 1) \times (n - 1)$  submatrix **until the matrix is reduced to upper triangular form**.

**Echelon form:** Use further row operations, if necessary, to reduce the upper triangular matrix to echelon form.

## Reduction to echelon form

**Gaussian elimination (GE):** Use elementary row operations to reduce a matrix to **upper triangular form** by introducing **zeros below the diagonals**. Here is an algorithm (**forward GE**).

- 1 Search the **first column** of  $A$  to find a **nonzero entry** and interchange rows to bring the **nonzero entry** to **(1, 1) position**. Use (1, 1) entry as the **pivot** and perform elementary row operations to introduce **zeros** in the **first column below the (1, 1) entry**. The **reduced matrix** would be of the form

$$\left[ \begin{array}{c|ccc} p_{11} & p_{12} & \cdots & p_{1n} \\ \hline 0 & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & p_{m2} & \cdots & p_{mn} \end{array} \right]$$

- 2 Repeat step 1 to the  $(m - 1) \times (n - 1)$  submatrix **until the matrix is reduced to upper triangular form**.

**Echelon form:** Use further row operations, if necessary, to reduce the upper triangular matrix to echelon form.

## Example 1

**Square system:** 
$$\begin{bmatrix} 2 & 1 & 1 \\ -1 & 2 & 0 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \\ -2 \end{bmatrix}$$

Forward elimination (**Forward GE**)  $\longrightarrow$  Upper triangular form:

$$\left[ \begin{array}{ccc|c} 2 & 1 & 1 & 2 \\ -1 & 2 & 0 & 1 \\ 1 & -1 & 2 & -2 \end{array} \right] \xrightarrow{R_3 \leftrightarrow R_1} \left[ \begin{array}{ccc|c} 1 & -1 & 2 & -2 \\ -1 & 2 & 0 & 1 \\ 2 & 1 & 1 & 2 \end{array} \right]$$

## Example 1

**Square system:** 
$$\begin{bmatrix} 2 & 1 & 1 \\ -1 & 2 & 0 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \\ -2 \end{bmatrix}$$

Forward elimination (**Forward GE**)  $\longrightarrow$  Upper triangular form:

$$\left[ \begin{array}{ccc|c} 2 & 1 & 1 & 2 \\ -1 & 2 & 0 & 1 \\ 1 & -1 & 2 & -2 \end{array} \right] \xrightarrow{R_3 \leftrightarrow R_1} \left[ \begin{array}{ccc|c} 1 & -1 & 2 & -2 \\ -1 & 2 & 0 & 1 \\ 2 & 1 & 1 & 2 \end{array} \right]$$

$$\xrightarrow{\substack{R_3 = R_3 - 2R_1 \\ R_2 = R_1 + R_2}} \left[ \begin{array}{ccc|c} 1 & -1 & 2 & -2 \\ 0 & 1 & 2 & -1 \\ 0 & 3 & -3 & 6 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & -1 & 2 & -2 \\ 0 & 1 & 2 & -1 \\ 0 & 0 & -9 & 9 \end{array} \right]$$

**Back substitution:**  $x_3 = -1$ ,  $x_2 = 1$  and  $x_1 = 1$ .

## Example 2

**Square System:** 
$$\begin{bmatrix} 0 & 1 & 5 \\ 1 & 4 & 3 \\ 2 & 7 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -4 \\ -2 \\ -1 \end{bmatrix}$$

Forward GE:

$$\left[ \begin{array}{ccc|c} 0 & 1 & 5 & -4 \\ 1 & 4 & 3 & -2 \\ 2 & 7 & 1 & -1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 4 & 3 & -2 \\ 0 & 1 & 5 & -4 \\ 2 & 7 & 1 & -1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 4 & 3 & -2 \\ 0 & 1 & 5 & -4 \\ 0 & -1 & -5 & 3 \end{array} \right]$$

## Example 2

**Square System:** 
$$\begin{bmatrix} 0 & 1 & 5 \\ 1 & 4 & 3 \\ 2 & 7 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -4 \\ -2 \\ -1 \end{bmatrix}$$

Forward GE:

$$\left[ \begin{array}{ccc|c} 0 & 1 & 5 & -4 \\ 1 & 4 & 3 & -2 \\ 2 & 7 & 1 & -1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 4 & 3 & -2 \\ 0 & 1 & 5 & -4 \\ 2 & 7 & 1 & -1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 4 & 3 & -2 \\ 0 & 1 & 5 & -4 \\ 0 & -1 & -5 & 3 \end{array} \right]$$

$$\rightarrow \left[ \begin{array}{ccc|c} 1 & 4 & 3 & -2 \\ 0 & 1 & 5 & -4 \\ 0 & 0 & 0 & -1 \end{array} \right] \Rightarrow \text{No solution}$$



## Example 3

**Nonsquare system:** 
$$\begin{bmatrix} 2 & 1 & 1 \\ 1 & -1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$$

Forward GE:

$$\begin{bmatrix} 2 & 1 & 1 & | & 2 \\ 1 & -1 & 2 & | & -2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 2 & | & -2 \\ 2 & 1 & 1 & | & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 2 & | & -2 \\ 0 & 3 & -3 & | & 6 \end{bmatrix}$$
$$\rightarrow \begin{bmatrix} 1 & -1 & 2 & | & -2 \\ 0 & 1 & -1 & | & 2 \end{bmatrix}$$

**Back substitution:**  $x_3 = t$ ,  $x_2 = 2 + t$  and  $x_1 = -t$  for  $t \in \mathbb{R}$ .

## Echelon form and consistency

**Definition:** A linear system  $A\mathbf{x} = \mathbf{b}$  is said to be **consistent** if it has a solution. A system is **inconsistent** if it is NOT consistent.

## Echelon form and consistency

**Definition:** A linear system  $A\mathbf{x} = \mathbf{b}$  is said to be **consistent** if it has a solution. A system is **inconsistent** if it is NOT consistent.

**Theorem:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$  is consistent  $\iff$  the last column of  $\text{ref}([A \mid \mathbf{b}])$  is not a pivot column.

**Proof:** If the last column is a pivot column then all the entries in the pivot row are zero except the last entry. ■

## Echelon form and consistency

**Definition:** A linear system  $A\mathbf{x} = \mathbf{b}$  is said to be **consistent** if it has a solution. A system is **inconsistent** if it is NOT consistent.

**Theorem:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$  is consistent  $\iff$  the last column of  $\text{ref}([A \mid \mathbf{b}])$  is not a pivot column.

**Proof:** If the last column is a pivot column then all the entries in the pivot row are zero except the last entry. ■

**Example:** Consider the augmented matrix

$$\begin{bmatrix} 0 & 1 & 5 & | & -4 \\ 1 & 4 & 3 & | & -2 \\ 2 & 7 & 1 & | & -1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 4 & 3 & | & -2 \\ 0 & 1 & 5 & | & -4 \\ 2 & 7 & 1 & | & -1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 4 & 3 & | & -2 \\ 0 & 1 & 5 & | & -4 \\ 0 & -1 & -5 & | & 3 \end{bmatrix}$$
$$\rightarrow \begin{bmatrix} 1 & 4 & 3 & | & -2 \\ 0 & 1 & 5 & | & -4 \\ 0 & 0 & 0 & | & -1 \end{bmatrix} = \text{echelon form} \Rightarrow \text{inconsistent}$$

## Reduced row echelon form (rref)

An  $m \times n$  matrix  $A$  is in **reduced row echelon form** provided:

## Reduced row echelon form (rref)

An  $m \times n$  matrix  $A$  is in **reduced row echelon form** provided:

- $A$  is in row echelon form.
- Each pivot (leading entry) in  $A$  is 1.
- Pivot is the only nonzero entry in a pivot column.

**Notation:**  $\text{rref}(A)$  = reduced row echelon form of  $A$ .

## Reduced row echelon form (rref)

An  $m \times n$  matrix  $A$  is in **reduced row echelon form** provided:

- $A$  is in row echelon form.
- Each pivot (leading entry) in  $A$  is 1.
- Pivot is the only nonzero entry in a pivot column.

**Notation:**  $\text{rref}(A)$  = reduced row echelon form of  $A$ .

**Matrices in echelon form:**

$$\begin{bmatrix} 1 & * & 0 & 0 & * & * & 0 & * \\ 0 & 0 & 1 & 0 & * & * & 0 & * \\ 0 & 0 & 0 & 1 & * & * & 0 & * \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & * \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & * & 0 & * & * \\ 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

# Gauss-Jordan elimination and reduction to rref

Step 1: Forward GE :  $m \times n$  matrix  $A \longrightarrow \text{ref}(A)$ .

Step 2: Backward GE:  $\text{ref}(A) \longrightarrow \text{rref}(A)$ .



# Gauss-Jordan elimination and reduction to rref

Step 1: Forward GE :  $m \times n$  matrix  $A \longrightarrow \text{ref}(A)$ .

Step 2: Backward GE:  $\text{ref}(A) \longrightarrow \text{rref}(A)$ .

Backward GE: Start GE from the bottom nonzero row to the top rows and use the pivot in each pivot column for elimination until the matrix is reduced to  $\text{rref}(A)$ .

# Gauss-Jordan elimination and reduction to rref

**Step 1:** Forward GE :  $m \times n$  matrix  $A \longrightarrow \text{ref}(A)$ .

**Step 2:** Backward GE:  $\text{ref}(A) \longrightarrow \text{rref}(A)$ .

**Backward GE:** Start GE from the bottom nonzero row to the top rows and use the pivot in each pivot column for elimination until the matrix is reduced to  $\text{rref}(A)$ .

**Example (backward GE):**

$$\begin{bmatrix} p & * & * & * & * \\ 0 & 0 & p & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} p & * & 0 & * & * \\ 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & * & 0 & * & * \\ 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

# Gauss-Jordan elimination and reduction to rref

**Step 1:** Forward GE :  $m \times n$  matrix  $A \longrightarrow \text{ref}(A)$ .

**Step 2:** Backward GE:  $\text{ref}(A) \longrightarrow \text{rref}(A)$ .

**Backward GE:** Start GE from the bottom nonzero row to the top rows and use the pivot in each pivot column for elimination until the matrix is reduced to  $\text{rref}(A)$ .

**Example (backward GE):**

$$\begin{bmatrix} p & * & * & * & * \\ 0 & 0 & p & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} p & * & 0 & * & * \\ 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & * & 0 & * & * \\ 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

**Gauss-Jordan elimination = Forward GE followed by backward GE.**

**Gauss-Jordan elimination:**  $m \times n$  matrix  $A \longrightarrow \text{rref}(A)$ .

**Theorem:** Reduced row echelon form of an  $m \times n$  matrix  $A$  is **unique**. (to be proved later).

## Example: Gauss-Jordan elimination

Forward GE:  $A \rightarrow \text{ref}(A)$

$$\begin{bmatrix} 0 & 3 & -6 & 6 & 4 & -5 \\ 3 & -7 & 8 & -5 & 8 & 9 \\ 3 & -9 & 12 & -9 & 6 & 15 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -3 & 4 & -3 & 2 & 5 \\ 0 & 1 & -2 & 2 & 1 & -3 \\ 0 & 0 & 0 & 0 & 1 & 4 \end{bmatrix}$$

## Example: Gauss-Jordan elimination

Forward GE:  $A \rightarrow \text{ref}(A)$

$$\begin{bmatrix} 0 & 3 & -6 & 6 & 4 & -5 \\ 3 & -7 & 8 & -5 & 8 & 9 \\ 3 & -9 & 12 & -9 & 6 & 15 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -3 & 4 & -3 & 2 & 5 \\ 0 & 1 & -2 & 2 & 1 & -3 \\ 0 & 0 & 0 & 0 & 1 & 4 \end{bmatrix}$$

Backward GE:  $\text{ref}(A) \rightarrow \text{rref}(A)$

$$\begin{bmatrix} 1 & -3 & 4 & -3 & 2 & 5 \\ 0 & 1 & -2 & 2 & 1 & -3 \\ 0 & 0 & 0 & 0 & 1 & 4 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & -2 & 3 & 5 & -4 \\ 0 & 1 & -2 & 2 & 1 & -3 \\ 0 & 0 & 0 & 0 & 1 & 4 \end{bmatrix}$$

$$\rightarrow \begin{bmatrix} 1 & 0 & -2 & 3 & 0 & -24 \\ 0 & 1 & -2 & 2 & 0 & -7 \\ 0 & 0 & 0 & 0 & 1 & 4 \end{bmatrix}.$$

# Rank of a matrix

**Definition:** The rank of an  $m \times n$  matrix  $A$ , denoted by  $\text{rank}(A)$ , is the number of pivots in  $\text{rref}(A)$ .

# Rank of a matrix

**Definition:** The rank of an  $m \times n$  matrix  $A$ , denoted by  $\text{rank}(A)$ , is the number of pivots in  $\text{rref}(A)$ .

**Example:**

$$A := \begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -2 \\ 2 & 1 & 4 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow \text{rank}(A) = 2.$$

# Rank of a matrix

**Definition:** The rank of an  $m \times n$  matrix  $A$ , denoted by  $\text{rank}(A)$ , is the number of pivots in  $\text{rref}(A)$ .

**Example:**

$$A := \begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -2 \\ 2 & 1 & 4 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 3 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow \text{rank}(A) = 2.$$

**Fact:**

- $\text{rank}(A) = \text{number of pivot columns in } \text{rref}(A) = \text{number of nonzero rows in } \text{rref}(A)$ .
- $\text{rank}(A) = \text{number of pivot columns in } \text{ref}(A) = \text{number of nonzero rows in } \text{ref}(A)$ .



## Leading and free variable:

**Free variable:** A variable in a system  $A\mathbf{x} = \mathbf{b}$  is called a **free variable** if the system has a solution for every value of that variable.

## Leading and free variable:

**Free variable:** A variable in a system  $A\mathbf{x} = \mathbf{b}$  is called a **free variable** if the system has a solution for every value of that variable.

Example:

$$\left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 2 & 1 & 4 & 1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{array}{l} x_1 = -1 - 3x_3 \\ x_2 = 3 + 2x_3 \\ x_3 : \text{ free} \end{array}$$

## Leading and free variable:

**Free variable:** A variable in a system  $A\mathbf{x} = \mathbf{b}$  is called a **free variable** if the system has a solution for every value of that variable.

Example:

$$\left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 2 & 1 & 4 & 1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{array}{l} x_1 = -1 - 3x_3 \\ x_2 = 3 + 2x_3 \\ x_3 : \text{free} \end{array}$$

**Leading variables:** Let  $[A \mid \mathbf{b}] \rightarrow \text{rref}([A \mid \mathbf{b}]) =: [R \mid \mathbf{d}]$ . Then the variables corresponding to the pivot columns of  $R$  are called **leading variable**.

**Theorem:** The number of free variables in a consistent  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$  is given by  $n - \text{rank}(A)$ .

## Leading and free variable:

**Free variable:** A variable in a system  $A\mathbf{x} = \mathbf{b}$  is called a **free variable** if the system has a solution for every value of that variable.

Example:

$$\left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 2 & 1 & 4 & 1 \end{array} \right] \rightarrow \left[ \begin{array}{ccc|c} 1 & 0 & 3 & -1 \\ 0 & 1 & -2 & 3 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{array}{l} x_1 = -1 - 3x_3 \\ x_2 = 3 + 2x_3 \\ x_3 : \text{free} \end{array}$$

**Leading variables:** Let  $[A \mid \mathbf{b}] \rightarrow \text{rref}([A \mid \mathbf{b}]) =: [R \mid \mathbf{d}]$ . Then the variables corresponding to the pivot columns of  $R$  are called **leading variable**.

**Theorem:** The number of free variables in a consistent  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$  is given by  $n - \text{rank}(A)$ .

**Proof:** # Free variables = # non-pivot columns =  $n - \text{rank}(A)$ .

# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = 0$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = \mathbf{0}$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

**Fact:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$

- is **inconsistent** if  $\text{rank}(A) \neq \text{rank}([A \mid \mathbf{b}])$ .

# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = 0$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

**Fact:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$

- is **inconsistent** if  $\text{rank}(A) \neq \text{rank}([A \mid \mathbf{b}])$ .
- **consistent** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}])$ .

# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = 0$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

**Fact:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$

- is **inconsistent** if  $\text{rank}(A) \neq \text{rank}([A \mid \mathbf{b}])$ .
- **consistent** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}])$ .
- has **unique solution** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}]) = n$ .



# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = 0$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

**Fact:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$

- is **inconsistent** if  $\text{rank}(A) \neq \text{rank}([A \mid \mathbf{b}])$ .
- **consistent** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}])$ .
- has **unique solution** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}]) = n$ .
- **infinitely many solutions** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}]) < n$ .

# Rank and consistency

**Fact:** An  $m \times n$  homogeneous system  $A\mathbf{x} = 0$  has

- infinitely many solutions if  $\text{rank}(A) < n$ ,
- unique (trivial) solution if  $\text{rank}(A) = n$ .

**Fact:** An  $m \times n$  system  $A\mathbf{x} = \mathbf{b}$

- is **inconsistent** if  $\text{rank}(A) \neq \text{rank}([A \mid \mathbf{b}])$ .
- **consistent** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}])$ .
- has **unique solution** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}]) = n$ .
- **infinitely many solutions** if  $\text{rank}(A) = \text{rank}([A \mid \mathbf{b}]) < n$ .

$$\left[ \begin{array}{cc|c} 1 & 2 & 1 \\ 1 & 2 & k \end{array} \right] \rightarrow \left[ \begin{array}{cc|c} 1 & 2 & 1 \\ 0 & 0 & k-1 \end{array} \right] \Rightarrow \text{inconsistent if } k \neq 1.$$

\*\*\*