

MA 1140: Lecture 6

Linear Transformation and Rank-Nullity Theorem

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Linear transformation, or linear map

Definition

A transformation (or map) between vector spaces which satisfies the rule of linearity is called linear transformation (or linear map).

More precisely, let V and W be vector spaces over \mathbb{R} . A linear transformation $T : V \rightarrow W$ is a function such that

$$T(c_1 v_1 + c_2 v_2) = c_1 T(v_1) + c_2 T(v_2)$$

for all $c_1, c_2 \in \mathbb{R}$ and $v_1, v_2 \in V$.

Example

Let A be an $m \times n$ matrix over \mathbb{R} . Then the map $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ defined by $T(X) := AX$ for all $X \in \mathbb{R}^n$ is a linear transformation.

Proof. $T(X + Y) = A(X + Y) = AX + AY = T(X) + T(Y)$ and $T(cX) = A(cX) = c(AX) = cT(X)$.

An observation on matrix multiplication

$$\bullet \begin{pmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} =$$
$$x_1 \begin{pmatrix} 1 \\ 5 \\ 9 \end{pmatrix} + x_2 \begin{pmatrix} 2 \\ 6 \\ 10 \end{pmatrix} + x_3 \begin{pmatrix} 3 \\ 7 \\ 11 \end{pmatrix} + x_4 \begin{pmatrix} 4 \\ 8 \\ 12 \end{pmatrix}.$$

$$\bullet [C_1 \ C_2 \ \cdots \ C_n]_{m \times n} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} =$$
$$x_1(C_1) + x_2(C_2) + \cdots + x_n(C_n), \quad \text{where } C_1, \dots, C_n \in \mathbb{R}^m.$$

Matrix representation of a linear map $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$

Theorem

A linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ can be represented by an $m \times n$ matrix.

Proof. Let $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation. Want to construct an $m \times n$ matrix A such that $T(X) = AX$ for all $X \in \mathbb{R}^n$. Let $\{e_1, \dots, e_n\}$ be the standard basis of \mathbb{R}^n . Set $A := [T(e_1) \ T(e_2) \ \cdots \ T(e_n)]$. Clearly A is an $m \times n$ matrix. We show that $T(X) = AX$ for every $X \in \mathbb{R}^n$.

- Consider $X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \in \mathbb{R}^n$. Then
- $$\begin{aligned} AX &= [T(e_1) \ T(e_2) \ \cdots \ T(e_n)] X \\ &= x_1 T(e_1) + x_2 T(e_2) + \cdots + x_n T(e_n) \text{ (by the observation)} \\ &= T(x_1 e_1 + x_2 e_2 + \cdots + x_n e_n) = T(X). \end{aligned}$$



All linear transformations from \mathbb{R}^n to \mathbb{R}^m

Corollary

There is a one to one correspondence between the set of all linear transformations from \mathbb{R}^n to \mathbb{R}^m and the collection of all $m \times n$ matrices over \mathbb{R} .

Proof. Use the last theorem and the example.

Differentiation and integration transformation

Example (Differentiation transformation)

Let $V = \mathbb{R}[x]$, the set of all polynomials in x over \mathbb{R} . Define a map $D : V \rightarrow V$ as follows: If $f = a_0 + a_1x + a_2x^2 + \cdots + a_rx^r$, then

$$D(f) := a_1 + 2a_2x + \cdots + ra_rx^{r-1}.$$

Then D is a linear transformation.

Example (Integration transformation)

Let V be the set of all continuous functions from \mathbb{R} into \mathbb{R} . Define a map $T : V \rightarrow V$ as follows: If $f \in V$, then $T(f)$ is given by

$$T(f)(x) = \int_0^x f(t)dt \quad \text{for all } x \in \mathbb{R}.$$

Then T is a linear transformation.

What is $T(0)$?

- Let $T : V \rightarrow W$ be a linear transformation. What is $T(0)$?
Answer: $T(0) = 0$, because $T(0) = T(0 + 0) = T(0) + T(0)$.

Remarks on linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$

Theorem

Consider the standard basis $\{e_1, \dots, e_n\}$ of \mathbb{R}^n .

Then any linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is uniquely determined by $T(e_i)$ for all $1 \leq i \leq n$.

Proof. Every vector $v = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \in \mathbb{R}^n$ has a unique expression:

$$v = x_1 \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + x_2 \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix} + \cdots + x_n \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix} = x_1 e_1 + x_2 e_2 + \cdots + x_n e_n.$$

Hence, by linearity, $T(v) = x_1 T(e_1) + \cdots + x_n T(e_n)$, which has a unique choice, once $T(e_i)$ is given for every i .

Another approach. Since $T \sim A$, $T(e_i) \sim$ the i th column of A .

Remarks on linear transformation $T : V \rightarrow W$

Theorem

Let V be finite dimensional, and $\{v_1, \dots, v_n\}$ be a basis of V . Then any linear transformation $T : V \rightarrow W$ is uniquely determined by $T(v_i)$ for all $1 \leq i \leq n$.

Proof. Every vector $v \in V$ has a unique expression:

$v = c_1 v_1 + c_2 v_2 + \dots + c_n v_n$, because if

$v = d_1 v_1 + d_2 v_2 + \dots + d_n v_n$ is another expression, then

$$(c_1 - d_1)v_1 + \dots + (c_n - d_n)v_n = 0 \implies c_i = d_i \text{ for all } i.$$

Hence, by linearity, $T(v) = c_1 T(v_1) + \dots + c_n T(v_n)$, which has a unique choice, once $T(v_i)$ is given for every i .

Some remarks on linear transformations

Theorem

*Let V be finite dimensional, and $\{v_1, \dots, v_n\}$ be a basis of V .
Let $\{w_1, \dots, w_n\}$ be any collection of n vectors in W .
Then there is EXACTLY one linear transformation $T : V \rightarrow W$
such that $T(v_i) = w_i$ for all $1 \leq i \leq n$.*

Proof. Once we show the existence, uniqueness follows from the last theorem. We define a map as follows: Every vector $v \in V$ has a UNIQUE expression: $v = c_1 v_1 + \dots + c_n v_n$ as before.

Define $T(v) := c_1 w_1 + \dots + c_n w_n$. Then

- $T : V \rightarrow W$ is a linear map because:
- If $v = c_1 v_1 + \dots + c_n v_n$ and $u = d_1 v_1 + \dots + d_n v_n$, then $v + u = (c_1 + d_1)v_1 + \dots + (c_n + d_n)v_n$. Hence $T(v + u) = T(v) + T(u)$.
- If $v = c_1 v_1 + \dots + c_n v_n$, then $cv = (cc_1)v_1 + \dots + (cc_n)v_n$. Hence $T(cv) = cT(v)$.

Null space and nullity of a linear transformation

- Let $T : V \rightarrow W$ be a linear transformation. Then
- $\text{Null}(T) := \{v \in V : T(v) = 0\}$ is a subspace of V , because:
- It is non-empty as $0 \in \text{Null}(T)$.
- If $u, v \in \text{Null}(T)$ and $c, d \in \mathbb{R}$,
then $T(cu + dv) = cT(u) + dT(v) = 0$,
hence $cu + dv \in \text{Null}(T)$.

Definition (Null space and nullity)

- $\text{Null}(T) := \{v \in V : T(v) = 0\}$ is called the **null space** of T .
- The **nullity** of T is the dimension of the null space of T .

Range (or Image) of a linear transformation, and rank

- Let $T : V \rightarrow W$ be a linear transformation. Then
- $\text{Image}(T) := \{w \in W : w = T(v) \text{ for some } v \in V\}$ is a subspace of W , because:
 - It is non-empty as $0 \in \text{Image}(T)$.
 - If $w_1, w_2 \in \text{Image}(T)$ and $c_1, c_2 \in \mathbb{R}$, then $w_1 = T(v_1)$ and $w_2 = T(v_2)$ for some $v_1, v_2 \in V$, hence $c_1 w_1 + c_2 w_2 = T(c_1 v_1 + c_2 v_2) \in \text{Image}(T)$.

Definition (Range space and rank)

- $\text{Image}(T) := \{w \in W : w = T(v) \text{ for some } v \in V\}$ is called the **range space** of T .
- The **rank** of T is the dimension of the range space of T .

Rank-Nullity Theorem

Theorem

Let $T : V \rightarrow W$ be a linear transformation, where $\dim(V)$ is finite. Then $\text{rank}(T) + \text{nullity}(T) = \dim(V)$.

Proof. Start with a basis $\{u_1, \dots, u_n\}$ of $\text{Null}(T)$. Extend this to a basis $\{u_1, \dots, u_n, v_1, \dots, v_r\}$ of V . It is enough to prove that

$\{T(v_1), \dots, T(v_r)\}$ is a basis of $\text{Image}(T)$.

Spanning: Any vector of $\text{Image}(T)$ looks like $T(v)$ for some $v \in V$. Write $v = c_1 u_1 + \dots + c_n u_n + d_1 v_1 + \dots + d_r v_r$. Then $T(v) = c_1 T(u_1) + \dots + c_n T(u_n) + d_1 T(v_1) + \dots + d_r T(v_r) = d_1 T(v_1) + \dots + d_r T(v_r)$.

Proof of Rank-Nullity Theorem contd...

Theorem

Let $T : V \rightarrow W$ be a linear transformation, where $\dim(V)$ is finite. Then $\text{rank}(T) + \text{nullity}(T) = \dim(V)$.

Proof. Start with a basis $\{u_1, \dots, u_n\}$ of $\text{Null}(T)$. Extend this to a basis $\{u_1, \dots, u_n, v_1, \dots, v_r\}$ of V . It is enough to prove that

$$\{T(v_1), \dots, T(v_r)\} \text{ is a basis of } \text{Image}(T).$$

Lin. Independence: Let $b_1 T(v_1) + \dots + b_r T(v_r) = 0$.

This implies that $b_1 v_1 + \dots + b_r v_r \in \text{Null}(T)$.

So $b_1 v_1 + \dots + b_r v_r = a_1 u_1 + \dots + a_n u_n$ for some $a_i \in \mathbb{R}$.

Thus $b_1 v_1 + \dots + b_r v_r - a_1 u_1 - \dots - a_n u_n = 0$.

Therefore $b_1 = \dots = b_r = 0$.

Row and column spaces

Definition

- Let A be an $m \times n$ matrix over \mathbb{R} .
- The subspace of \mathbb{R}^m generated by all columns (column vectors) of A is called the **column space** of A .
- The subspace of \mathbb{R}^n generated by all rows (row vectors) of A is called the **row space** of A .

Example

- Let $A = \begin{pmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \end{pmatrix}$.
- Column space of A is **Span** $\left\{ \begin{pmatrix} 1 \\ 5 \\ 9 \end{pmatrix}, \begin{pmatrix} 2 \\ 6 \\ 10 \end{pmatrix}, \begin{pmatrix} 3 \\ 7 \\ 11 \end{pmatrix}, \begin{pmatrix} 4 \\ 8 \\ 12 \end{pmatrix} \right\}$.
- Column space of A is a subspace of \mathbb{R}^3 .

Examples: Row and column spaces

Example

- Let $A = \begin{pmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \end{pmatrix}$.
- Row space of A is **Span** $\left\{ \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix}, \begin{pmatrix} 5 \\ 6 \\ 7 \\ 8 \end{pmatrix}, \begin{pmatrix} 9 \\ 10 \\ 11 \\ 12 \end{pmatrix} \right\}$.
- Row space of A is a subspace of \mathbb{R}^4 .

Example

If $A = \begin{pmatrix} 1 & 0 & 2 & 0 \\ 0 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$, Column Sp. is $\left\{ \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \in \mathbb{R}^3 : x_3 = 0 \right\}$.

Row rank and column rank

Definition

- Let A be an $m \times n$ matrix over \mathbb{R} .
- The dimension of the column space of A is called **column rank** of A .
- The dimension of the row space of A is called **row rank** of A .

Example

- Let $A = \begin{pmatrix} 1 & 0 & 2 & 0 \\ 0 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$ and $B = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 0 & 2 & 1 & 1 \\ 0 & 0 & 3 & 1 \end{pmatrix}$.
- Column rank of A is 2. Row rank of A is 2.
- Column rank of B is 3. Row rank of B is 3.

As a consequence of Rank-Nullity Theorem, we will prove that for an arbitrary matrix D , $\text{row rank}(D) = \text{column rank}(D)$.

Thank You!