

# Linear Mapping and Linear Transformation

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## Abstract

This is the note of Linear Mapping and Linear Transformation, maded by Len Fu while his learning progress. The main content is from *Linear Algebra Done Right* , . and *Linear Algebra Allenby*. It's also the notes from the classes of BIT.

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# 1 Linear Mapping

To prove a mapping is not linear mapping, you just need to find a counterexample.

## 1.1 Mapping

**Definition 1.1** (Mapping). Suppose  $X$  and  $Y$  are two non-empty sets. A mapping  $\sigma$  from  $X$  to  $Y$ , denoted as  $\sigma : X \rightarrow Y$ , is a rule that assigns to each element  $x \in X$  exactly one element  $y$  in the set  $Y$ . The assignment  $y = \sigma(x)$  is called the image of  $x$  under the mapping  $\sigma$ , and  $x$  is called the preimage.

**Properties 1.1** (Domain). Every element  $x$  in the set  $X$  must be mapped to some element in  $Y$ .

**Properties 1.2** (Uniqueness). For each  $x$  in  $X$ , there is a unique  $y$  in  $Y$  such that  $\sigma(x) = y$ .

The set  $X$  is called the domain of the mapping  $\sigma$ , and the set  $Y$  is called the codomain. The image of a set, which is the set of all elements in  $Y$  that are mapped to by elements in  $X$ , denoted by as  $Im(\sigma)$  or  $\sigma(X)$ . , or

$$\sigma(X) = \{y \in Y \mid \exists x \in X \text{ such that } \sigma(x) = y\}.$$

**Definition 1.2** (Injective Mapping). A mapping  $\sigma$  is called an *injective mapping* or an *into mapping* if for each  $y$  in  $Y$ , there is a unique  $x$  in  $X$  such that  $\sigma(x) = y$ . Formally, for all  $x_1, x_2 \in X$ , if  $\sigma(x_1) = \sigma(x_2)$ , then  $x_1 = x_2$ .

**Definition 1.3** (Surjective Mapping). A mapping  $\sigma$  is called a *surjective mapping* or a *onto mapping* if for every  $y$  in  $Y$ , there exists an  $x$  in  $X$  such that  $\sigma(x) = y$ .

**Definition 1.4** (Bijective Mapping). A mapping  $\sigma$  is called a *bijective mapping* or a *one-to-one mapping* if it is both injective and surjective.

**Definition 1.5** (Product of mappings). Set  $\sigma$  as a mapping from  $X$  to  $Y$ , and  $\tau$  as a mapping from  $Y$  to  $Z$ , then we can define a new mapping  $\tau \circ \sigma$  from  $X$  to  $Z$  by

$$\tau \circ \sigma(x) = \tau(\sigma(x)), \text{ for all } x \in X.$$

## 1.2 Linear Mapping

**Definition 1.6** (Linear Mapping). Set the  $V_1$  and  $V_2$  as vector spaces on the field  $F$ . If a mapping  $\tau$  from  $V_1$  to  $V_2$  keeps the adding property and the scalar multiplication property, then we say that  $\tau$  is a *linear mapping* or a *linear transformation*.

$$\sigma(\alpha + \beta) = \sigma(\alpha) + \sigma(\beta), \sigma(k\alpha) = k\sigma(\alpha), \text{ for any } \alpha \text{ and } \beta \in V_1, k \in F.$$

The necessary and sufficient condition for a Linear Mapping is

$$\sigma(k\alpha + l\beta) = k\sigma(\alpha) + l\sigma(\beta).$$

### 1.3 Unitary Mapping

Set  $V$  as a vector space on the field  $F$ , a mapping

$$\epsilon : V \rightarrow V$$

is defined as  $\epsilon(\alpha) = \alpha$ , for all  $\alpha \in V$ .

### 1.4 Zero Mapping

Set the  $V_1$  and  $V_2$  as vector spaces on the field  $F$ . A mapping

$$\tau : V_1 \rightarrow V_2$$

is defined as  $\tau(0) = 0$ , for all  $\alpha \in V_1$ .

### 1.5 Properties

If  $\tau$  is a linear mapping, then it has follow properties:

**Properties 1.3.**  $\tau(\theta) = \theta$ ,  $\tau(-\alpha) = -\tau(\alpha)$

**Properties 1.4.** Linear Mappings keep the linear combination and linear coefficients unchanged.

**Properties 1.5.** Linear Mappings transform the linear relative vector group into another linear relative groups.

### 1.6 Matrix Representation of the Linear Mapping

**Definition 1.7.** Set  $\sigma$  as a linear mapping from  $V_1$  to  $V_2$ , choose a basis  $\alpha_1, \alpha_2, \dots, \alpha_n$  in the  $V_1$  and choose a basis  $\beta_1, \beta_2, \dots, \beta_m$  in the  $V_2$ . If the image of the basis  $\alpha_1, \alpha_2, \dots, \alpha_n$  is

$$\begin{cases} \sigma(\alpha_1) = a_{11}\beta_1 + a_{21}\beta_2 + \dots + a_{m1}\beta_m \\ \sigma(\alpha_2) = a_{12}\beta_1 + a_{22}\beta_2 + \dots + a_{m2}\beta_m \\ \dots \\ \sigma(\alpha_n) = a_{1n}\beta_1 + a_{2n}\beta_2 + \dots + a_{mn}\beta_m \end{cases}$$

and can be expressed as

$$[\sigma(\alpha_1), \sigma(\alpha_2), \dots, \sigma(\alpha_n)] = [\beta_1, \beta_2, \dots, \beta_m]A.$$

where  $A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}$  is called the linear mapping matrix of  $\sigma$  under the basis  $\alpha$  and  $\beta$ .

**Theorem 1.1.** If  $\sigma$  is a linear mapping from  $V_1$  to  $V_2$ , take a basis  $\alpha_1, \alpha_2, \dots, \alpha_n$  in the  $V_1$ , and take a basis  $\beta_1, \beta_2, \dots, \beta_m$  in the  $V_2$ , then the linear mapping matrix of  $\sigma$  under the basis  $\alpha$  and  $\beta$  is  $A$ .

For every  $\alpha \in V$ , if the coordinate of  $\alpha$  under the basis  $\alpha$  is  $(x_1, x_2, \dots, x_n)^T$ , then the coordinate of  $\sigma(\alpha)$  under the basis  $\beta$  is  $(y_1, y_2, \dots, y_n)^T$ . Then

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = A \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}.$$

*Proof.* Since

$$[\sigma(\alpha_1), \sigma(\alpha_2), \dots, \sigma(\alpha_n)] = [\beta_1, \beta_2, \dots, \beta_n]A,$$

$$\alpha = [\alpha_1, \alpha_2, \dots, \alpha_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \sigma(\alpha) = [\sigma(\alpha_1), \sigma(\alpha_2), \dots, \sigma(\alpha_n)] \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},$$

and

$$\begin{aligned} \sigma\alpha &= \sigma([\alpha_1, \alpha_2, \dots, \alpha_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}) \\ &= [\sigma(\alpha_1, \alpha_2, \dots, \alpha_n)] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = [\beta_1, \beta_2, \dots, \beta_n]A \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \end{aligned}$$

Then we have

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = A \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}.$$

□

## 2 Exercise

**Exercise 2.1.** Set  $D : R[x]_{n+1} \rightarrow R[x]_n$  as *Derivative Map*, you should find the matrix representation of  $D$  under the basis  $1, x, x^2, \dots, x_n$  and  $1, x, x^2, \dots, x_{n-1}$ .

**Solution 2.1.1.** Set  $f_1 = 1, f_2 = x, \dots, f_{n+1} = x^n$ , then

$$D(f_1) = 0, D(f_2) = 1, D(f_3) = 2x, \dots, D(f_{n+1}) = nx^{n-1}.$$

$$\begin{aligned}
& \begin{cases} D(f_1) = 0f_1 + 0f_2 + 0f_3 + \cdots + 0f_{n-1} \\ D(f_2) = 1f_1 + 0f_2 + 0f_3 + \cdots + 0f_{n-1} \\ D(f_3) = 0f_1 + 2f_2 + 0f_3 + \cdots + 0f_{n-1} \\ \vdots \\ D(f_{n+1}) = 0f_1 + 0f_2 + \cdots + nf_{n-1} \end{cases} \\
& [D(f_1), D(f_2), D(f_3), \dots, D(f_{n+1})] \\
& = [0, 1, 2x, \dots, nx^{n-1}] \\
& = [1, x, \dots, x^{n-1}] \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & n \end{bmatrix}
\end{aligned}$$

Thus, the matrix representation of  $D$  under the basis  $1, x, x^2, \dots, x^n$  and basis  $1, x, x^2, \dots, x^{n-1}$  is

$$\begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & n \end{bmatrix}$$

**Exercise 2.2.** In  $R^3$ , we form a mapping  $\sigma : R^3 \rightarrow R^3$  by  $\sigma[(x_1, x_2, x_3)] = (x_3, 0, x_2 - 2x_1)$ ,  $(x_1, x_2, x_3) \in R$ .

1. Prove  $\sigma$  is a linear mapping.
2. Find the matrix representation of  $\sigma$  under the basis  $(1, 0, 0), (1, 1, 0), (1, 1, 1)$ .

**Solution 2.2.1.** Choose any  $(x_1, x_2, x_3)$  and  $(y_1, y_2, y_3) \in R^3$ ,  $k \in R$ , Since

$$\begin{aligned}
\sigma[(x_1, x_2, x_3) + (y_1, y_2, y_3)] &= \sigma[(x_1 + y_1, x_2 + y_2, x_3 + y_3)] \\
&= (x_3 + y_3, 0, x_2 + y_2 - 2(x_1 + y_1)) \\
&= (x_3, 0, x_2 - 2x_1) + (y_3, 0, y_2 - 2y_1) \\
&= \sigma[(x_1, x_2, x_3)] + \sigma[(y_1, y_2, y_3)] \\
\sigma[k(x_1, x_2, x_3)] &= \sigma[(kx_1, kx_2, kx_3)] \\
&= (kx_3, 0, kx_2 - 2kx_1) \\
&= k(x_3, 0, x_2 - 2x_1) \\
&= k\sigma[(x_1, x_2, x_3)]
\end{aligned}$$

**Solution 2.2.2.** Choose the natrual basis of  $R^3$ ,  $(1, 0, 0), (0, 1, 0), (0, 0, 1)$ .

$$\begin{aligned}
\sigma[(1, 0, 0)] &= (0, 0, -2) \\
\sigma[(0, 1, 0)] &= (0, 0, 1) \\
\sigma[(0, 0, 1)] &= (1, 0, 0)
\end{aligned}$$

and

$$\begin{cases} (0, 0, -2) &= a_{11}(1, 0, 0) + a_{12}(1, 1, 0) + a_{13}(1, 1, 1) \\ (0, 0, 1) &= a_{21}(1, 0, 0) + a_{22}(1, 1, 0) + a_{23}(1, 1, 1) \\ (1, 0, 0) &= a_{31}(1, 0, 0) + a_{32}(1, 1, 0) + a_{33}(1, 1, 1) \end{cases}$$

$$\begin{cases} a_{11} = 0, & a_{12} = 2, & a_{13} = -2 \\ a_{21} = 0, & a_{22} = -1, & a_{23} = 1 \\ a_{31} = 1, & a_{32} = 0, & a_{33} = 0 \end{cases}$$

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

That is the answer.