

## **MA283: Linear Algebra**

70% Exam

30% Continuous Assessment (Homework)

10% Optional Project (Bonus)

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## Contents

<b>1</b>	<b>Review of Matrix Algebra</b>	<b>3</b>
<b>2</b>	<b>Systems of linear equations</b>	<b>6</b>
2.1	Linear equations and Solution Sets . . . . .	6
2.1.1	Interpreting Linear Systems as Matrix Equations . . . . .	6
2.2	Elementary Row Operations . . . . .	6
2.2.1	REF and Strategy . . . . .	6
2.2.2	Row Reduced Echelon Form . . . . .	7
2.3	Leading variables and free variables . . . . .	7
2.4	Consistent and Inconsistent Systems . . . . .	7
2.5	Possible Outcomes when solving a system of equations . . . . .	7
2.6	Elementary Row Operations as Matrix Transformations . . . . .	8
2.6.1	Multiplying a Row by a Non-Zero Scalar . . . . .	8
2.6.2	Switching Two Rows . . . . .	8
2.6.3	Adding a Multiple of One Row to Another . . . . .	8
2.7	EROs and Inverses . . . . .	10
<b>3</b>	<b>Vector Spaces and Subspace Structure</b>	<b>11</b>
3.1	The Image and Kernel of a Linear Transformation . . . . .	11
3.2	Subspaces . . . . .	11
3.3	The span : how to make subspaces . . . . .	11
3.4	Spanning sets . . . . .	12
3.5	Linear Dependence and Linear Independence . . . . .	13
3.5.1	Test for linear independence . . . . .	13
3.6	Finite Dimensional Spaces . . . . .	13
3.7	Basis . . . . .	14
3.8	Steinitz Replacement Lemma . . . . .	14
3.9	Recap of span, linear independence and basis . . . . .	14
3.10	Consequences of the replacement theorem . . . . .	15
3.11	Every basis has the same number of elements . . . . .	15
3.12	Row rank and column rank . . . . .	16
3.13	Row rank = column rank . . . . .	16

# 1 Review of Matrix Algebra

## Matrix Addition

If a matrix has  $m$  rows and  $n$  columns, we say it is  $m \times n$ . **Two matrices can only be added if they have the same size..** In this case, we just add the entries in each position.

The  $m \times n$  **zero** matrix is a matrix with all entries equal to 0. It is the **Identity element** for matrix addition (adding it to any matrix does not change the matrix)

## Matrix Multiplication by a Scalar

This simply means multiplying each entry of the matrix by the scalar. For example:

$$\alpha \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} \alpha & 2\alpha \\ 3\alpha & 4\alpha \end{bmatrix}$$

**Remark:** Now that we have addition and scalar multiplication, we can subtract matrices ( $A - B = A + (-1)B$ ), provided they are the same size.

## Vector Space

With these operations of addition and scalar multiplication, the set of  $m \times n$  matrices is a vector space. A **vector space** algebraic structure whose elements can be added, subtracted and multiplied by scalars.

## Linear Combinations

### Definition 1.1: Linear Combinations

Suppose  $v_1, v_2, \dots, v_k$  are elements that can be added together and multiplied by scalars.

A Linear Combination of  $v_1, v_2, \dots, v_k$  is an expression of the form:

$$\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k$$

where  $\alpha_i \in \mathbb{R}$  are scalars, called **coefficients**.

## Matrix-Vector Multiplication

### Definition 1.2

Let  $A$  be a  $m \times n$  matrix, and  $\mathbf{v}$  be a column vector with  $n$  entries ( $n \times 1$  matrix).

Then the matrix vector product  $Av$  is the column vector, with  $m$  entries, obtained by taking the linear combination of the columns of  $A$  with the entries of  $\mathbf{v}$  as coefficients.

$$\begin{bmatrix} -1 & 2 & 4 \\ 0 & 1 & 3 \end{bmatrix} \begin{bmatrix} 7 \\ 6 \\ 9 \end{bmatrix} = 7 \begin{bmatrix} -1 \\ 0 \end{bmatrix} + 6 \begin{bmatrix} 2 \\ 1 \end{bmatrix} + 9 \begin{bmatrix} 4 \\ 3 \end{bmatrix} = \begin{bmatrix} 41 \\ 33 \end{bmatrix}.$$

**Remark:**  $Av$ , if defined, has the same number of rows as  $A$  and the same number of columns as  $\mathbf{v}$ .

## Matrix-Matrix Multiplication

### Definition 1.3

Let  $A$  and  $B$  be matrices of size  $m \times p$  and  $p \times n$ , respectively. Write  $v_1, \dots, v_n$  for the columns of  $B$ . Then the product  $AB$  is the  $m \times n$  matrices whose columns are  $Av_1, \dots, Av_n$ .

The entry at row  $i$  and column  $j$  of the matrix  $A$  is given by  $A_{ij}$ . The entry in the  $i, j$  position of the product  $AB$  is the  $i$ th entry of the vector  $Av_j$ , where the vector  $v_j$  is the  $j$ th column of  $B$ . In other words, the entry in the  $i, j$  position of the product  $AB$  is given by:

$$(AB)_{ij} = A_{i1}B_{1j} + A_{i2}B_{2j} + \dots + A_{ip}B_{pj} = \sum_{k=1}^p A_{ik}B_{kj}$$

**Definition 1.4**

If  $A$  is  $m \times p$  with rows  $u_1, \dots, u_m$  and  $B$  is  $p \times n$  with columns  $v_1, \dots, v_n$ , then the product  $AB$  is:

$$AB = \begin{bmatrix} u_1 \cdot v_1 & u_1 \cdot v_2 & \dots & u_1 \cdot v_n \\ u_2 \cdot v_1 & u_2 \cdot v_2 & \dots & u_2 \cdot v_n \\ \vdots & \vdots & \ddots & \vdots \\ u_m \cdot v_1 & u_m \cdot v_2 & \dots & u_m \cdot v_n \end{bmatrix}$$

**Example:**

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \quad B = \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} \quad AB = \begin{bmatrix} 1 \cdot 7 + 2 \cdot 9 + 3 \cdot 11 & 1 \cdot 8 + 2 \cdot 10 + 3 \cdot 12 \\ 4 \cdot 7 + 5 \cdot 9 + 6 \cdot 11 & 4 \cdot 8 + 5 \cdot 10 + 6 \cdot 12 \end{bmatrix} = \begin{bmatrix} 58 & 64 \\ 139 & 154 \end{bmatrix}$$

For matrices  $A$  and  $B$ , the products  $AB$  and  $BA$  are generally not equal, even if they are both defined and even if both have the same size.

**Linear Transformations****Definition 1.5**

Let  $m$  and  $n$  be positive integers.

A **linear transformation**  $T$  from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  is a function  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  that satisfies:

- $T(\mathbf{u} + \mathbf{v}) = T(\mathbf{u}) + T(\mathbf{v})$  for all  $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$
- $T(\lambda \mathbf{u}) = \lambda T(\mathbf{u})$  for all  $\mathbf{u} \in \mathbb{R}^n$  and  $\lambda \in \mathbb{R}$

**Matrix of a Linear Transformation**

Suppose  $T : \mathbb{R}^3 \rightarrow \mathbb{R}^2$  is the linear transformation:

$$T \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad T \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 4 \end{bmatrix} \quad T \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -6 \\ 7 \end{bmatrix}$$

Then for the vector in  $\mathbb{R}^3$  with entries  $a, b, c$ :

$$T \begin{bmatrix} a \\ b \\ c \end{bmatrix} = aT \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + bT \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + cT \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 & 1 & -6 \\ -3 & 4 & 7 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

Where the  $2 \times 3$  matrix  $M_T$  is called the **standard matrix** of  $A$ . A linear transformation  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  can be completely represented by an  $m \times n$  matrix  $M_T$ .

**Understanding the Matrix Representation**

- The columns of matrix  $M_T$  are the images of the standard basis vectors  $e_1, e_2, \dots, e_n$  under  $T$ .
- For any vector  $v \in \mathbb{R}^n$ , we calculate  $T(v)$  by multiplying:  $M_T \cdot v$ .
- Therefore, matrix-vector multiplication is simply evaluating a linear transformation.

**Correspondence:** Any  $m \times n$  matrix  $A$  defines a linear transformation  $T_A : \mathbb{R}^n \rightarrow \mathbb{R}^m$  by:  $T_A(v) = Av$ . Linear transformations include rotations, reflections and scaling

**Efficiency of Representation:** A remarkable property of linear transformations is their information efficiency:

- To completely define  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ , we need only  $mn$  values.
- These values are the coordinates of the  $n$  transformed basis vectors in  $\mathbb{R}^m$ .
- This differs fundamentally from general continuous functions  $f : \mathbb{R} \rightarrow \mathbb{R}$ , which cannot be fully determined by their values at finitely many points.

### Matrix multiplication is composition

Suppose that  $T : \mathbb{R}^n \rightarrow \mathbb{R}^p$  and  $S : \mathbb{R}^p \rightarrow \mathbb{R}^m$  are linear transformations. Then the composition  $S \circ T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is also a linear transformation from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  defined for  $\mathbf{v} \in \mathbb{R}^n$  by:

$$S \circ T(\mathbf{v}) = S(T(\mathbf{v}))$$

To see how that the  $m \times n$  matrix  $M_{S \circ T}$  depends on the matrix  $M_S(m \times p)$  and  $M_T(p \times n)$  we look at the definition of  $M_{S \circ T}$ :

- The first column has coordinates  $S \circ T(e_1) = S(T(e_1))$
- $T(e_1)$  is first column of  $M_T$
- Then  $S(T(e_1))$  is the matrix-vector product  $M_S \cdot M_T(e_1)$
- Same for all other columns  $\implies M_{S \circ T} = M_S \cdot M_T$

Thus, we conclude **matrix multiplication is composition of linear transformations**.

## 2 Systems of linear equations

### 2.1 Linear equations and Solution Sets

A linear equation in the variables  $x$  and  $y$  is an equation of the form

$$2x + y = 3$$

If we replace  $x$  and  $y$  with some numbers, the statement **becomes true or false**.

#### Definition 2.1: Solution to a linear equation

A pair,  $(x_0, y_0) \in \mathbb{R}$ , is a solution to a linear equation if setting  $x = x_0$  and  $y = y_0$  **makes the equation true**.

#### Definition 2.2: Solution set

The **solution set** is the set of all solutions to a linear equation.

$$a_1X_1 + a_2X_2 + \dots + a_nX_n = b \quad \text{where } a_i, b \in \mathbb{R}$$

is an **affine hyperplane** in  $\mathbb{R}^n$ ; geometrically resembles a copy of  $\mathbb{R}^{n-1}$  inside  $\mathbb{R}^n$ .

#### 2.1.1 Interpreting Linear Systems as Matrix Equations

$$\begin{array}{rrcrcl} x & + & 2y & - & z & = & 5 \\ 3x & + & y & - & 2z & = & 9 \\ -x & + & 4y & + & 2z & = & 0 \end{array} \Rightarrow \begin{bmatrix} 1 & 2 & -1 \\ 3 & 1 & -2 \\ -1 & 4 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 5 \\ 9 \\ 0 \end{bmatrix}$$

### 2.2 Elementary Row Operations

To solve a system of linear equations we associate an **augmented matrix** to the system of equations. For example:

$$\begin{array}{rrcrcl} x & + & 2y & - & z & = & 5 \\ 3x & + & y & - & 2z & = & 9 \\ -x & + & 4y & + & 2z & = & 0 \end{array} \Rightarrow \left[ \begin{array}{ccc|c} 1 & 2 & -1 & 5 \\ 3 & 1 & -2 & 9 \\ -1 & 4 & 2 & 0 \end{array} \right]$$

To solve, we can perform the following **Elementary Row Operations (EROs)**:

1. Multiply a row by a non-zero constant.
2. Add a multiple of one row to another row.
3. Swap two rows.

The goal of these operations is to transform the augmented matrix into **row echelon form (REF)** or **reduced row echelon form (RREF)**.

#### 2.2.1 REF and Strategy

We say a matrix is in **row echelon form (REF)** if:

- The first non zero entry in each row is a 1 (called the **leading 1**).
- If a column has a leading 1, then all entries below it are 0.
- The leading 1 in each row is to the right of the leading 1 in the previous row.
- All rows of 0s are at the bottom of the matrix.

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

*Example of REF*

We have produced a new system of equations. This is easily solved by back substitution.

#### Concept 2.1: Strategy for Obtaining REF

- Get a 1 as the top left entry
- Use this 1 to clear the entries below it
- Move to the next column and repeat
- Continue until all leading 1s are in place
- Use back substitution to solve the system

### 2.2.2 Row Reduced Echelon Form

A matrix is in **reduced row echelon form** (RREF) if:

- It is in REF
- The leading 1 in each row is the only non-zero entry in its column.

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

*Example of RREF*

### 2.3 Leading variables and free variables

We'll start by an example:

$$\begin{array}{rrrrrrrrcl} x_1 & - & x_2 & - & x_3 & + & 2x_4 & = & 0 \\ 2x_1 & + & x_2 & - & x_3 & + & 2x_4 & = & 8 \\ x_1 & - & 3x_2 & + & 2x_3 & + & 7x_4 & = & 2 \end{array} \Rightarrow \left[ \begin{array}{cccc|c} 1 & -1 & -1 & 2 & 0 \\ 2 & 1 & -1 & 2 & 8 \\ 1 & -3 & 2 & 7 & 2 \end{array} \right]$$

Solving this system of equations, we get:

$$\text{RREF: } \left[ \begin{array}{cccc|c} 1 & 0 & 0 & 2 & 4 \\ 0 & 1 & 0 & -1 & 2 \\ 0 & 0 & 0 & 1 & 2 \end{array} \right] \Rightarrow \begin{array}{rcl} x_1 + 2x_4 & = & 4 \\ x_2 - x_4 & = & 2 \\ x_3 + x_4 & = & 2 \end{array} \Rightarrow \begin{array}{rcl} x_1 & = & 4 - 2x_4 \\ x_2 & = & 2 + x_4 \\ x_3 & = & 2 - x_4 \end{array}$$

This RREF tells us how the **leading variables** ( $x_1, x_2, x_3$ ) depend on the **free variable** ( $x_4$ ). The free variable can take any value in  $\mathbb{R}$ . We write the solution set as:

$$x_1 = 4 - 2t, \quad x_2 = 2 + t, \quad x_3 = 2 - t, \quad x_4 = t \quad \text{where } t \in \mathbb{R}$$

$$(x_1, x_2, x_3, x_4) = (4 - 2t, 2 + t, 2 - t, t); \quad t \in \mathbb{R}$$

#### Definition 2.3: Leading and Free Variables

- **Leading variable** : A variable whose columns in the RREF contain a leading 1
- **Free variable** : A variable whose columns in the RREF do not contain a leading 1

### 2.4 Consistent and Inconsistent Systems

Consider the following system of equations:

$$\begin{array}{rrrrrrcl} 3x & + & 2y & - & 5z & = & 4 \\ x & + & y & - & 2z & = & 1 \\ 5x & + & 3y & - & 8z & = & 6 \end{array} \Rightarrow \left[ \begin{array}{ccc|c} 3 & 2 & -5 & 4 \\ 1 & 1 & -2 & 1 \\ 5 & 3 & -8 & 6 \end{array} \right] \Rightarrow \left[ \begin{array}{ccc|c} 1 & 1 & -2 & 1 \\ 0 & 1 & -1 & 1 \\ 0 & 0 & 0 & 1 \end{array} \right] \quad (\text{REF})$$

We can see the last row of the REF is:

$$0x + 0y + 0z = 1$$

This equation clearly has no solution, and hence the system has no solutions. We say the system is **inconsistent**. Alternatively, we say the system is **consistent** if it has at least one solution.

### 2.5 Possible Outcomes when solving a system of equations

- The system may be **inconsistent** (no solutions) - i.e:

$$[0 \ 0 \ \dots \ 0 \ | \ a] \quad a \neq 0$$

- The system may be **consistent** which occurs if:

- **Unique Solutions** each column (aside from the rightmost) contains a single leading 1. - i.e:

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

- **Infinitely many solutions** at least one variable does not appear as a leading 1 in any row, making it a free variable - i.e:

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

## 2.6 Elementary Row Operations as Matrix Transformations

Elementary row operations may be interpreted as **matrix multiplication**. To see this, first we introduce the **Identity matrix**:

$$I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The  $I_m$  Identity matrix is an  $m \times m$  matrix with 1s on the diagonal and 0s elsewhere. We also introduce the  $E_{i,j}$  matrix which has 1 in the  $(i, j)$  position and 0s elsewhere. For example:

$$E_{1,2} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Then:

$$I_3 + 4E_{1,2} = \begin{bmatrix} 1 & 4 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Performing a row operation on  $A$  is the same as multiplying  $A$  by an appropriate matrix  $E$  on the left. These matrices are called **elementary matrices**. They are **always invertible**, and **their inverses are also elementary matrices**. The statement:

*"every matrix can be reduced to RREF through EROs"*

is equivalent to saying that

*"for every matrix  $A$  with  $m$  rows, there exists a  $m \times m$  matrix  $B$  which is a product of elementary matrices such that  $BA$  is in RREF."*

### 2.6.1 Multiplying a Row by a Non-Zero Scalar

When multiplying row  $i$  of matrix  $A$  by a scalar  $\alpha \neq 0$ , we can use the matrix:

$$I_m + (\alpha - 1)E_{i,i}$$

This works because it modifies only the  $(i, i)$  entry of the identity matrix to be  $\alpha$  while keeping all other entries unchanged. When multiplied with  $A$ , it scales row  $i$  by  $\alpha$  and leaves all other rows intact.

**Example:** If  $\alpha = 5$  and  $i = 2$ , then:

$$I_3 + 4E_{2,2} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \quad (I_3 + 4E_{2,2})A = \begin{bmatrix} 1 & 2 & 3 \\ 20 & 25 & 30 \\ 7 & 8 & 9 \end{bmatrix}$$

### 2.6.2 Switching Two Rows

To swap rows  $i$  and  $k$ , we use:

$$S = I_m + E_{i,k} + E_{k,i} - E_{i,i} - E_{k,k}$$

This works by:

- Removing the 1's at positions  $(i, i)$  and  $(k, k)$  from the identity matrix
- Adding 1's at positions  $(i, k)$  and  $(k, i)$

**Example:** Swapping rows 1 and 3:

$$S = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \quad SA = \begin{bmatrix} 7 & 8 & 9 \\ 4 & 5 & 6 \\ 1 & 2 & 3 \end{bmatrix}$$

### 2.6.3 Adding a Multiple of One Row to Another

To replace row  $k$  with row  $k + \alpha \times$  row  $i$ , use:

$$I_m + \alpha E_{k,i}$$

This adds  $\alpha$  times row  $i$  to row  $k$  while leaving all other rows unchanged because:

- For any row  $j \neq k$ , the corresponding row in this matrix is just the standard basis row
- Row  $k$  becomes the sum of the standard basis row  $k$  plus  $\alpha$  times the standard basis row  $i$

**Example:** Adding 3 times row 1 to row 2:

$$I_3 + 3E_{2,1} = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \quad (I_3 + 3E_{2,1})A = \begin{bmatrix} 1 & 2 & 3 \\ 7 & 11 & 15 \\ 7 & 8 & 9 \end{bmatrix}$$



**Example 2.1**

Write the inverse of an elementary matrix and show it is an elementary matrix.

**Multiplying a row by a nonzero scalar:**

- **Operation:** Multiply row  $i$  by  $\alpha \neq 0$ .
- **Elementary Matrix:**  $E = I_m + (\alpha - 1)E_{i,i}$
- **Inverse:** To reverse the operation, multiply row  $i$  by  $1/\alpha$ . Hence, the inverse is

$$E^{-1} = I_m + \left(\frac{1}{\alpha} - 1\right) E_{i,i} = I_m + \frac{1 - \alpha}{\alpha} E_{i,i}.$$

**Swapping two rows:**

- **Operation:** Swap rows  $i$  and  $k$ .
- **Elementary Matrix:**  $S = I_m - E_{i,i} - E_{k,k} + E_{i,k} + E_{k,i}$
- **Inverse:** Since swapping the same two rows twice returns them to their original positions,

$$S^{-1} = S.$$

**Adding a multiple of one row to another:**

- **Operation:** Add  $\alpha$  times row  $i$  to row  $k$ .
- **Elementary Matrix:**  $E = I_m + \alpha E_{k,i}$
- **Inverse:** To undo the operation, subtract  $\alpha$  times row  $i$  from row  $k$ . Therefore,

$$E^{-1} = I_m - \alpha E_{k,i}.$$

**Example 2.2**

Prove that every invertible matrix in  $M_n(\mathbb{R})$  is a product of elementary matrices.

Let  $A$  be an invertible matrix in  $M_n(\mathbb{R})$ . Since  $A$  is invertible, we can use Gaussian elimination to transform  $A$  into the identity matrix  $I_n$ .

Let  $E_1, E_2, \dots, E_k$  be the elementary matrices corresponding to the row operations used in the elimination process. Then, we have:

$$\text{Multiplying a row by a scalar: } I_n + (\alpha - 1)E_{i,i}$$

$$\text{Swapping two rows: } I_n + E_{i,k} + E_{k,i} - E_{i,i} - E_{k,k}$$

$$\text{Adding a multiple of one row to another: } I_n + \alpha E_{k,i}$$

Applying these in sequence to  $A$  gives:

$$E_k \cdots E_2 E_1 A = I_n$$

Since  $E_k \cdots E_2 E_1 = I_n$ , we can multiply both sides by  $(E_k \cdots E_2 E_1)^{-1}$  on the left to obtain:

$$A = (E_k \cdots E_2 E_1)^{-1} I_n = (E_k \cdots E_2 E_1)^{-1}$$

Using the property:

$$(E_k \cdots E_2 E_1)^{-1} = E_1^{-1} E_2^{-1} \cdots E_k^{-1},$$

we can express  $A$  as a product of elementary matrices:

$$A = E_1^{-1} E_2^{-1} \cdots E_k^{-1}$$

Since each  $E_i$  is an elementary matrix, its inverse is also an elementary matrix. Therefore,  $A$  can be expressed as a product of elementary matrices.

## 2.7 EROs and Inverses

Elementary Row Operations can be used to find the inverse of a square matrix. Consider a square matrix  $A \in M_n(\mathbb{F})$  (that is, an  $n \times n$  matrix over a field  $\mathbb{F}$ ). If  $A$  is invertible, let

$$A^{-1} = \begin{bmatrix} | & | & \cdots & | \\ \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_n \\ | & | & \cdots & | \end{bmatrix}$$

be its inverse, where each  $\mathbf{v}_i$  is the  $i$ th column of  $A^{-1}$ . By definition of the matrix inverse, we have

$$A A^{-1} = A \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_n \end{bmatrix} = \begin{bmatrix} A\mathbf{v}_1 & A\mathbf{v}_2 & \cdots & A\mathbf{v}_n \end{bmatrix} = I_n,$$

the  $n \times n$  identity matrix. This implies that

$$A\mathbf{v}_i = \mathbf{e}_i, \quad \text{for each } i = 1, 2, \dots, n,$$

where  $\mathbf{e}_i$  is the  $i$ th column of  $I_n$  (which has a 1 in the  $i$ th row and 0 everywhere else). In other words, each column  $\mathbf{v}_i$  of  $A^{-1}$  is the unique solution to the linear system

$$A\mathbf{v}_i = \mathbf{e}_i.$$

To find  $A^{-1}$  effectively, we form the augmented matrix  $[A \mid I_n]$  and apply EROs to transform  $A$  into  $I_n$ . When this is achieved, the augmented portion becomes  $A^{-1}$ . Thus, we have

$$\text{RREF}([A \mid I_n]) = [I_n \mid A^{-1}].$$

### Example 2.3

Find  $A^{-1}$  if  $A = \begin{bmatrix} 3 & 4 & -1 \\ 1 & 0 & 3 \\ 2 & 5 & -4 \end{bmatrix}$ .

We form a  $3 \times 6$  matrix  $A' = [A \mid I_3]$ :

$$A' = \begin{bmatrix} 3 & 4 & -1 & | & 1 & 0 & 0 \\ 1 & 0 & 3 & | & 0 & 1 & 0 \\ 2 & 5 & -4 & | & 0 & 0 & 1 \end{bmatrix}$$

We apply the following EROs to  $A'$ :

- $R_1 \leftrightarrow R_2$
- $R_2 \rightarrow R_2 - 3R_1$
- $R_3 \rightarrow R_3 - 2R_1$
- $R_3 \rightarrow R_3 + R - 2$
- $R_3 \leftrightarrow R_2$
- $R_3 \rightarrow R_3 - 4R_2$
- $R_3 \times (-\frac{1}{10})$
- $R_1 \rightarrow R_1 - 3R_3$

To obtain:

$$\begin{bmatrix} 1 & 0 & 0 & | & \frac{3}{2} & -\frac{11}{10} & -\frac{6}{5} \\ 0 & 1 & 0 & | & -1 & 1 & 1 \\ 0 & 0 & 1 & | & -\frac{1}{2} & \frac{7}{10} & \frac{2}{5} \end{bmatrix}$$

That is:

$$A^{-1} = \begin{bmatrix} \frac{3}{2} & -\frac{11}{10} & -\frac{6}{5} \\ -1 & 1 & 1 \\ -\frac{1}{2} & \frac{7}{10} & \frac{2}{5} \end{bmatrix}$$

It is easily checked that  $AA^{-1} = I_3$ .

### 3 Vector Spaces and Subspace Structure

#### 3.1 The Image and Kernel of a Linear Transformation

$T : \mathbb{R}^3 \rightarrow \mathbb{R}^3$  is the linear transformation defined with:

$$M_T = \begin{bmatrix} 1 & 2 & 0 \\ 2 & -1 & 5 \\ 1 & 1 & 1 \end{bmatrix}$$

The **image** of  $T$  is the subset of  $\mathbb{R}^3$  consisting of all elements  $T(\mathbf{v})$ ,  $\mathbf{v} \in \mathbb{R}^3$ . This is the set of all vectors of the form:

$$a \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + b \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} + c \begin{bmatrix} 0 \\ 5 \\ 1 \end{bmatrix}$$

In matrix terms, this is the **column space** of  $M_T$ .

The **kernel** of  $T$  is the set of all vectors  $\mathbf{v} \in \mathbb{R}^3$  such that  $T(\mathbf{v}) = \mathbf{0}$ . This is the set of all column vectors, whose entries,  $a, b, c$  satisfies:

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & -1 & 5 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = a \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + b \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} + c \begin{bmatrix} 0 \\ 5 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

**The kernel is a line and the image is a plane**

$$\begin{bmatrix} 1 & 2 & 0 \\ 2 & -1 & 5 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 2 & 0 & | & 0 \\ 0 & -5 & 5 & | & 0 \\ 1 & 1 & 1 & | & 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 0 & 2 & | & 0 \\ 0 & 1 & -1 & | & 0 \\ 0 & 0 & 0 & | & 0 \end{bmatrix}$$

The kernel (or nullspace) is  $(2, 1, 1)t, t \in \mathbb{R}$ , which is a line in  $\mathbb{R}^3$ . The fact that  $(-2, 1, 1)$  is in the kernel of  $T$ , means that column 3 of  $M_T$  is a linear combination of columns 1 and 2.

$$-2 \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + 1 \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} + 1 \begin{bmatrix} 0 \\ 5 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 \\ 5 \\ 1 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix}$$

It follows that every linear combination of all three columns of  $M_T$  is just a linear combination of columns 1 and 2.

The column space of  $M_T$  is:

$$\left\{ a \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} + b \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} : a, b \in \mathbb{R} \right\}$$

#### 3.2 Subspaces

##### Definition 3.1

A non empty subset  $\mathbf{V}$  of  $\mathbb{R}^n$  is a **subspace** if:

- **Closed under addition:**  $u + v \in \mathbf{V}, u, v \in \mathbf{V}$
- **Closed under scalar multiplication:**  $\alpha u \in \mathbf{V}, u \in \mathbf{V}, \alpha \in \mathbb{R}$

##### Examples of subspaces

- $\{(x, y, z) \in \mathbb{R}^3 : x + y + z = 1\}$  is not a subspace of  $\mathbb{R}^3$ . the  $[1, 0, 0]$  and  $(0, 1, 0)$  vectors are in the set, but their sum  $(1, 1, 0)$  is not in the set.
- $\{(x, y, z) \in \mathbb{R}^3 : (x, y, z) \cdot (1, 2, 3) = 0\}$  is a subspace of  $\mathbb{R}^3$ .
- $\{(x, y, z) \in \mathbb{R}^3 : (x, y, z) \cdot (1, 2, 3) \neq 0\}$  is not a subspace of  $\mathbb{R}^3$ .
- The kernel of any linear transformation is a subspace of  $\mathbb{R}^n$ .
- The image of any linear transformation is a subspace of  $\mathbb{R}^n$ .

#### 3.3 The span : how to make subspaces

##### Definition 3.2

Let  $S = \{v_1, \dots, v_k\}$  be any finite subset of  $\mathbb{R}^n$

The subset of  $\mathbb{R}^n$  consisting of all linear combinations of the elements of  $S$  is a subspace of  $\mathbb{R}^n$  and is called the **span** of  $S$  and is denoted by  $\langle\langle S \rangle\rangle$ .

**Proof that  $\langle S \rangle$  is a subspace of  $\mathbb{R}^n$**

- **Closed under addition:**

Let  $u, v \in \langle S \rangle$ . Then  $u = a_1v_1 + a_2v_2 + \cdots + a_kv_k$  and  $v = b_1v_1 + b_2v_2 + \cdots + b_kv_k$  for some  $a_i, b_i \in \mathbb{R}$ . We see that:

$$u + v = (a_1 + b_1)v_1 + (a_2 + b_2)v_2 + \cdots + (a_k + b_k)v_k$$

So  $S$  is closed under addition.

- **Closed under scalar multiplication:**

Let  $u \in \langle S \rangle$  and  $\alpha \in \mathbb{R}$ . We need to show that  $cu$  is a linear combination of  $v_1, \dots, v_k$ . We have  $u = a_1v_1 + a_2v_2 + \cdots + a_kv_k$  for some  $a_i \in \mathbb{R}$ . Then:

$$cu = c(a_1v_1 + a_2v_2 + \cdots + a_kv_k) = (ca_1)v_1 + (ca_2)v_2 + \cdots + (ca_k)v_k$$

so  $cu \in \langle S \rangle$ .

### 3.4 Spanning sets

#### Definition 3.3

Let  $V$  be a subspace of  $\mathbb{R}^n$ .

A subset  $S$  of  $V$  is a **spanning set** for  $V$  if  $\langle S \rangle = V$ .

This means that every element of  $V$  can be expressed as a linear combination of the elements of  $S$ .

#### Example

The set  $\{e_1, e_2, e_3\}$  is a spanning set of  $\mathbb{R}^3$ . We know that:

$$e_1 = [1, 0, 0], \quad e_2 = [0, 1, 0], \quad e_3 = [0, 0, 1]$$

We can represent every element of  $\mathbb{R}^3$  as a linear combination of  $e_1, e_2, e_3$ :

$$\begin{bmatrix} 2 \\ -3 \\ 4 \end{bmatrix} = 2e_1 - 3e_2 + 4e_3$$

**Remark** A set  $S$  of three column vectors in  $\mathbb{R}^3$  is a spanning set of  $\mathbb{R}^3$  if and only if the three vectors are linearly independent. This occurs only if the  $3 \times 3$  matrix whose columns are the three vectors has  $S$  as an **inverse**.

#### Questions about spanning sets

- Does  $\mathbb{R}^3$  have a spanning set fewer than three vectors?
  - **No.** A spanning set for  $\mathbb{R}^3$  must contain at least three linearly independent vectors, since the dimension of  $\mathbb{R}^3$  is 3. Fewer than three vectors cannot span all of  $\mathbb{R}^3$ .
- Does every spanning set of  $\mathbb{R}^3$  have three vectors?
  - **No.** A spanning set can have more than three vectors, but not necessarily exactly three. Redundant vectors (linearly dependent ones) can be included, so a spanning set might have more than three vectors.
- Does every spanning set of  $\mathbb{R}^3$  contain one with exactly three elements?
  - **Yes.** Every spanning set of  $\mathbb{R}^3$  contains a basis, and since the dimension is 3, there exists a subset of exactly three linearly independent vectors that still span  $\mathbb{R}^3$ .
- If  $V$  is a subspace of  $\mathbb{R}^3$  does  $V$  have a spanning set with at most three elements?
  - **Yes.** Any subspace of  $\mathbb{R}^3$  has a basis, and since  $\mathbb{R}^3$  has dimension 3, the basis of any of its subspaces can have at most 3 elements. Hence, every subspace can be spanned by at most three vectors.
- If  $V$  is a proper subspace of  $\mathbb{R}^3$ , does  $V$  have a spanning set with fewer than three elements?
  - **Yes.** A proper subspace of  $\mathbb{R}^3$  has dimension less than 3, so it can be spanned by fewer than three vectors.

### 3.5 Linear Dependence and Linear Independence

#### Definition 3.4

A set of at least two vectors in  $\mathbb{R}^n$  is **linearly dependent** if one of its elements is a linear combination of the others.

A set of vectors in  $\mathbb{R}^n$  is **linearly independent** if it is not linearly dependent.

For a subset  $\{v_1, \dots, v_k\}$  of  $\mathbb{R}^n$ , suppose that  $v_k$  is a linear combination of  $\{v_1, \dots, v_{k-1}\}$ . Then every linear combination of  $\{v_1, \dots, v_k\}$  is **already a linear combination** of  $v_1, \dots, v_{k-1}$ :

$$\langle v_1, \dots, v_k \rangle = \langle v_1, \dots, v_{k-1} \rangle$$

If we are interested in the span of  $\{v_1, \dots, v_k\}$ , we can throw away  $v_k$  and this wouldn't change the span.

**Linear independence** means that throwing away any element of the set **shrinks the span**

#### Example 3.1

$$\begin{array}{cccccc} x_1 & + & 3x_2 & + & 5x_3 & - & 9x_4 = 5 \\ 3x_1 & - & x_2 & - & 5x_3 & + & 13x_4 = 5 \\ 2x_1 & - & 3x_2 & - & 8x_3 & + & 18x_4 = 1 \end{array} \Rightarrow \left[ \begin{array}{cccc|c} 1 & 3 & 5 & -9 & 5 \\ 3 & -1 & -5 & 13 & 5 \\ 2 & -3 & -8 & -18 & 1 \end{array} \right] \Rightarrow \left[ \begin{array}{cccc|c} 1 & 0 & -1 & 3 & 2 \\ 0 & 1 & 2 & -4 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{array} \right]$$

The three equations of the system form a linearly dependent set. One row was eliminated by adding a linear combination of the other two rows. Thus, all the information in the system was contained in the first two equations.

The non-zero rows of the RREF are linearly independent, they span the row space of the matrix. The row space is the subspace of  $\mathbb{R}^5$  spanned by the rows of the matrix.

#### 3.5.1 Test for linear independence

A set is linearly independent if none of its elements is a linear combination of the others. While this makes sense, to use it as a test would mean checking every element. We have an alternative formulation, which is easier to check:

**"A set of vectors is linearly independent if the only way to write the zero vector as a linear combination of the vectors in the set is to use all zero coefficients."**

To decide if the set  $\{v_1, \dots, v_k\}$  is linearly independent, try to write the zero vector as a linear combination of the vectors in the set:

$$\sum_{i=1}^k \alpha_i v_i = \alpha_1 v_1 + \dots + \alpha_k v_k = 0 \quad \text{for } \alpha_i \in \mathbb{R}$$

If  $\forall i \rightarrow \alpha_i = 0$ , then the set is linearly independent. If not, the set is linearly dependent.

#### Example 3.2

Decide whether the set  $\{[1, 0, 1], [1, 0, -1], [1, 1, 1]\}$  is linearly independent or dependent.

To solve, we use ERO and find:

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & -1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow a = b = c = 0$$

The set is linearly independent

### 3.6 Finite Dimensional Spaces

#### Definition 3.5

A vector space  $V$  is finite dimensional if it contain a finite spanning set.

This means a set  $\{v_1, \dots, v_k\}$  of elements, with the property that every element of  $V$  is a linear combination of  $v_1, \dots, v_k$ .

#### Examples

- $\mathbb{R}^n$  is finite dimensional with  $\{e_1, \dots, e_n\}$  as a spanning set. The dimension of  $\mathbb{R}^n$  is  $n$ .
- $M_{m \times n}(\mathbb{R})$  is finite dimensional, with  $\{E_{ij}\}_{1 \leq i \leq m, 1 \leq j \leq n}$  as a spanning set with  $mn$  elements.
- An example of an infinite dimensional space is the set,  $\mathbb{R}[x]$ , of all polynomials with real coefficients. This set is infinite dimensional because it contains an infinite number of linearly independent vectors, such as  $\{1, x, x^2, \dots\}$ .

### 3.7 Basis

#### Definition 3.6

A **basis** for a vector space is a **linearly independent spanning set**.

- A basis is a minimal spanning set, one in which every element is needed and does not contain a smaller spanning set.
- Example:  $\{e_1, \dots, e_n\}$  is a basis for  $\mathbb{R}^n$ .
- $\{(1, 3), (1, 4)\}$  is a basis for  $\mathbb{R}^2$ .
- If  $S$  is a finite spanning set of a vector space  $V$ , then  $S$  contains a basis of  $V$ . If  $S$  is not linearly independent, then some  $v \in S$  is a linear combination of the other elements of  $S$ . Throwing away  $v$  leaves a smaller set that still spans  $V$ . This process can be repeated until a basis is obtained.

### 3.8 Steinitz Replacement Lemma

#### Lemma 3.1

Let  $V$  be a vector space that has a basis with  $n$  elements.

Then every linearly independent set with  $n$  elements in  $V$  is a basis for  $V$ .

#### Proof (for $n = 3$ )

Suppose  $B = \{b_1, b_2, b_3\}$  is a basis of  $V$  and let  $\{y_1, y_2, y_3\}$  be a linearly independent subset of  $V$ .

#### Step 1.

$y_1 = a_1 b_1 + a_2 b_2 + a_3 b_3$  for scalars  $a_1, a_2, a_3$ , not all zero. We can assume (after maybe relabelling the  $b_i$ ), that  $a_1 \neq 0$ . Then

$$b_1 = a_1^{-1} y_1 - a_1^{-1} a_2 b_2 - a_1^{-1} a_3 b_3.$$

So  $b_1 \in \langle y_1, b_2, b_3 \rangle$  and  $\{y_1, b_2, b_3\}$  spans  $V$ . (Note that we have to use the fact that we can divide by non-zero scalars to write  $b_1$  as a linear combination of  $y_1, b_2, b_3$ .)

#### Step 2.

Now  $y_2 \in \langle y_1, b_2, b_3 \rangle$  and  $y_2$  is not a scalar multiple of  $y_1$  (because  $\{y_1, y_2, y_3\}$  is linearly independent).

So  $b_2$  (or  $b_3$ ) has non-zero coefficient in any description of  $y_2$  as a linear combination of  $y_1, b_2, b_3$ .

Replace again:  $\{y_1, y_2, b_2\}$  spans  $V$ .

#### Step 3.

Same reasoning: we can replace  $b_2$  with  $y_3$  to conclude  $\{y_1, y_2, y_3\}$  spans  $V$ .

**Conclusion:**  $\{y_1, y_2, y_3\}$  is a basis of  $V$ .

### 3.9 Recap of span, linear independence and basis

Let  $V$  be a vector space, e.g.  $V = \mathbb{R}^n$  and  $S$  be a finite subset of  $V$ . Let  $V$  be a vector space (e.g.  $V = \mathbb{R}^n$ ). Let  $S$  be a (finite) subset of  $V$ .

1.  $S$  is a spanning set of  $V$  (or  $S$  spans  $V$ ) if every element of  $V$  is a linear combination of the elements of  $S$ .
2. The span of  $S$ , denoted  $\langle S \rangle$ , is the set of all linear combinations of elements of  $S$ , a subspace of  $V$ .
3.  $S$  is linearly independent if no element of  $S$  is a linear combination of the other elements of  $S$ .  
Equivalently, if no proper subset of  $S$  spans  $\langle S \rangle$ .
4.  $S$  is a basis of  $V$  if  $S$  is linearly independent **AND**  $S$  spans  $V$ .  
A basis is a minimal spanning set.  
A basis is a maximal linearly independent set.
5. Every finite spanning set of  $V$  contains a basis of  $V$ .
6. Every linearly independent subset of  $V$  can be extended to a basis of  $V$  (we have not proved this yet!).

### 3.10 Consequences of the replacement theorem

#### Theorem 3.1

Let  $V$  be a vector space that has a basis with  $n$  elements.

Then every linearly independent set with  $n$  elements in  $V$  is a basis for  $V$ .

If  $V$  has a spanning set with  $n$  elements, a linearly independent set in  $V$  cannot have more than  $n$  elements.

If  $V$  has a linearly independent set with  $n$  elements, a spanning set in  $V$  must have at least  $n$  elements. More concisely:

#### Concept 3.1

The number of elements of a linearly independent set cannot exceed the number in a spanning set. Every spanning set has at least as many elements as the biggest independent set.

### 3.11 Every basis has the same number of elements

Let  $V$  be a finite dimensional vector space and let  $B$  and  $B'$  be the bases of  $V$ . Then:

- $B$  is linearly independent and  $B'$  is a spanning set, so  $B$  has **at most** as many elements as  $B'$ .
- $B$  is a spanning set and  $B'$  is linearly independent, so  $B$  has **at least** as many elements as  $B'$ .

It follows that  $B$  and  $B'$  have the same number of elements.

#### Definition 3.7

The dimension of  $V$  is the number of elements in a basis of  $V$ .

**Note:** Every vector space that has a finite spanning set has a finite basis (since we can discard elements from a finite spanning set until a basis remains).

#### Examples:

- The set  $\{1, x, x^2, x^3\}$  is a basis for the vector space  $P_3$  of all polynomials of degree at most 3 with real coefficients.

It is linearly independent because the only way to write the zero polynomial as

$$a_3x^3 + a_2x^2 + a_1x + a_0 = 0$$

is by taking  $a_0 = a_1 = a_2 = a_3 = 0$ .

Another basis of  $P_3$ , preferable for some applications, consists of the first four Legendre polynomials:

$$\{1, x, \frac{1}{2}(3x^2 - 1), \frac{1}{2}(5x^3 - 3x)\}.$$

- The **row space** of an  $m \times n$  matrix is the subspace of  $\mathbb{R}^n$  spanned by its rows. When we reduce a matrix to row-reduced echelon form (RREF), we are computing a basis of its row space.
- In  $\mathbb{R}^2$ , the reflection in the line  $y = 2x$  sends:

$$(1, 0) \mapsto \left(-\frac{3}{5}, \frac{4}{5}\right), \quad (0, 1) \mapsto \left(\frac{4}{5}, \frac{3}{5}\right).$$

Its standard matrix is:

$$\begin{bmatrix} -\frac{3}{5} & \frac{4}{5} \\ \frac{4}{5} & \frac{3}{5} \end{bmatrix}.$$

The same reflection sends:

$$(1, 2) \mapsto (1, 2), \quad (2, -1) \mapsto (-2, 1).$$

It is easier to describe this transformation in terms of the basis:

$$\left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}.$$

### 3.12 Row rank and column rank

Let  $A$  be an  $m \times n$  matrix.

The **row rank** of  $A$ , denoted  $r$ , is the dimension of the row space of  $A$ —the subspace of  $\mathbb{R}^n$  spanned by the rows of  $A$ .

The **column rank** of  $A$ , denoted  $c$ , is the dimension of the column space of  $A$ —the subspace of  $\mathbb{R}^m$  spanned by the columns of  $A$ . Equivalently, it is the dimension of the image of the linear transformation represented by  $A$ .

- The row rank is the number of linearly independent rows in  $A$ .
- The column rank is the number of linearly independent columns in  $A$ .

Since the row rank is at most  $m$  and the column rank at most  $n$ , both values can be strictly less than  $m$  or  $n$ , respectively.

### 3.13 Row rank = column rank

#### Theorem 3.2

The row rank and column rank are the same for every matrix

Therefore, we refer to this common value simply as the **rank** of the matrix.

Let  $A$  be an  $m \times n$  matrix. The row rank  $r$  is the number of non-zero rows in the RREF of  $A$ , and the column rank  $c$  is the number of linearly independent columns of  $A$ . To show that  $c \leq r$ , consider a basis for the row space of  $A$  and arrange its vectors as the rows of an  $r \times n$  matrix  $P$ . Since every row of  $A$  is a linear combination of the rows of  $P$ , there exists an  $m \times r$  matrix  $Q$  such that

$$A = QP.$$

It follows that each column of  $A$  is a linear combination of the  $r$  columns of  $Q$ , implying that  $\dim(\text{col}(A)) \leq r$ . Hence,  $c \leq r$ .

Conversely, to show that  $r \leq c$ , take a basis for the column space of  $A$  and arrange its vectors as the columns of an  $m \times c$  matrix  $P'$ . Since every column of  $A$  is a linear combination of the columns of  $P'$ , there exists a  $c \times n$  matrix  $Q'$  such that

$$A = P'Q'.$$

Therefore, each row of  $A$  is a linear combination of the  $c$  rows of  $Q'$ , and  $\dim(\text{row}(A)) \leq c$ . Hence,  $r \leq c$ . Combining both inequalities, we conclude that  $r = c$ , i.e., the row rank and column rank are equal.

#### Example 3.3

**Step 1: Determine the Rank.** Reduce  $A$  to its reduced row echelon form (RREF):

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & 6 \\ 1 & 1 & 1 \end{bmatrix} \quad \text{RREF}(A) = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{bmatrix}.$$

There are 2 non-zero rows, so the row rank is  $r = 2$ . Examining the columns, we observe that the third column is a linear combination of the first two, so the column rank  $c = 2$  as well.

**Step 2: Show that  $c \leq r$  via  $A = QP$ .** Choose a basis for the row space from the non-zero rows of RREF

$$A = QP = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & 6 \\ 1 & 1 & 1 \end{bmatrix}.$$

Thus, each column of  $A$  is a linear combination of the  $r = 2$  columns of  $Q$ , implying that  $\dim(\text{col}(A)) \leq r$ .

**Step 3: Show that  $r \leq c$  via  $A = P'Q'$ .** Take a basis for the column space of  $A$

$$A = P'Q' = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & 6 \\ 1 & 1 & 1 \end{bmatrix}.$$

So, each row of  $A$  is a linear combination of the  $c = 2$  rows of  $Q'$ , and  $\dim(\text{row}(A)) \leq c$ .

**Conclusion.** Since  $c \leq r$  and  $r \leq c$ , it follows that  $r = c = 2$ . This example confirms that the row rank equals the column rank.