### VV285 RC Part I

# Elements of Linear Algebra "Matrices are just linear maps!"

### Xingjian Zhang

Univerity of Michigan-Shanghai Jiao Tong University Joint Institute

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### Overview of Linear Algebra



- 1. Systems of Linear Equations
- 2. Finite-Dimensional Vector Spaces
- 3. Inner Product Spaces
- 4. Linear Maps
- 5. Matrices
- 6. Theory of Systems of Linear Equations
- 7. Determinants

### Overview



- Linear System
   Homogeneous vs. Inhomogeneous
   Underdetermined vs. Overdetermined
- 2. Equivalency of Linear System
- 3. The Gauß Jordan Algorithm
- 4. Diagonalizable (Existence and Uniqueness of Linear System)
- 5. Fundamental Lemma for Homogeneous Equations

### Linear System



A *linear system* of m (algebraic) equations in n unknowns  $x_1, x_2, \ldots, x_n \in V$  is a set of equations

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$$

$$\vdots$$

$$(1)$$

 $a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n = b_m$ 

where  $b_1, b_2, \ldots, b_m \in V$  and  $a_{ij} \in \mathbb{F}$ ,  $i = 1, \ldots, m, \ j = 1, \ldots, n$ . If  $b_1 = b_2 = \cdots = b_m = 0$ , then (1) is called a *homogeneous system*. Otherwise, it is called an *inhomogeneous system*.

If m < n we say that the system in *underdetermined*, if m > n the system is called *overdetermined*. A solution of a linear system of equations (1) is a tuple of elements  $(y_1, y_2, \ldots, y_n) \in V^n$  such that the predicate (1) becomes a true statement.

### Linear System



We say that two systems of linear equations are *equivalent* if any solution of the first system is also a solution of the second system and vice-versa. Thus the systems

$$x_1 + 3x_2 - x_3 = 1$$
  $x_1 = 2$   
 $-5x_2 + x_3 = 1$  and  $x_2 = 0$   
 $10x_2 + x_3 = 1$   $x_3 = 1$ 

are equivalent.

# Gauß-Jordan Algorithm



The goal of the *Gauß-Jordan algorithm* (also called Gaußian elimination) is to transform a system

first into the form

$$\begin{array}{c|cccc}
1 & * & * & \diamond \\
0 & 1 & * & \diamond \\
0 & 0 & 1 & \diamond
\end{array}$$
(2)

and subsequently into

$$\begin{array}{c|ccccc}
1 & 0 & 0 & \diamond \\
0 & 1 & 0 & \diamond \\
0 & 0 & 1 & \diamond
\end{array} \tag{3}$$

# Elementary Row Manipulations



#### Include:

- 1. Swapping (interchanging) two rows,
- 2. Multiplying each element in a row with a number,
- 3. Adding a multiple of one row to another row.

**Result:** Transform a system into a equivalent system. Since each row represents an equation, we are essentially **manipulating equations**.

**Extension:** The application of Gauß-Jordan Algorithm

### Diagonalization



A system of *m* equations with *n* unknowns will have a unique solution if and only if it is *diagonalizable*. i.e. It can be transformed into diagonal form.

**Remark:** *Diagonalization* turns out to be an important topic in VV286, especially in terms of *ordinary differential equation systems*.

# Fundamental Lemma for Homogeneous Equations



The homogeneous system

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = 0$$
  
 $\vdots$   
 $a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n = 0$ 

of m equations in n real or complex unknowns  $x_1, x_2, \ldots, x_n$  has a **non-trivial** solution if n > m.

**Remark:** This fundamental lemma contributes to prove that any basis of a vector space has the same length.

### Overview



- 1. Linear Independence
- 2. Span
- 3. Basis
- 4. Dimension
- 5. Basis Extension Theorem
- 6. Sum of Vector Space

# Linear Independence



Let V be a real or complex vector space and  $v_1, v_2, \ldots, v_n \in V$ . Then the vectors  $v_1, v_2, \ldots, v_n$  are said to be *independent* if for all  $\lambda_1, \lambda_2, \ldots, \lambda_n \in \mathbb{F}$ 

$$\sum_{k=1}^{n} \lambda_k v_k = 0 \qquad \Rightarrow \qquad \lambda_1 = \lambda_2 = \cdots = \lambda_n = 0.$$

A finite set  $M \subset V$  is called an *independent set* if the elements of M are independent.

# Span



Let  $v_1, v_2, \ldots, v_n \in V$  and  $\lambda_1, \lambda_2, \ldots, \lambda_n \in \mathbb{F}$ . Then the expression

$$\sum_{k=1}^{n} \lambda_k v_k = \lambda_1 v_1 + \dots + \lambda_n v_n$$

is called a *linear combination* of the vectors  $v_1, v_2, \ldots, v_n$ . The set

$$span\{v_1,\ldots,v_n\} = \left\{ y \in V : y = \sum_{k=1}^n \lambda_k v_k, \lambda_1,\ldots,\lambda_n \in \mathbb{F} \right\}$$

is called the *(linear)* span or the *linear hull* of the vectors  $v_1, v_2, \ldots, v_n$ .

# Independence $\sim$ Span



The vectors  $v_1, v_2, \ldots, v_n \in V$  are independent if and only if none of them is contained in the span of all the others.

(How to prove?)

### Basis



Let V be a real or complex vector space. An n-tuple  $\mathcal{B}=(b_1,\ldots,b_n)\in V^n$  is called an *(ordered and finite) basis* of V if every vector v has a **unique** representation

$$v = \sum_{i=1}^{n} \lambda_i b_i, \qquad \lambda_i \in \mathbb{F}.$$
 (4)

The numbers  $\lambda_i$  are called the *coordinates* of v with respect to  $\mathcal{B}$ .

The tuple of vectors  $(e_1, e_2, \dots, e_n)$ ,  $e_i \in \mathbb{R}^n$ ,

$$e_i = (0, \dots, 0, 1, 0, \dots, 0),$$
  $i = 1, \dots, n,$ 

is called the *standard basis* or *canonical basis* of  $\mathbb{R}^n$ .

# $\mathsf{Basis} = \mathsf{Independence} + \mathsf{Span}$



Let V be a real or complex vector space.

An *n*-tuple  $\mathcal{B} = (b_1, \ldots, b_n) \in V^n$  is a basis of V if and only if

- 1. the vectors  $b_1, b_2, \ldots, b_n$  are linearly independent, i.e.,  $\mathcal{B}$  is an independent set,
- 2.  $V = \operatorname{span} \mathcal{B}$ .

(How to prove?)

**Remark:** This theorem is more practical than the definition of basis when proving some set is a basis of some vector space. It helps one decompose the proof into two parts: 1. prove linear independence (uniqueness of (4)) 2. prove the span is large enough (existence of (4)).

### **Dimension**



Let V be a real or complex finite-dimensional vector space,  $V \neq \{0\}$ . Then any basis of V has the same length (number of elements).

**Remark:** This theorem can be proved by contradiction (Use the definition of basis and the fundamental lemma for homogeneous equations). With such a premise, we can then define the *dimension* of vector space.

Let V be a real or complex vector space. Then V is called *finite-dimensional* if either

- ightharpoonup V = 0 or
- V possesses a finite basis.

If V is not finite-dimensional, we say that it is *infinite-dimensional*.

### Basis Extension Theorem



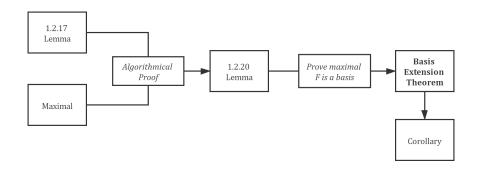


Figure: Logic Flow of Basic Extension Theorem

An interpretation of "maximal": the max (in size) independent subset of some set.

### Basis Extension Theorem



Let V be a finite-dimensional vector space and  $A' \subset V$  an independent set. Then there exists a basis of V containing A'.

#### Remark:

The basis extension theorem is fundamental. It tells us that for any independent subset A' of a finite-dimensional vector space V, we can always find and add dim V-|A'| elements to A' to extend it into a basis of V. And two useful corollaries follow immediately:

Let V be an n-dimensional vector space,  $n \in \mathbb{N}$ . Then

- 1. any independent set A with n elements is a basis of V.
- 2. an independent set A may have at most n elements.

(How to prove?)

# Sum of Vector Space



Let V be a real or complex vector space and U, W be sets in V.

(i) We define the sum of U and W by

$$U+W:=\left\{v\in V: \exists \exists v\in W: v=u+w\right\}.$$

(ii) If U and W are subspaces of V with  $U \cap W = \{0\}$ , the sum U + W is called *direct*, and we denote it by  $U \oplus W$ .

Two properties about sum of vector space:

- 1. The sum U+W of vector spaces U,W is direct if and only if all  $x \in U+W$ ,  $x \neq 0$ , have a **unique** representation  $x = u+w, \ u \in U, w \in W$ .
- 2. Let V be a vector space and  $U, W \subset V$  be finite-dimensional subspaces of V. Then

$$\dim(U+W)+\dim(U\cap W)=\dim U+\dim W.$$

### Proof I



Suppose

$$\{v_1,\ldots,v_p\}$$

is a basis for  $U \cap W$ . By Basis Extension Theorem, we can find a basis

$$\{v_1,\ldots,v_p,u_1,\ldots,u_q\}$$

for U and a basis

$$\{v_1,\ldots,v_p,w_1,\ldots,w_r\}$$

for W.

Then we just need to show that

$$B = \{v_1, \dots, v_p, u_1, \dots, u_q, w_1, \dots, w_r\}$$

is a basis for U + W

### Proof II



Suppose

$$\alpha_1 \mathbf{v}_1 + \dots + \alpha_p \mathbf{v}_p + \beta_1 \mathbf{u}_1 + \dots + \beta_q \mathbf{u}_q + \gamma_1 \mathbf{w}_1 + \dots + \gamma_r \mathbf{w}_r = 0$$

Then

$$x = \underbrace{\alpha_1 v_1 + \dots + \alpha_p v_p + \beta_1 u_1 + \dots + \beta_q u_q}_{\in U} = -(\underbrace{\gamma_1 w_1 + \dots + \gamma_r w_r}_{\in W})$$

belongs to  $U \cap W$ . Thus

$$x = \delta_1 v_1 + \dots + \delta_p v_p$$

and therefore

$$\delta_1 v_1 + \dots + \delta_p v_p = -(\gamma_1 w_1 + \dots + \gamma_r w_r)$$

### Proof III



so that

$$\delta_1 v_1 + \dots + \delta_p v_p + \gamma_1 w_1 + \dots + \gamma_r w_r = 0$$

Since the set  $\{v_1,\ldots,v_p,w_1,\ldots,w_r\}$  is linearly independent, we conclude

$$\delta_1 = 0, \ldots, \delta_p = 0, \gamma_1 = 0, \ldots, \gamma_r = 0$$

and also that

$$\alpha_1 \mathbf{v}_1 + \cdots + \alpha_p \mathbf{v}_p + \beta_1 \mathbf{u}_1 + \cdots + \beta_q \mathbf{u}_q = \mathbf{0}$$

So, from linear independence of  $\{v_1,\ldots,v_p,u_1,\ldots,u_q\}$  we get

$$\alpha_1 = 0, \ldots, \alpha_p = 0, \beta_1 = 0, \ldots, \beta_q = 0$$

Therefore, the set B is independent. It is clear that span B = U + W. So we conclude B is a basis for U + W, and furthermore,

$$\dim(U+W)+\dim(U\cap W)=\dim U+\dim W.$$

### Corollary



Let V be a vector space and  $U, W \subset V$  be finite-dimensional subspaces of V. Then

$$\dim(U+W) \leq \dim U + \dim W.$$

The condition for "=": the sum is direct. i.e.

$$\dim(U \oplus W) = \dim U + \dim W.$$

### Overview



- 1. Inner Product Spaces
- 2. Induced Norm
- 3. Orthogonality & Orthonormal System
- 4. The Projection Theorem
- 5. Gram-Schmidt Orthonormalization

# Inner Product Space I



Let V be a real or complex vector space. Then a map  $\langle \,\cdot\,,\,\cdot\,\rangle:V\times V\to \mathbb{F}$  is called a scalar product or inner product if for all  $u,v,w\in V$  and all  $\lambda\in\mathbb{F}$ 

1. Positive-definite

$$\langle v, v \rangle \ge 0$$
 and  $\langle v, v \rangle = 0$  if and only if  $v = 0$ ,

2. Linearity in the 2nd argument

$$\langle u, v + w \rangle = \langle u, v \rangle + \langle u, w \rangle$$

- 3. Linearity in the 2nd argument  $\langle u, \lambda v \rangle = \lambda \langle u, v \rangle$
- 4. Conjugate symmetry

$$\langle u, v \rangle = \overline{\langle v, u \rangle}$$

The pair  $(V, \langle \cdot, \cdot \rangle)$  is called an *inner product space*.

### Inner Product Space II



#### Prove that

1.

$$\langle \lambda u, v \rangle = \overline{\lambda} \langle u, v \rangle.$$

2.

$$\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle$$

This is called the *conjugate linearity* in the 1st argument.

What if  $\mathbb{F} = \mathbb{R}$ ?

Ans: Conjugate symmetry reduces to symmetry, and conjugate linearity reduces to linearity. So, an inner product on a real vector space is a positive-definite symmetric *bilinear map*.

**Remark:** Multi-linear map will be discussed in detail in *Differential Calculus - Second Derivative*.

### Induced Norm



Let  $(V, \langle \cdot, \cdot \rangle)$  be an inner product space. The map

$$\|\cdot\|:V\to\mathbb{R},\qquad \|v\|=\sqrt{\langle\,v\,,\,v\,\rangle}$$

is called the *induced norm* on V.

(How to prove that an induced norm is actually a norm?)

By the Cauchy-Schwarz inequality, we define the angle  $\alpha(u, v) \in [0, \pi]$  between u and v by

$$\cos \alpha(u, v) = \frac{\langle u, v \rangle}{\|u\| \|v\|}.$$
 (5)

We are particularly interested in the case that  $\alpha=\pi/2$ . i.e.  $\langle \, u\,,\, v\, \rangle=0$ . Therefore, we introduce *orthogonality*.

# Orthogonality I



Let  $(V, \langle \cdot, \cdot \rangle)$  be an inner product vector space.

- 1. Two vectors  $u, v \in V$  are called *orthogonal* or *perpendicular* if  $\langle u, v \rangle = 0$ . We then write  $u \perp v$ .
- 2. We call

$$M^{\perp} := \left\{ v \in V : \bigvee_{m \in M} \langle m, v \rangle = 0 \right\}$$

the *orthogonal complement* of a set  $M \subset V$ .

For short, we sometimes write  $v \perp M$  instead of  $v \in M^{\perp}$  or  $v \perp m$  for all  $m \in M$ .

**Remark:** The orthogonal complement  $M^{\perp}$  is a subspace of V. (How to prove?)

# Orthonormal Systems & Bases I



Let  $(V, \langle \cdot, \cdot \rangle)$  be an inner product vector space. A tuple of vectors  $(v_1, v_2, \dots, v_r) \in V$  is called a *(finite) orthonormal system* if

$$\langle v_j, v_k \rangle = \delta_{jk} := \begin{cases} 1 & \text{for } j = k, \\ 0 & \text{for } j \neq k, \end{cases}, \qquad j, k = 1, \dots, r,$$

i.e., if  $||v_k|| = 1$  and  $v_j \perp v_k$  for  $j \neq k$ .

Let  $(V, \langle \cdot, \cdot \rangle)$  be a finite-dimensional inner product vector space and  $\mathcal{B} = (e_1, \dots, e_n)$  a basis of V. If  $\mathcal{B}$  is also an orthonormal system, we say that  $\mathcal{B}$  is an *orthonormal basis* (ONB).

# Orthonormal Systems & Bases II



Parseval's Theorem Let  $(V, \langle \cdot, \cdot \rangle)$  be a finite-dimensional inner product vector space and  $\mathcal{B} = \{e_1, \dots, e_n\}$  an orthonormal basis of V. Then

$$||v||^2 = \sum_{i=1}^n |\langle v, e_i \rangle|^2$$

for any  $v \in V$ .

**Remark:** Parseval's Theorem gives a alternative way to calculate a vector's induced norm.

# Projection Theorem I



Let  $(V, \langle \cdot, \cdot \rangle)$  be a (possibly infinite-dimensional) inner product vector space and  $(e_1, e_2, \dots, e_r)$ ,  $r \in \mathbb{N}$ , be an orthonormal system in V. Denote  $U := \operatorname{span}\{e_1, \dots, e_r\}$ .

Then for every  $v \in V$  there exists a unique representation

$$v = u + w$$
 where  $u \in U$  and  $w \in U^{\perp}$ 

and  $u = \sum_{i=1}^{r} \langle e_i, v \rangle e_i, w := v - u$ . The vector

$$\pi_U v := \sum_{i=1}^r \langle e_i, v \rangle e_i$$

is called the *orthogonal projection* of v onto U.

### Projection Theorem II



The projection theorem essentially states that  $\pi_U v$  always exists and is independent of the choice of the orthonormal system (it depends only on the span U of the system).

Moreover, it generalize the idea of projection:

$$\pi_{e_i} v \rightarrow \pi_U v$$

A vector in an inner product space can be decomposed not only on its orthonormal basis but also on its subspaces.

# Orthonormal System $\sim$ Best Approximation



Why is orthonormal system extremely useful?

Let V be a (infinite) vector space. We can approximate an element  $v \in V$  using a (finite) linear combination of some orthonormal basis. This is useful in engineering problems.

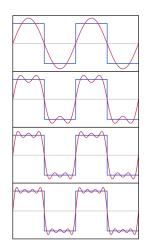


Figure: The Fourier Series Approximation of A Square Wave

### Gram-Schmidt Orthonormalization



Just remember how to do it.

How to use Gram-Schmidt Orthonormalization to obtain *Legendre* polynomials?