# **2.2 Linear Vector Space**

# **2.2.1 Linear vector space**

- **Def** A set V is defined as a **linear vector space** over a scalar field  $\mathcal{F}$ , if the operation of addition is defined for members of  $V$  and multiplication of elements of  $V$  by an element of the field  $\mathcal F$  is defined. That is,
	- 1. If  $\underline{x} \in \mathcal{V}, y \in \mathcal{V}$ , then  $\underline{x} + y \in \mathcal{V}$  and unique.
	- 2. If  $\underline{x} \in \mathcal{V}, \alpha \in \mathcal{F}$ , then  $\alpha \underline{x} \in \mathcal{V}$ .

These operations must obey the following properties.

- 1.  $\underline{x} + y = y + \underline{x}$
- 2.  $(\underline{x} + y) + \underline{z} = \underline{x} + (y + \underline{z})$
- 3. There is a unique vector  $\underline{0}$  in  $V$ , called zero vector, such that

 $x + 0 = x$  for all  $x \in \mathcal{V}$ 

4. For each vector  $\underline{x} \in \mathcal{V}$ , there is a unique vector  $-\underline{x}$  such that

 $x + (-x) = 0$ 

- 5.  $1x = x$  for all  $x \in \mathcal{V}$ .
- 6. If  $\alpha, \beta \in \mathcal{F}$ , then  $\alpha(\beta x) = (\alpha \beta)x$  for all  $x \in \mathcal{V}$ .
- 7. If  $\alpha \in \mathcal{F}, \underline{x}, y \in \mathcal{V}$ , then  $\alpha(\underline{x} + y) = \alpha \underline{x} + \alpha y$
- 8. If  $\alpha, \beta \in \mathcal{F}, x \in \mathcal{V}$ , then  $(\alpha + \beta)x = \alpha x + \beta x$

#### **Example**

- $\mathbb{R}^n$ : Collection of all *n*-dimensional vectors with real components
- $\mathcal{C}^n$ : Collection of all *n*-dimensional vectors with complex components
- $\mathbb{R}^{m \times n}$ : Collection of all  $m \times n$  matrices with real components

# **2.2.2 Linearly independent set**

**Def** A set of vectors  $\{x_i\} \in \mathbb{R}^n$  is said to be **linearly dependent** if there exists n scalars  $\{\alpha_i\} \in \Re$ , such that

$$
\alpha_1 \underline{x}_1 + \alpha_2 \underline{x}_2 + \cdots + \alpha_n \underline{x}_n = 0
$$

where not all of the  $\{\alpha_i\}$  are zero.

If no such set of scalars exists, the vectors  $\{x_i\}$  are **linearly independent**.

For linearly dependent set, one of the vectors can be written as a **linear combination** of the other elements in the space.

$$
\underline{x}_1 = -\frac{1}{\alpha_1} \sum_{j=2}^n \alpha_j \underline{x}_j
$$

# **Example** in  $\mathbb{R}^3$

Most obvious example of a linearly independent set

$$
\begin{aligned}\n\underline{e}_1^T &= (1, 0, 0) \\
\underline{e}_2^T &= (0, 1, 0) \\
\underline{e}_3^T &= (0, 0, 1)\n\end{aligned}
$$

These are called base vectors or basis.

#### **Example** in  $\Re^{2\times 2}$

Basis

$$
\left[\begin{array}{cc} 1 & 0 \\ 0 & 0 \end{array}\right], \left[\begin{array}{cc} 0 & 1 \\ 0 & 0 \end{array}\right], \left[\begin{array}{cc} 0 & 0 \\ 1 & 0 \end{array}\right], \left[\begin{array}{cc} 0 & 0 \\ 0 & 1 \end{array}\right]
$$

# **2.2.3 Subspace**

**Def** Let W be a non-empty subset of  $\mathbb{R}^n$ . Then, W is a subspace of  $\mathbb{R}^n$  if

1.  $\underline{x}, \underline{y} \in \mathcal{W}$  implies  $(\underline{x} + \underline{y}) \in \mathcal{W}$ 

2.  $x \in \mathcal{W}$  and  $\alpha \in \Re$  implies  $\alpha x \in \mathcal{W}$ .

**Ex 1**: All vectors of the form  $\underline{x}^T = (\alpha_1, \alpha_2, \ldots, \alpha_r, 0, \ldots, 0)$ . (last  $n - r$ elements of the vector are zero).

**Ex 2**: All  $2 \times 2$  matrices that are symmetric. W is a subset of  $\mathbb{R}^{2 \times 2}$ .

**Theorem** Let A be a set of vectors in  $\mathbb{R}^n$  and let W be the set of all linear combination of elements in A, Then, W is a subspace of  $\mathbb{R}^n$  and each elements in  $W$  is written as

$$
\underline{y} = \alpha_1 \underline{x}_1 + \alpha_2 \underline{x}_2 + \cdots + \alpha_m \underline{x}_m
$$

where  $\{x_i\} \in \mathcal{A}$ , can  $\{\alpha_i\} \in \Re$ .

- **Def** Let  $W \subset \mathbb{R}^n$  be a subspace and let B a set of vectors from  $\mathbb{R}^n$ . Then B is a basis for  $W$  if
	- 1. the elements of  $\beta$  are linearly independent
	- 2. B spans or generates W, that is each vector in W is a linear combination of elements of B.
- **Def** If W is a subspace of  $\mathbb{R}^n$ , the dimension of W is the number of elements in a basis for W.
- **Theorem** The dimension of a subspace  $W$  is unique even though the components of the basis are not.

#### **2.2.4 Linear dependence**

Linear dependence of a set of  $n$  vectors:

For  $(\underline{a}_1, \underline{a}_2, \ldots, \underline{a}_n)$  (each  $\underline{a}_i \in \Re^n$ ) and for a set of numbers  $\{\alpha_i\} \in \Re$ ,

 $\underline{a}_1\alpha_1 + \underline{a}_2\alpha_2 + \cdots + \underline{a}_n\alpha_n = 0$ 

where each vector  $\underline{a}_i$  can be written as

$$
\underline{a}_i^T = (a_{1i}, a_{2i}, \dots, a_{ni})
$$

Then,

$$
\begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{bmatrix} \alpha_1 + \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{n2} \end{bmatrix} \alpha_2 + \cdots + \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{nn} \end{bmatrix} \alpha_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
$$

In matrix form



or

$$
\underline{A} \underline{\alpha} = \underline{0}
$$

That is, linear dependence  $\equiv$  nontrivial solution (other than  $\underline{\alpha} = \underline{0}$ ) of homogeneous linear equation

- **case I** If  $\text{rank}(\underline{A}) = n$ , the inverse matrix is well-defined and  $\underline{\alpha} = \underline{0}$  is the unique solution  $\longrightarrow \{\underline{a}_i\}$  is linearly independent
- **case II** For the matrix with  $\text{rank}(\underline{\underline{A}}) = n 1$ Assume an ordering



For submatrix  $\underline{\tilde{A}}$ ,

$$
\underline{\underline{\tilde{A}}} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1,n-1} \\ a_{21} & a_{22} & \cdots & a_{2,n-1} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n-1,1} & a_{n-1,2} & \cdots & a_{n-1,n-1} \end{bmatrix}
$$

 $\det(\underline{\underline{\tilde{A}}} ) \neq 0 \longrightarrow \underline{\tilde{A}}^{-1}$  exists. Neglecting the last row,

$$
\underline{\underline{\tilde{A}}}\begin{bmatrix}\n\alpha_1 \\
\alpha_2 \\
\vdots \\
\alpha_{n-1}\n\end{bmatrix} = -\alpha_n \begin{bmatrix}\na_{1n} \\
a_{2n} \\
\vdots \\
a_{n-1,n}\n\end{bmatrix}
$$

 $\longrightarrow$  Assume  $\alpha_n$ , then we can determine  $\alpha_1, \ldots, \alpha_{n-1}$ .

 $\longrightarrow$  Then,

$$
\underline{a}_1\alpha_1 + \dots + \underline{a}_{n-1}\alpha_{n-1} + \underline{a}_n\alpha_n = 0
$$

 $\longrightarrow \underline{a}_n$  is a linear combination of the first  $n-1$  vectors. That is,  $\{a_i\}$  is linearly dependent

# **2.3 Linear Transformation and Linear Equation Sets**

# **2.3.1 Linear transformation**

- $n \times m$  **matrix** transformation that takes an element of  $\mathbb{R}^m$  into an element of  $\mathbb{R}^n$ .
	- has the properties of linear transformation

**Def** A linear transformation from  $\mathbb{R}^m$  to  $\mathbb{R}^n$  is a matrix  $\underline{\underline{A}} : \mathbb{R}^m \to \mathbb{R}^n$  such that

$$
\underline{A}(\alpha \underline{x} + \beta \underline{y}) = \alpha \underline{A} \underline{x} + \beta \underline{A} \underline{y}
$$

where  $\underline{x}, \underline{y} \in \Re^m, \alpha, \beta \in \Re$ .

### **2.3.2 Range and null space**

**Def** If  $\underline{A} \in \mathbb{R}^{n \times m}$ , the subspace of  $\mathbb{R}^n$  spanned by the columns  $\{\underline{a}_i\}, i = 1, \ldots, m$ of  $\underline{A}$  is called the **range** of  $\underline{A}$  and is written as  $\mathcal{R}(\underline{A})$ .

 $\dim(\mathcal{R}(\underline{\underline{A}}))$  = number of linearly independent columns of  $\underline{\underline{A}}$ 

**Def** For  $\underline{A} \in \mathbb{R}^{n \times m}$ , the **null space** of  $\underline{A}$ ,  $\mathcal{N}(\underline{A})$ , is the subspace of  $\mathbb{R}^m$  formed by all vectors, <u>x</u> such that  $\underline{A} \underline{x} = 0$ .

 $\dim(\mathcal{N}(\underline{\underline{A}})) =$  dimension of the basis of  $\mathcal{N}(\underline{\underline{A}})$ 

#### **2.3.3 Homogeneous equation set**

For homogeneous equation set  $\underline{A} \underline{x} = \underline{0}$ , following theorem holds.

**Theorem** If  $\underline{A} \in \mathbb{R}^{n \times m}$ , the null space of  $\underline{A}$ ,  $\mathcal{N}(\underline{A})$ , has  $\dim(\mathcal{N}(\underline{A})) = m - r$ where  $r = \text{rank}(\underline{A})$ . If  $r = m$ , then  $\underline{x} = \underline{0}$  is the only solution.

#### **2.3.4 Nonhomogeneous equation set**

- **Theorem** Let  $\underline{A} \in \mathbb{R}^{n \times m}$  and  $\underline{A} = (\underline{a_1}, \underline{a_2}, \dots, \underline{a_m})$  where  $\underline{a_i} \in \mathbb{R}^n$ . Then,  $\underline{A} \underline{x} = \underline{b}$ , where  $\underline{b} \in \mathbb{R}^n$ , has a solution  $\underline{x} \in \mathbb{R}^m$  (*i.e.*, is soluble) iff  $\dim(\underline{a}_1, \underline{a}_2, \ldots, \underline{a}_m, \underline{b})$  is equal to  $\dim(\mathcal{R}(\underline{A}))$ . That is  $\underline{b}$  is a linear combination of  $\{\underline{a}_i\}.$
- **Theorem** Let  $\underline{A} \in \mathbb{R}^{n \times m}$ . If  $\underline{b} \in \mathcal{R}(\underline{A})$  and  $\dim(\mathcal{R}(\underline{A})) = m$ , then  $\underline{A} \underline{x} = \underline{b}$ possesses a unique solution.

**Theorem** Let  $\underline{A} \in \mathbb{R}^{n \times m}$  and  $\underline{b} \in \mathcal{R}(\underline{A})$ . If  $\text{rank}(\underline{A}) = r < m$ , then  $\underline{A} \underline{x} = \underline{b}$  has the general solution  $\underline{x} = \underline{x}_o + \underline{z}$  where  $\underline{x}_o$  is a particular solution of  $\underline{A} \underline{x} = \underline{b}$ and z is any solution of the corresponding problem  $\underline{A} x = \underline{0}$ . *i.e.*  $z \in \mathcal{N}(\underline{A})$ where  $\dim(\mathcal{N}(\underline{\underline{A}}))=m-r.$