

# 1 September 10th, 2020

## 1.1 More Linear Algebra Review

**Definition 1.1.** If  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$ , then the **image** of  $T$  is:

$$\text{image } T = \{y \in \mathbb{R}^n : \exists x \in \mathbb{R}^m \text{ s.t. } y = T(x)\}.$$

The image

**Definition 1.2.** Let  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  be a linear transformation. The **rank** of  $T$  is the dimension of the image of  $T$ .

### Lemma 1.3

If  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  is linear, then:

1.  $\text{rank } T \leq n$
2.  $\text{rank } T \leq m$

*Proof.* The proof of 1) is trivial. For 2), we use the theorem below. □

### Theorem 1.4

$$\text{rank } T + \dim \ker T = m.$$

**Definition 1.5.** A linear transformation  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  has **full rank** if:

$$\text{rank } T = \min\{n, m\}.$$

### Lemma 1.6

If  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  has full rank, and:

1. if  $m \geq n$ , then the matrix of  $T$  relative to certain basis is  $\begin{bmatrix} I_n & 0 \end{bmatrix}$
2. if  $m \leq n$ , then the matrix of  $T$  relative to a certain basis is  $\begin{bmatrix} I_m \\ 0 \end{bmatrix}$

### Example 1.7

Fix  $e \in \mathbb{R}^n$ , define  $T : \mathbb{R}^n \rightarrow \mathbb{R}$  by  $T(x) = \langle x, e \rangle$ ,  $\forall x \in \mathbb{R}^n$ , then:

- its rank is 1 if  $e \neq 0$
- its rank is 0 if  $e = 0$ .

**Definition 1.8.** In the case we choose  $e = e_j$ , which is the  $j$ -th standard basis of  $\mathbb{R}^n$ , then the map  $T$  above is called the **projection to the  $j$ -th coordinate**, symbolically written as  $\Pi_j$ .

**Definition 1.9.** For a given  $c \in \mathbb{R}$ , then the set  $\{x \in \mathbb{R}^n : T(x) = c\}$  forms a **hyperplane**

**Definition 1.10.** Let  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  be a linear transformation whose matrix relative to the standard basis is

$$\begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1m} \\ \vdots & \ddots & & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{mn} \end{bmatrix}$$

then the **norm** of  $T$  is

$$\|T\| = \sqrt{\sum_{i,j} t_{ij}^2} = \sqrt{\text{tr}(TT^\top)}.$$

### Theorem 1.11

Let  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$  be linear. Then for every  $x \in \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \in \mathbb{R}^m$ , then:

$$\|T(x)\| \leq \|T\| \|x\|.$$

*Proof.* Denote the matrix  $T$  relative to the standard basis as above. If  $x \in \mathbb{R}^m$ , we have:

$$\begin{aligned} \|T(x)\|^2 &= \left\| T \left( \sum_{i=1}^m x_i e_i \right) \right\|^2 \\ &= \left\| \sum_{i=1}^m x_i T(e_i) \right\|^2 \\ &= \left\| \sum_{i=1}^m \sum_{j=1}^n x_i t_{ij} e_j \right\|^2 \\ &= \sum_{j=1}^n \left( \sum_{i=1}^m x_i t_{ij} \right)^2 \\ &\leq \sum_{j=1}^n \left( \left( \sum_{i=1}^m x_i^2 \right) \left( \sum_{i=1}^m t_{ij}^2 \right) \right) \quad \text{Cauchy-Schwarz} \\ &= \sum_{j=1}^n \sum_{i=1}^m t_{ij}^2 \|x\|^2 \\ &= \|T\|^2 \|x\|^2 \\ &= \|T\| \|x\| \end{aligned}$$

□

**Lemma 1.12** 1. If  $\|T\| = 0$ , then  $T = 0$

2. If  $T, S : \mathbb{R}^m \rightarrow \mathbb{R}^n$  are linear, then:  $\|T + S\| \leq \|T\| + \|S\|$

3. If  $T : \mathbb{R}^m \rightarrow \mathbb{R}^n$ ,  $S : \mathbb{R}^\ell \rightarrow \mathbb{R}^m$  are linear, then  $\|TS\| \leq \|T\|\|S\|$

**Definition 1.13.** For a given sequence  $\{a_n\}$  of real numbers,  $\{a_n\}$  converges to  $a \in \mathbb{R}$  if for every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$ , such that  $n > N$  implies that  $|a_n - a| < \epsilon$

**Definition 1.14.** For a given sequence  $\{v_n\}$  of vectors in  $\mathbb{R}^n$ ,  $\{v_n\}$  converges to  $v \in \mathbb{R}^n$  if for every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$ , such that  $n > N$  implies that  $\|v_n - v\| < \epsilon$

**Definition 1.15.** For a given sequence  $\{T_n\}$  of linear transformations  $\mathbb{R}^\ell \rightarrow \mathbb{R}^n$ ,  $\{T_n\}$  converges to  $T$  if for every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$ , such that  $n > N$  implies that  $\|T_n - T\| < \epsilon$

**Lemma 1.16**

Let  $\{v_n\}$  be a sequence in  $\mathbb{R}^m$  which converges to  $v \in \mathbb{R}^m$ . Then:  $\forall j \in \{1, \dots, m\}$ ,  $\{\Pi_j(v_n)\}$  converges to  $\Pi_j(v)$

*Proof.* Since  $\{v_n\}$  converges,  $\forall \epsilon > 0$ ,  $\exists N \in \mathbb{N}$  s.t. if  $n > N$ , then  $\|v_n - v\| < \epsilon$ . Thus if  $n > N$ , then  $|\Pi_j(v_n) - \Pi_j(v)| = |\Pi_j(v_n - v)|$ . For every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$  such that if  $n > N$ , then  $|\Pi_j(v_n) - \Pi_j(v)| \leq \|v_n - v\| < \epsilon$   $\square$

**Lemma 1.17**

Let  $\{v_n\}$  be a sequence in  $\mathbb{R}^m$  so that  $\forall j \in \{1, \dots, m\}$ ,  $\{\Pi_j(v_n)\}$  converges. Then  $\{v_n\}$  is a convergent sequence of vectors.

*Proof.* Suppose that  $\{\Pi_j(v_n)\}$  converges to  $a_j$  and let  $v = \begin{bmatrix} a_1 \\ \vdots \\ a_m \end{bmatrix}$ . Thus if  $n > N_j$ , then  $|\Pi_j(v_n - v)| < \frac{\epsilon}{m}$  if  $n > N = \max\{N_1, N_2, \dots, N_m\}$ , we have:

$$\|v_n - v\| < \sum_j |\Pi_j(v_n - v)| < \frac{\epsilon}{m} \times m = \epsilon.$$

Since  $\square$