CHAPTER 2

Linear Transformations and Matrices

2.1 Linear Transformations

Definition 2.1. A linear transformation T from a vector space V to a vector space W is a map

$$T: V \longrightarrow W$$

such that for all vectors $\mathbf{u}, \mathbf{v} \in V$ and scalar $c \in K$:

(1)
$$T(\mathbf{u} + \mathbf{v}) = T(\mathbf{u}) + T(\mathbf{v})$$

(2)
$$T(c \cdot \mathbf{u}) = c \cdot T(\mathbf{u})$$

V is called **domain** and W is called **codomain** of T.

The set of all such linear transformations $T: V \longrightarrow W$ is denoted by L(V, W).

Fact. Any $T \in L(V, W)$ is uniquely determined by the image on any basis \mathcal{B} of V.

Example 2.1. The identity map $Id: V \longrightarrow V$ given by $Id(\mathbf{v}) = \mathbf{v}$.

Example 2.2. Differential operators on the space of real-valued differentiable functions.

Example 2.3. $Tr: M_{3\times 3}(\mathbb{R}) \longrightarrow \mathbb{R}$ on the space of 3×3 matrices with real entries.

Example 2.4. Matrix multiplication: $\mathbb{R}^n \longrightarrow \mathbb{R}^m$.

Theorem 2.2. Let V, W be finite dimensional vector spaces with dim V = n, dim W = m. Then every linear transformation $T \in L(V, W)$ can be represented by an $m \times n$ matrix.

Let $\mathcal{B} \subset V, \mathcal{B}' \subset W$ be their bases. If $T(\mathbf{u}) = \mathbf{w}$, then the matrix is given by

$$T]^{\mathcal{B}}_{\mathcal{B}'}: \mathbb{R}^n \longrightarrow \mathbb{R}^m$$
$$[\mathbf{u}]_{\mathcal{B}} \mapsto [\mathbf{w}]_{\mathcal{B}'}$$

It is called the matrix of T with respect to the bases \mathcal{B} and \mathcal{B}' .

Definition 2.3.

• The **kernel** or **null space** of *T* is:

$$\operatorname{Ker}(T) := \{ \mathbf{u} \in V : T(\mathbf{u}) = \mathbf{0} \}$$

• The **image** or **range** of *T* is:

$$\operatorname{Im}(T) := \{ \mathbf{w} \in W : \mathbf{w} = T(\mathbf{u}) \text{ for some } \mathbf{u} \in V \}$$

Theorem 2.4. Let $T \in L(V, W)$. Then

- The kernel of T is a subspace of V.
- The image of T is a subspace of W.

Example 2.5. If $T : \mathbb{R}^n \longrightarrow \mathbb{R}^m$ is represented by a matrix **A**, then

- The kernel of **A** is the **null space** Nul**A**. It is the set of all solutions to $\mathbf{A}\mathbf{x} = \mathbf{0}$ of *m* homogeneous linear equations in *n* unknown. It is a subspace of \mathbb{R}^n .
- The image of **A** is the **column space** Col**A**. It is the set of all linear combinations of the columns of **A**. It is a subspace of \mathbb{R}^m .

Rule. For a matrix **A**, the row operations do not affect linear dependence of the columns. Use the *reduced echelon form* to find the basis of Nul**A** and Col**A**.

Example 2.6. The kernel of $\frac{d}{dx}$ on the space of differentiable functions is the set of all constant functions.

2.2 Injection, Surjection and Isomorphism

Definition 2.5. A linear transformation $T: V \longrightarrow W$ is called

- one-to-one or injective if $T(\mathbf{u}) = T(\mathbf{v})$ implies $\mathbf{u} = \mathbf{v}$
- onto or surjective if for every $\mathbf{w} \in W$, there exists $\mathbf{u} \in V$ such that $T(\mathbf{u}) = \mathbf{w}$
- isomorphism if T is one-to-one and onto.

Definition 2.6. If there exists an isomorphism $T \in L(V, W)$, we say V is **isomorphic** to W, written as $V \simeq W$.

Properties 2.7. Let $T \in L(V, W)$.

- If T is injective, then $\mathcal{N}(T) = \{\mathbf{0}\}$, i.e. $T(\mathbf{u}) = \mathbf{0} \Longrightarrow \mathbf{u} = \mathbf{0}$.
- If T is injective, it maps linearly independent set to linearly independent set.
- If T is injective, and $H \subset V$ is a subspace, then dim $T(H) = \dim H$.
- If T is surjective, then $\mathcal{R}(T) = W$.
- If T is isomorphism, then $\dim V = \dim W$.

Theorem 2.8. If $\mathcal{B} = {\mathbf{b}_1, ..., \mathbf{b}_n}$ is a basis for a vector space V, then the **coordinate mapping**

 $\mathbf{x} \mapsto [\mathbf{x}]_{\mathcal{B}}$

is an isomorphism $V \simeq K^n$.

Example 2.7.
$$\left\{ \begin{pmatrix} x \\ y \\ 0 \end{pmatrix} : x, y \in \mathbb{R} \right\} \neq \mathbb{R}^2$$
 but $\left\{ \begin{pmatrix} x \\ y \\ 0 \end{pmatrix} : x, y \in \mathbb{R} \right\} \simeq \mathbb{R}^2$

Example 2.8. $\mathbb{P}_n(K) \simeq K^{n+1}$ Example 2.9. $M_{m \times n}(K) \simeq K^{mn}$

Example 2.10. $\mathbb{C} \simeq \mathbb{R}^2$ as vector spaces over \mathbb{R} .

2.3 Rank

Definition 2.9.

- The **rank** of *T* is the dimension of the image of *T*.
- The **nullity** of *T* is the dimension of the kernel of *T*.

Below we have the **Fundamental Theorem of Linear Algebra**, which consists of the Rank-Nullity Theorem and the Theorem of Column Rank = Row Rank :

Theorem 2.10 (Rank–Nullity Theorem). Let $T \in L(V, W)$. Then

 $\dim \operatorname{Im}(T) + \dim \operatorname{Ker}(T) = \dim V$

Let T be represented by a $m \times n$ matrix **A** (i.e. $V = \mathbb{R}^n, W = \mathbb{R}^m$). Then **rank** of **A** is the dimension of Col**A**. The **row space** is the space spanned by the rows of **A**. It is a subspace of \mathbb{R}^n . The **row rank** is the dimension of the row space.

The row space of **A** is the column space of \mathbf{A}^{T} , hence the row rank of **A** equals the rank of \mathbf{A}^{T} .

Theorem 2.11 (Column Rank = Row Rank). Rank of \mathbf{A} = Rank of \mathbf{A}^T .

Theorem 2.12 (Invertible Matrix Theorem). Let \mathbf{A} be an $n \times n$ matrix. Then \mathbf{A} is invertible iff any one of the statements hold:

- (1) Columns of **A** form a basis of \mathbb{R}^n
- (2) $\operatorname{Col} \mathbf{A} = \mathbb{R}^n$
- (3) Rank of $\mathbf{A} = n$
- (4) $\operatorname{Nul} \mathbf{A} = \{\mathbf{0}\}$
- (5) Nullity of $\mathbf{A} = 0$.

2.4 Change of Basis

Recall that for $\mathbf{x} \in V$ and $\mathcal{B} = {\mathbf{b}_1, ..., \mathbf{b}_n}$ a basis of V,

$$[\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix} \in \mathbb{R}^n$$

is the \mathcal{B} -coordinate vector of \mathbf{x} if

$$\mathbf{x} = c_1 \mathbf{b}_1 + \ldots + c_n \mathbf{b}_n.$$

If $\mathcal{B}' = \{\mathbf{b}'_1, ..., \mathbf{b}'_n\}$ is another basis of V, then

$$[\mathbf{x}]_{\mathcal{B}'} = \begin{pmatrix} c'_1 \\ \vdots \\ c'_n \end{pmatrix} \in \mathbb{R}^n$$

is the \mathcal{B}' -coordinate vector of \mathbf{x} if

$$\mathbf{x} = c_1' \mathbf{b}_1' + \dots + c_n' \mathbf{b}_n'.$$

The relationship between the vectors $[\mathbf{x}]_{\mathcal{B}}$ and $[\mathbf{x}]_{\mathcal{B}'}$ is given by

Theorem 2.13 (Change of Basis formula). There exists an $n \times n$ matrix $P_{\mathcal{B}'}^{\mathcal{B}}$ such that

$$[\mathbf{x}]_{\mathcal{B}'} = P^{\mathcal{B}}_{\mathcal{B}'} \cdot [\mathbf{x}]_{\mathcal{B}}$$

where *column-wise* it is given by

$$P_{\mathcal{B}'}^{\mathcal{B}} = \begin{pmatrix} [\mathbf{b}_1]_{\mathcal{B}'} & [\mathbf{b}_2]_{\mathcal{B}'} & \cdots & [\mathbf{b}_n]_{\mathcal{B}'} \end{pmatrix}$$

 $P_{\mathcal{B}'}^{\mathcal{B}}$ is called the **change-of-coordinate matrix** from \mathcal{B} to \mathcal{B}' .

In other words, it is the matrix of the identity map Id with respect to the basis \mathcal{B} and \mathcal{B}' (see Theorem 2.2).

Properties 2.14. The $n \times n$ matrix $\mathcal{P}^{\mathcal{B}}_{\mathcal{B}'}$ is invertible. We have

$$[\mathbf{x}]_{\mathcal{B}} = \left(P_{\mathcal{B}'}^{\mathcal{B}}\right)^{-1} \cdot [\mathbf{x}]_{\mathcal{B}'}$$

Hence

$$P_{\mathcal{B}}^{\mathcal{B}'} = \left(P_{\mathcal{B}'}^{\mathcal{B}}\right)^{-1}$$

Example 2.11. If \mathcal{B} is a basis of \mathbb{R}^n and \mathcal{E} is the standard basis of \mathbb{R}^n , then

$$[\mathbf{b}_i]_{\mathcal{E}} = \mathbf{b}_i.$$

Hence we simply have

$$P_{\mathcal{E}}^{\mathcal{B}} = \begin{pmatrix} \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_n \end{pmatrix}$$

 $P_{\mathcal{E}}^{\mathcal{B}} = \begin{pmatrix} \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_n \end{pmatrix}$ $P^{\mathcal{B}} := P_{\mathcal{E}}^{\mathcal{B}} \text{ is called the$ **change-of-coordinate matrix** $from <math>\mathcal{B}$ to the standard basis of \mathbb{R}^n .

Properties 2.15. We have

- $P_{\mathcal{B}''}^{\mathcal{B}'} \cdot P_{\mathcal{B}'}^{\mathcal{B}} = P_{\mathcal{B}''}^{\mathcal{B}}$
- $P_{\mathcal{B}'}^{\mathcal{B}} = (P^{\mathcal{B}'})^{-1} \cdot P^{\mathcal{B}}$

Example 2.12. Let $\mathcal{E} = \{ \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix} \}$ be the standard basis of \mathbb{R}^2 . Let

$$\mathcal{B} = \{ \mathbf{b}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \mathbf{b}_2 = \begin{pmatrix} 1 \\ -1 \end{pmatrix} \},$$
$$\mathcal{B}' = \{ \mathbf{b}'_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \mathbf{b}'_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \}$$

be two other bases of \mathbb{R}^2 . Then

$$P^{\mathcal{B}} = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

$$P^{\mathcal{B}'} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$$

$$P^{\mathcal{B}}_{\mathcal{B}'} = (P^{\mathcal{B}'})^{-1} \cdot P^{\mathcal{B}}$$

$$= \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}^{-1} \cdot \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} = \begin{pmatrix} 0 & 2 \\ 1 & -1 \end{pmatrix}$$

One can check that this obeys the formula from Theorem 2.13.

$$\begin{aligned} \mathbf{b}_1 &= \mathbf{0} \cdot \mathbf{b}_1' + \mathbf{1} \cdot \mathbf{b}_2' \\ \mathbf{b}_2 &= 2 \cdot \mathbf{b}_1' + (-1) \cdot \mathbf{b}_2'. \end{aligned}$$