

# LINEAR ALGEBRA

Kuangyu Wen

Huazhong University of Science and Technology

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# Vector spaces

## Some operations on vectors

- $1 \cdot v = v$  for all  $v \in \mathbb{R}^N$
- if  $c_1, c_2 \in \mathbb{R}$  and  $v \in \mathbb{R}^N$ , then  $(c_1 c_2) \cdot v = c_1 (c_2 v)$  for all  $v \in \mathbb{R}^N$  and  $c_1, c_2 \in \mathbb{R}$
- $(v + w) + z = v + (w + z)$
- $c(v + w) = cv + cw$
- $(c_1 + c_2)v = c_1 v + c_2 v$

## Definition 1

A vector space consists of a non-empty set  $V$  together with operations of addition and multiplication by numbers, denoted by  $v + w$  and  $cv$  where  $v$  and  $w$  in  $V$  and  $c$  is a number, and these operations satisfy rules above with  $\mathbb{R}^N$  everywhere replaced by  $V$ .

# Vector spaces

## Definition 2

$W$  is a subspace of a vector space  $V$ , if  $W$  is a subset of  $V$  and  $W$  is itself a vector space under the operations of addition and multiplication by numbers defined on  $V$ .

$$v, w \in V$$
$$av + bw \in V?$$

## Example 3

$\mathbb{R}^2$  is a vector space and  $\{(v_1, v_2) \in \mathbb{R}^2 \mid v_1 + v_2 = 0\}$  is a subspace of  $\mathbb{R}^2$ .

# Linear independence and bases

## Definition 4

If  $V$  is a vector space, the vector  $v \in V$  is a linear combination of the vectors  $v_1, v_2, \dots, v_N$ , if there are numbers  $c_1, c_2, \dots, c_N$  such that  $v = c_1v_1 + c_2v_2 + \dots + c_Nv_N$ .

## Definition 5

If  $v_1, v_2, \dots, v_N \in V$ , their linear span is set of all linear combinations of  $v_1, v_2, \dots, v_N$ . The vectors  $v_1, v_2, \dots, v_N$  span  $V$ , if  $V$  is the linear span of  $v_1, v_2, \dots, v_N$ .

## Remark 6

*The linear span of  $v_1, v_2, \dots, v_N$  is a subspace of  $V$  and is the smallest subspace containing  $v_1, v_2, \dots, v_N$ .  $\mathbb{R}^2$  is the linear span of  $(0, 1)$  and  $(1, 0)$ .*

# Linear independence and bases

## Definition 7

The vectors  $v_1, v_2, \dots, v_N \in V$  are linearly dependent if there exist numbers  $c_1, c_2, \dots, c_N$ , not all of which are zero, such that

$$c_1 v_1 + c_2 v_2 + \dots + c_N v_N = 0$$

The vectors  $v_1, v_2, \dots, v_N \in V$  are linearly independent if they are not linearly dependent.

## Example 8

$(1, 0, 0)$	$(0, 1, 0)$	$(0, 0, 1)$	independent
$(1, 0, 0)$	$(0, 1, 0)$	$(1, 1, 0)$	dependent

# Linear independence and bases

## Definition 9

A basis for a vector space  $V$  is a set of independent vectors in  $V$  that spans  $V$ .

## Example 10

Let  $e_n = (0, \dots, 1, \dots, 0) \in \mathbb{R}^N$  where the 1 is in the  $n$ -th position. Then  $e_1, e_2, \dots, e_N$  is the standard basis of  $\mathbb{R}^N$ .

## Theorem 11

*If  $v_1, v_2, \dots, v_M$  span a vector space  $V$ , then any independent set of vectors in  $V$  has no more than  $M$  elements.*

## Definition 12

A vector space is finite dimensional, if it has a finite basis.

# Linear Independence and Bases

## Definition 13

The dimension of a finite dimensional vector space  $V$ , denoted by  $\dim V$ , is the number of vectors in a basis of  $V$ .

## Corollary

If  $V$  is a vector space of dimension  $N$ , then any  $N$  vectors in  $V$  that span  $V$  are independent and so are a basis of  $V$ .

## Corollary

If  $V$  is a finite dimensional vector space, a basis for  $V$  is any smallest or minimal set of vectors that span  $V$ .



## Linear independence and bases

### Lemma 14

*If  $v_1, v_2, \dots, v_M$  are independent vectors in  $V$ , and  $w \in V$  does not belong to the span of  $v_1, v_2, \dots, v_M$ . Then  $v_1, v_2, \dots, v_M, w$  are independent*

### Corollary

If  $V$  is a vector space of dimension  $N$ , then any  $n$  independent vectors in  $V$  span  $V$  and so are a basis for  $V$ .

### Theorem 15

*If the vectors  $v_1, v_2, \dots, v_N$  span the vector space  $V$  and  $\dim V > 0$ , then some subset of  $v_1, v_2, \dots, v_N$  form a basis for  $V$ .*

## Linear independent and bases

### Theorem 16

*If  $V$  is finite dimensional, non-zero vector space, any largest or maximal set of independent vectors in  $V$  is a basis for  $V$ .*

### Application

This theorem suggests a way to construct a basis for a non-zero vector space  $V$ .

### Theorem 17

*Let  $W$  be a non-zero subspace of a finite dimensional vector space  $V$  such that  $W \neq V$ , then  $\dim W < \dim V$ .*

### Theorem 18

*If  $v_1, v_2, \dots, v_N$  is a basis of the vector space  $V$ , and  $v \in V$ , then the numbers  $c_1, c_2, \dots, c_N$  such that  $v = \sum_{n=1}^N c_n v_n$  are unique.*

# The row and column ranks of a matrix

## Definition 19

Let  $A$  be an  $M \times N$  matrix. The linear span of the rows of  $A$  is a subspace of  $\mathbb{R}^N$ , which is called row space. The linear span of the columns of  $A$  is a subspace of  $\mathbb{R}^M$ , which is called column space. The row rank of  $A$  is the dimension of the row space and the column rank of  $A$  is the dimensional of the column space.

## Theorem 20

*The row and column ranks of any matrix are equal.*

# Linear transformation

## Definition 21

A and B are non-empty sets. A function  $f : A \rightarrow B$  assigns a single point  $f(a)$  in B to every point  $a$  in A.

set A: domain

set B: codomain

$f$ : function mapping

## Definition 22

Let  $V, W$  be vector spaces, then  $T : V \rightarrow W$  is linear if for all numbers  $a, b$  and for all vectors  $v_1, v_2 \in V$

$$T(a_1v_1 + a_2v_2) = a_1T(v_1) + a_2T(v_2)$$

and when  $a_1 = a_2 = 0$ ,  $T(0) = 0$ .

# Invertible matrices and linear transformation

## Theorem 23

*Matrices can be used to represent linear transformation from one finite dimensional vector space to another.*

### Proof.

Suppose  $v_1, \dots, v_N$  is a basis for  $V$  and  $w_1, \dots, w_M$  is a basis for  $W$ .

For  $v \in V$ , there exist  $x_1, \dots, x_N$  such that  $v = \sum_{n=1}^N x_n v_n$  and

$y_1, \dots, y_M$  such that  $T(v) = \sum_{m=1}^M y_m w_m$ . Let  $T(v_n) = \sum_{m=1}^M$

$a_{mn} w_m$ , then  $T(v) = T(\sum_{n=1}^N x_n v_n) = \sum_{n=1}^N x_n T(v_n) = \sum_{m=1}^M$

$\sum_{n=1}^N a_{mn} x_n w_n = \sum_{m=1}^M y_m w_m$ .

Therefore we have  $y_m = \sum_{n=1}^N a_{mn} x_n \iff y = Ax$ , where

$A = [a_{mn}]$ . □

## Invertible matrices and linear transformation

### Remark 24

*If the  $M \times N$  matrix  $A$  represents the linear transformation  $T$  and the  $J \times M$  matrix  $B$  represents the linear transformation  $S$ , then the  $J \times N$  matrix  $BA$  represents the linear transformation  $S \circ T$ .*

### Remark 25

*$N \times N$  identity matrix  $I$  represents the identity function  $id_V : V \rightarrow V$ .*

## Invertible matrices and linear transformation

### Definition 26

A function  $f : V \rightarrow W$  is invertible if there exists  $f^{-1} : W \rightarrow V$  such that  $f \circ f^{-1} = id_W$  and  $f^{-1} \circ f = id_V$ , that is for all  $w \in W$ ,  $f(f^{-1}(w)) = w$  and for all  $v \in V$ ,  $f(f^{-1}(v)) = v$ .

### Definition 27

A function  $f : V \rightarrow W$  is onto, if for all  $w \in W$ , there exist a  $v \in V$  such that  $f(v) = w$ .

### Definition 28

A function  $f : V \rightarrow W$  is one-to-one, if for every  $v_1, v_2 \in V$ ,  $f(v_1) \neq f(v_2)$  if  $v_1 \neq v_2$ .

## Invertible matrices and linear transformation

### Remark 29

$f : V \rightarrow W$  is invertible if and only if  $f$  is onto and one-to-one.

### Theorem 30

If  $T : V \rightarrow W$  is an invertible linear transformation. Then  $T^{-1}$  is linear.

### Proof.

Let  $w_1, w_2 \in W$  and  $v_1 = T^{-1}(w_1), v_2 = T^{-1}(w_2)$ , then

$$T(c_1v_1 + c_2v_2) = c_1T(v_1) + c_2T(v_2) = c_1w_1 + c_2w_2$$

$$\begin{aligned} c_1T^{-1}(w_1) + c_2T^{-1}(w_2) &= c_1v_1 + c_2v_2 \\ &= T^{-1} \circ T(c_1v_1 + c_2v_2) = T^{-1}(c_1w_1 + c_2w_2) \end{aligned}$$





# Invertible matrices and linear transformation

## Theorem 31

*Let  $T : V \rightarrow V$  be a linear transformation,  $v_1, v_2, \dots, v_N$  is a basis for  $V$ ,  $A : N \times N$  represents  $T$  with respect to  $v_1, v_2, \dots, v_N$ . Then  $T$  is invertible if and only if  $A$  is invertible and  $A^{-1}$  represents  $T^{-1}$ .*

## Proposition 32

*Let  $T : V \rightarrow W$  be an invertible linear transformation,  $v_1, v_2, \dots, v_N$  are a basis for  $V$  if and only if  $T(v_1), T(v_2), \dots, T(v_N)$  is a basis for  $W$ .*

## Corollary

Let  $T : V \rightarrow W$  be an invertible linear transformation and  $V$  is finite dimensional, then  $W$  is finite dimensional and

$$\dim W = \dim V.$$

# The range, rank, kernel and nullity of linear transformation

## Definition 33

If  $f : A \rightarrow B$  is a function, the range of  $f$  is  $\{f(x) : x \in A\}$ .

## Definition 34

If  $T : V \rightarrow W$  is a linear transformation, the kernel of  $T$  is  $\{v \in V | T(v) = 0\}$ .

## Theorem 35

*If  $T : V \rightarrow W$  is a linear transformation, then the range of  $T$  is a subspace of  $W$ , the kernel of  $T$  is a subspace of  $V$ .*

## Definition 36

If  $T : V \rightarrow W$  is a linear transformation, the rank of  $T$  is the dimension of the range of  $T$  and the nullity of  $T$  is the dimension of the kernel of  $T$ .

# The range, rank, kernel and nullity of linear transformation

## Theorem 37

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

## Proof.

Let  $\dim(V) = N$ ,  $v_1, v_2, \dots, v_K$  is a basis for the null space of  $T$ ,  $v_1, v_2, \dots, v_N$  is an extension of  $v_1, v_2, \dots, v_K$  to a basis for  $V$ .

Then we want to show

$$T(v_{K+1}), T(v_{K+2}), \dots, T(v_N)$$

is a basis for the range of  $T$ . □

# The range, rank, kernel and nullity of linear transformation

Proof.

Since  $T(v_1) = \cdots = T(v_K) = 0$ ,  $T(v_{K+1}), T(v_{K+2}), \cdots, T(v_N)$  span the range of  $T$ . Want to show they are linearly independent.

Suppose  $\sum_{n=K+1}^N c_n T(v_n) = 0$ .

$$T\left(\sum_{n=K+1}^N c_n v_n\right) = \sum_{n=K+1}^N c_n T(v_n) = 0$$

$\sum_{n=K+1}^N c_n v_n$  belongs to the kernel of  $T$ , then

$$\sum_{n=K+1}^N c_n v_n = \sum_{n=1}^K b_n v_n$$

Therefore  $\sum_{n=K+1}^N c_n v_n - \sum_{n=1}^K b_n v_n = 0$ . Since  $v_1, \cdots, v_N$  is a basis for  $V$ , they are independent and

$$b_1 = b_2 = \cdots = b_K = 0 = c_{K+1} = \cdots = c_N$$

$T(v_{K+1}), \cdots, T(v_N)$  are independent.

# The range, rank, kernel and nullity of linear transformation

## Theorem 38

*Let  $T : V \rightarrow W$  be a linear transformation and suppose  $A : M \times N$  representing  $T$  with respect to the bases  $v_1, \dots, v_N$  and  $w_1, \dots, w_M$ . Then the rank of  $T$  equals column rank of  $A$  and nullity of  $T$  equals  $N - \text{column(row) rank of } A$*

## Singular and non-singular linear transformation

### Definition 39

If  $T : V \rightarrow W$  is a linear transformation,  $T$  is non-singular if the kernel of  $T$  is  $\{0\}$ .  $T$  is singular if it is not non-singular, i.e. if  $T(v) = 0$  for some  $v \neq 0$ .

### Remark 40

*The linear transformation  $T$  is non-singular if and only if  $T$  is one-to-one.*

Proof.

$$T(v_1) = T(v_2) \iff T(v_1 - v_2) = 0$$



## Singular and non-singular linear transformation

### Lemma 41

*If  $T : V \rightarrow W$  is linear transformation.  $T$  is non-singular if and only  $T(v_1), T(v_2), \dots, T(v_N)$  are independent whenever  $v_1, v_2, \dots, v_N$  are independent.*

### Theorem 42

*$T : V \rightarrow W$  is linear transformation, and  $\dim(V) = \dim(W)$ , then the following are equivalent*

- *$T$  is invertible*
- *$T$  is non-singular*
- *$T$  is onto*
- *if  $v_1, v_2, \dots, v_N$  is a basis for  $V$ , then  $T(v_1), T(v_2), \dots, T(v_N)$  is a basis for  $W$ .*
- *there is basis  $v_1, v_2, \dots, v_N$  for  $V$  such that  $T(v_1), T(v_2), \dots, T(v_N)$  is a basis for  $W$ .*

## The inner product and norm

### Definition 43

The inner product on  $\mathbb{R}^N$  is the function  $\langle x, y \rangle$  or  $x \cdot y$

$$x \cdot y = \sum_{i=1}^N x_i y_i \quad \mathbb{R}^N \times \mathbb{R}^N \rightarrow \mathbb{R}$$

### Definition 44

$$\|x\| = \sqrt{x \cdot x} \quad \text{length of } x$$

### Remark 45

- if  $x, y$  are non-zero vectors in  $\mathbb{R}^N$  and if  $\theta$  is the angle between  $x$  and  $y$

$$\cos \theta = \frac{x \cdot y}{\|x\| \cdot \|y\|}$$

- Cauchy-Schwarz inequality

$$\left| \frac{x \cdot y}{\|x\| \cdot \|y\|} \right| \leq 1 \iff |x \cdot y| \leq \|x\| \cdot \|y\|$$



# Orthonormal bases and orthogonal complement

## Definition 46

A set of vector  $v_1, v_2, \dots, v_M$  in  $\mathbb{R}^N$  is orthogonal if  $v_n \cdot v_m = 0$  if  $m \neq n$ .

## Theorem 47

*Orthogonal non-zero vectors are independent.*

## Definition 48

A basis  $v_1, \dots, v_M$  for a subspace  $V$  of  $\mathbb{R}^N$  is orthonormal if it is orthogonal and  $\|v_m\| = 1$  for all  $m$ .

## Theorem 49

*Every non-zero subspace  $V$  of  $\mathbb{R}^N$  has an orthonormal basis. (Gram-Schmidt process)*

# Orthonormal bases and orthogonal complement

## Definition 50

If  $S$  is a subset of  $V$ , which is a subspace of  $\mathbb{R}^N$ , the orthogonal complement of  $S$  in  $V$ , denoted by  $S^\perp$

$$S^\perp = \{y \in V \mid y \cdot x = 0 \text{ for all } x \in S\}$$

## Theorem 51

*If  $W$  is a subspace of  $V$  and  $V$  is a subspace of  $\mathbb{R}^N$ , then*

$$\dim(W) + \dim(W^\perp) = \dim(V)$$

# Orthogonal projection

## Definition 52

Let  $W$  be a subspace of  $V$ , which is a subspace of  $\mathbb{R}^N$ . An orthogonal projection  $\pi : V \rightarrow W$  is a linear transformation such that  $(V - \pi(V)) \in W^\perp$  for all  $v \in V$  and  $[V - \pi(V)] \cdot W = 0$  for all  $w \in W$ .

## Theorem 53

*$W$  is subspace of  $V$ ,  $V$  subspace of  $\mathbb{R}^N$ , there exists a unique orthogonal projection from  $V$  to  $W$ .*