

06.10.2015  
Tuesday

DEFINITION: A field is a set  $F$  together with two mappings called addition and multiplication shown as:

$$\oplus: F \times F \rightarrow F$$

$$\odot: F \times F \rightarrow F$$

which have properties

(A1)  $a \oplus b = b \oplus a \quad \forall a, b \in F$  (commutativity)

(A2)  $a \oplus (b \oplus c) = (a \oplus b) \oplus c \quad \forall a, b, c \in F$  (associativity)

(A3) There is an element in  $F$ , denoted by  $0_F$  such that

$$a \oplus 0_F = a \quad \forall a \in F \quad (\text{additive identity})$$

(A4) For each  $a \in F$ , there is an element in  $F$  denoted as  $-a$  such that

$$a \oplus -a = 0_F \quad \forall a \in F \quad (\text{additive inverse})$$

(M1)  $a \odot b = b \odot a \quad \forall a, b \in F$  (commutativity)

(M2)  $a \odot (b \odot c) = (a \odot b) \odot c \quad \forall a, b, c \in F$  (associativity)

(M3)  $\exists 1_F$  s.t.

$$a \odot 1_F = a \quad \forall a \in F \quad (\text{multiplicative identity})$$

(M4) For each  $a \neq 0_F$ ,  $\exists$  an element in  $F$  denoted by  $a^{-1}$  s.t.

$$a \odot a^{-1} = 1_F \quad (\text{multiplicative inverse})$$

(D) The operations  $\oplus$  and  $\odot$  satisfy

$$a \odot (b \oplus c) = (a \odot b) \oplus (a \odot c) \quad \forall a, b, c \quad (\text{distributive law})$$

EXAMPLE: Set of real numbers  $\mathbb{R}$  with standard addition and multiplication operations.

$$F = \mathbb{R}$$

EXAMPLE: Let  $F = \mathbb{R} \times \mathbb{R} = \mathbb{R}^2$ . The operation  $\oplus$  and  $\odot$  are defined as

$$x = (x_1, x_2) \in F$$

$$y = (y_1, y_2) \in F$$

$$x \oplus y = (x_1 + y_1, x_2 + y_2)$$

$$x \odot y = (x_1 y_1 - x_2 y_2, x_2 y_1 + x_1 y_2)$$

$$(x_1 + j x_2) \odot (y_1 + j y_2) = x_1 y_1 - x_2 y_2 + j(x_2 y_1 + x_1 y_2)$$

$$F = \mathbb{C}$$

$$0_F = (0, 0)$$

$$1_F = (1, 0)$$

EXAMPLE: Let  $F = \mathbb{R}$

$$x \oplus y = xy$$

$$x \odot y = x + y$$

}

Is  $F$  with  $\oplus, \odot$  a field?

$$\ast x \oplus y = y \oplus x \quad \ast 1_F = 0$$

$$\ast 0_F \neq 1$$

$$\ast x^{-1} = -x$$

$$\ast -x = 1/x$$

$$\ast x \odot (y \oplus z) \stackrel{?}{=} (x \odot y) \oplus (x \odot z)$$

$$x + yz \stackrel{?}{\neq} (x+y)(x+z)$$

Nb,  $F$  with  $\oplus, \odot$  is not a field because  $\oplus \& \odot$  do not satisfy distributive law.

$$\left(\frac{1}{x^2+1}\right)$$

- Are polynomials a field? No  $\rightarrow$  you cannot set up field out of Poly.

- Are matrices a field? No  $\rightarrow$  "

Review

09. 10. 2015  
Friday

$F, \oplus, \odot$

$x, y, z \in F$

$$\oplus: x \oplus y = y \oplus x$$

$$x \oplus (y \oplus z) = (x \oplus y) \oplus z$$

$$\exists 0_F \quad x \oplus 0_F = x$$

$$\exists -x \in F \quad x \oplus -x = 0_F$$

$$\odot: x \odot y = y \odot x$$

$$x \odot (y \odot z) = (x \odot y) \odot z$$

$$\exists 1_F \in F \quad x \odot 1_F = x$$

$$\exists x' \in F \quad x \odot x' = 1_F$$

called as a  
FIELD

$\oplus, \odot$

$$x \odot (y \oplus z) = (x \odot y) \oplus (x \odot z)$$

$F = \mathbb{R}$

$F = \mathbb{C} \rightarrow$  complex number

$F = \text{rational number}$

$F \neq \text{integer}$

Polynomial?  $\rightarrow$  not a field ( $\frac{1}{x+1}$ )

Matrices?  $\rightarrow$  not a field  $\rightarrow$  we don't always have inverse of Matrices

## LINEAR (VECTOR) SPACES

DEFINITION: A linear space  $V$  is a set whose elements are called vectors, associated with a field  $F$ , whose elements are called scalars, and two operations: addition  $\oplus$ , and scalar multiplication  $\odot_V$ .

$(V, F)$   
vectors      scalars

The following axioms should hold for the addition and scalar multiplication.

$$A1) x \oplus y = y \oplus x \quad \forall x, y \in V \quad (\text{commutativity})$$

$$A2) (x \oplus y) \oplus z = x \oplus (y \oplus z) \quad \forall x, y, z \in V \quad (\text{associativity})$$

$$A3) \exists \text{ a vector } O_V \text{ s.t.}$$

$$x \oplus O_V = x \quad \forall x \in F \quad (\text{additive identity})$$

$$A4) \text{ For every element } x \in V \exists \text{ a unique element } -x \text{ s.t.}$$

$$x \oplus -x = O_V \quad (\text{additive inverse})$$

$$SM1) a \odot_V (b \odot_V x) = (a \odot_F b) \odot_V x \quad \forall x \in V \quad \forall a, b \in F$$

$$SM2) a \odot (x \oplus y) = (a \odot x) \oplus (a \odot y) \quad \forall x, y \in V \quad \forall a \in F$$

$$SM3) (a \oplus b) \odot_V x = (a \odot_V x) \oplus_V (b \odot_V x) \quad x \in V \quad a, b \in F$$

SM4) With  $1_F$  being the multiplicative identity of the field  $F$ , we have

$$1_F \odot x = x \quad \forall x \in V$$

EXAMPLE: Show that

$$\underset{F}{\odot} x = O_V \quad \forall x \in V$$

$$\oplus_V: V \times V \rightarrow V$$

$$O_V: F \times V \rightarrow V$$

$$O_F \odot x = (O_F \oplus O_F) \odot x$$

$$\underset{\substack{\curvearrowleft \\ \in V}}{O_F \odot x} = \underset{\substack{\curvearrowleft \\ \in V}}{(O_F \odot x)} \oplus \underset{\substack{\curvearrowleft \\ \in V}}{(O_F \odot x)}$$

$$3 - (0_F \odot x)$$

Add both sides  $- (0_F \odot x)$

$$(0_F \odot x) \oplus - (0_F \odot x) = (0_F \odot x) \oplus (0_F \odot x) \oplus - (0_F \odot x)$$

$$0_V = (0_F \odot x) \oplus 0_V = 0_F \odot x$$

$$\boxed{0_F \odot x = 0_V} \quad \text{QED.}$$

EXAMPLE: Linear space  $(F^n, F)$

$\checkmark$        $\vee$   
 $\vee$   
 Set of vectors

i.e., the linear space of  $n$ -tuple in  $F$  over the field  $F$ .

$$x = (x_1, x_2, \dots, x_n) \text{ where } x_i \in F \quad \forall i$$

$$y = (y_1, y_2, \dots, y_n) \quad " \quad y_i \quad " \quad$$

Addition  $\oplus$

$$x \oplus y = (x_1 \underset{F}{\oplus} y_1, x_2 \underset{F}{\oplus} y_2, \dots, x_n \underset{F}{\oplus} y_n)$$

Scalar Multiplication  $\odot$

$$a \odot x = (a \underset{F}{\odot} x_1, a \underset{F}{\odot} x_2, \dots, a \underset{F}{\odot} x_n)$$

The most common examples are  $R^n$  &  $R^{\infty}$

EXAMPLE: The set of all real-valued functions  $t \rightarrow f(t)$  defined over the real time.

$$F: R$$

$V$ : real valued functions

addition:

$$(f \oplus g)(t) = f(t) + g(t) \quad \forall t \in R$$

scalar mult:

$$(af)(t) = a f(t) \quad \forall t \in R$$

EXAMPLE: Set of all polynomials of degree  $n=2$

$$V = \{ a_0 t^2 + a_1 t + a_2 \mid a_0, a_1, a_2 \in \mathbb{R} \}$$

$a_0 \neq 0$

$$F = \mathbb{R}$$

$$(2t^2 + t + 3) \oplus (-2t^2 + 2t + 6) = 3t + 7 \notin V$$

NOT A VECTOR SPACE

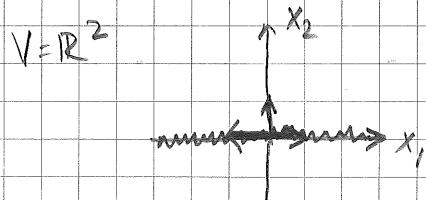
EXAMPLE: Set of all polynomials with degree  $n \leq 2$

THIS IS VECTOR SPACE

DEFINITION: Let  $V$  be a vector space over the field  $F$ . A subset

$W$  of  $V$  is a subspace of  $V$  if and only if, (W, F)  
iff

is itself a vector space.



$$W = \left\{ \begin{bmatrix} a \\ 0 \end{bmatrix} \mid a \in \mathbb{R} \right\}$$

$$W \subseteq V$$

We can check whether a subset  $W$  is a subspace or not by  
checking only the following:

$$(S1) \quad w_1 + w_2 \in W \quad \forall w_1, w_2 \in W$$

$$(S2) \quad a w_1 \in W \quad \forall w_1 \in W \quad \forall a \in F$$

Subset has to be closed under addition and scalar multiplication.

All other properties are inherited from the original linear space

Prove that  $W = \left\{ \begin{bmatrix} a \\ 0 \end{bmatrix} \mid a \in \mathbb{R} \right\}$  is a subspace of  $V = \mathbb{R}^2$

$$x = \begin{bmatrix} x_1 \\ 0 \end{bmatrix} \in W$$

$$y = \begin{bmatrix} y_1 \\ 0 \end{bmatrix} \in W$$

$$\star x+y = \begin{bmatrix} x_1 \\ 0 \end{bmatrix} + \begin{bmatrix} y_1 \\ 0 \end{bmatrix} = \begin{bmatrix} x_1+y_1 \\ 0 \end{bmatrix} \in W \checkmark$$

$$\star ax = \begin{bmatrix} ax_1 \\ 0 \end{bmatrix} \in W \checkmark$$

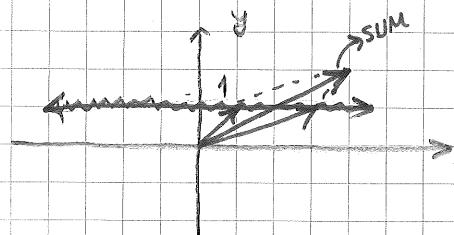
$\Rightarrow W$  is a subspace

EXAMPLE:  $V = \mathbb{R}^2$

$$W = \left\{ \begin{bmatrix} a \\ 1 \end{bmatrix} \mid a \in \mathbb{R} \right\}$$

$$x = \begin{bmatrix} x_1 \\ 1 \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ 1 \end{bmatrix}$$

$$x+y = \begin{bmatrix} x_1+y_1 \\ 2 \end{bmatrix} \notin W$$



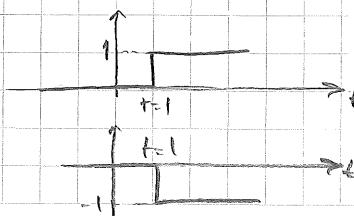
$\therefore W$  is NOT a subspace

EXAMPLE:  $V$ : set of real valued functions.

$W_1$ : set of all continuous functions.

$W_1$  is a subspace

$W_2$ : set of all real valued functions which are discontinuous at  $t=1$ .



$$f(t) = \begin{cases} -1 & t < 1 \\ 1 & t \geq 1 \end{cases} \Rightarrow W_2 \text{ is NOT a subspace}$$

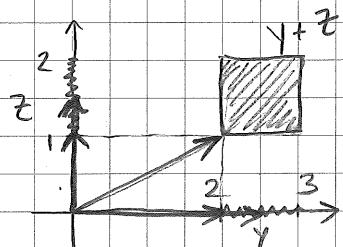
DEFINITION: The sum  $Y+Z$  of two subsets  $Y$  &  $Z$  of a linear space  $X$  is the set of all vectors  $y+z$  where  $y \in Y$  &  $z \in Z$ .

$$Y+Z \triangleq \{y+z \mid y \in Y, z \in Z\}$$

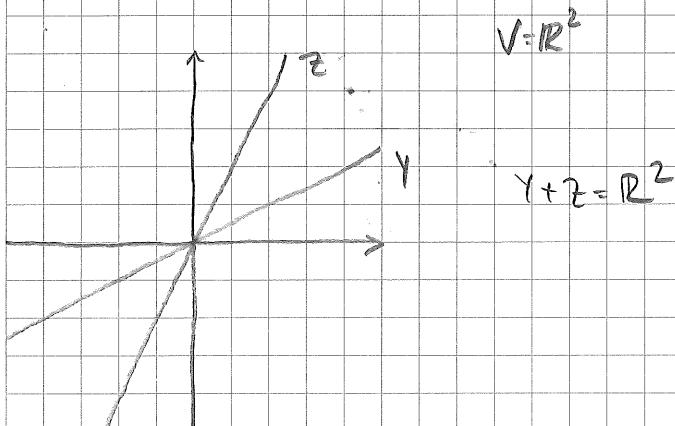
EXAMPLE:  $X = \mathbb{R}^2$

$$Y = \left\{ \begin{bmatrix} a \\ 0 \end{bmatrix} \mid 2 \leq a \leq 3 \right\}$$

$$Z = \left\{ \begin{bmatrix} 0 \\ b \end{bmatrix} \mid 1 \leq b \leq 2 \right\}$$



$$Y+Z = \left\{ \begin{bmatrix} a \\ b \end{bmatrix} \mid \begin{array}{l} 2 \leq a \leq 3 \\ 1 \leq b \leq 2 \end{array} \right\}$$



\* O vector is itself subspace & it is the smallest subspace.

EXAMPLE: Show that  $Y+Z$  is a subspace if both  $Y$  &  $Z$  are subspaces.

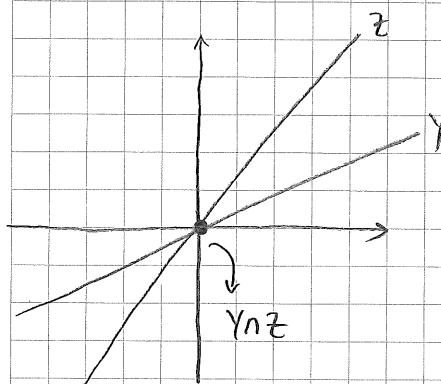
$$x_1 \in Y+Z \Rightarrow x_1 = y_1 + z_1 \text{ where } y_1 \in Y, z_1 \in Z$$

$$x_2 \in Y+Z \Rightarrow x_2 = y_2 + z_2 \text{ where } y_2 \in Y, z_2 \in Z$$

$$x_1 + x_2 = y_1 + z_1 + y_2 + z_2 \underset{\substack{\in Y \\ \in Z}}{\substack{\underbrace{+} \\ +}} \Rightarrow x_1 + x_2 \in Y+Z$$

$$\alpha x_1 = \alpha y_1 + \alpha z_1 \underset{\substack{\in Y \\ \in Z}}{\substack{\underbrace{=} \\ =}} \Rightarrow \alpha x_1 \in Y+Z$$

### EXAMPLE:



Show that if  $Y$  &  $Z$  are subspaces then so is their intersection  $Y \cap Z$ .

$$x_1, x_2 \in Y \cap Z$$

$$x_1 \in Y \quad x_1 \in Z$$

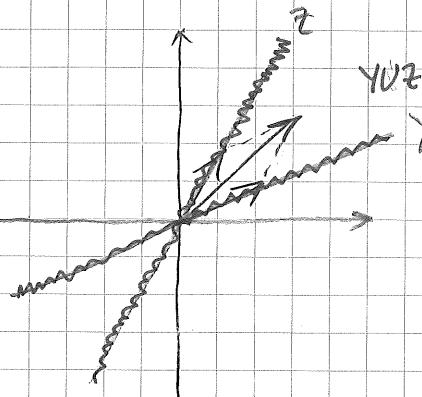
$$x_2 \in Y \quad x_2 \in Z$$

$$x_1 + x_2 \in Y \quad x_1 + x_2 \in Z \Rightarrow x_1 + x_2 \in Y \cap Z$$

$$\alpha x_1 \in Y \quad \alpha x_1 \in Z \Rightarrow \alpha x_1 \in Y \cap Z$$

$\Rightarrow Y \cap Z$  is a SUBSPACE

### EXAMPLE: If $Y$ & $Z$ are subspaces, Is $Y \cup Z$ a subspace?



$Y \cup Z$  does NOT have to be a subspace  
in general.

### DEFINITION: (Product Space)

Let  $(V, F)$  and  $(W, F)$  be two linear space defined over the same field  $F$ . The product space of  $(V, F)$  &  $(W, F)$  is defined as

$$V \times W = \{(v, w) \mid v \in V, w \in W\}$$

$$(v_1, w_1), (v_2, w_2) \in V \times W$$

vector addition

$$(v_1, w_1) + (v_2, w_2) = (v_1 + v_2, w_1 + w_2)$$

scalar multiplication

$$\alpha \in F \quad \alpha(v_1, w_1) = (\alpha v_1, \alpha w_1)$$

EXAMPLE:

$$\underbrace{(\mathbb{R}^2, \mathbb{R})}_{V \times W} = (\mathbb{R}, \mathbb{R}) \times (\mathbb{R}, \mathbb{R})$$

$\downarrow F$        $V F$        $W F$

$$x_1 + x_2$$

$$\alpha x_1$$

13.10.2015  
Tuesday

Review:  $F \oplus \circledcirc$

$$(U, F)$$

$$\circledcirc: U \times U \rightarrow U$$

$$\circledcirc: F \times V \rightarrow V$$

$$W \subset V$$

$$w_1, w_2 \in W$$

$$w_1 + w_2 \in W$$

$$\alpha w_1 \in W$$

$\nwarrow$   
 $\epsilon F$

$W_1, W_2$  are subspaces

$W_1 + W_2$  is a subspace

$W_1 \cap W_2$  "

$W_1 \cup W_2$  is general no a subspace

$$W_1 \times W_2$$

$$\mathbb{R}^2 = \mathbb{R} \times \mathbb{R}$$

DEFINITION: A linear combination of  $n$ -vectors  $x_1, x_2, \dots, x_n$  of a linear space  $V$  is a vector of the form

$$a_1x_1 + a_2x_2 + \dots + a_nx_n = \sum_{i=1}^n a_i x_i$$

where  $a_i \in F$  for  $i = 1, 2, \dots, n$

The set of all linear combinations of  $x_1, x_2, \dots, x_n$

i.e.  $\left\{ \sum_{i=1}^n a_i x_i \mid a_i \in F, i = 1, 2, \dots, n \right\}$

is called the span of  $\{x_1, x_2, \dots, x_n\}$

We denote span of  $x_1, \dots, x_n$  as  $\text{span}\{x_1, \dots, x_n\}$

\*  $x_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad x_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

$$\text{Span}\{x_1, x_2\} = \left\{ a_1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mid a_1, a_2 \in \mathbb{R} \right\}$$

$$= \left\{ \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \mid a_1, a_2 \in \mathbb{R} \right\} = \mathbb{R}^2$$

\*  $x_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad x_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad x_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$\text{Span}\{x_1, x_2, x_3\} = \mathbb{R}^2 \rightarrow \text{in this case, } x_3 \text{ is linearly dependent with } x_1 \text{ & } x_2.$$

\* Every set is subspace of itself!

EXAMPLE: Show that  $\text{span}\{x_1, \dots, x_n\}$  is a subspace.

$$w_1, w_2 \in \text{span}\{x_1, \dots, x_n\}$$

$$w_1 = \sum_{i=1}^n a_i x_i \quad a_i \in F$$

$$w_2 = \sum_{i=1}^n b_i x_i \quad b_i \in F$$

$$w_1 + w_2 = \sum_{i=1}^n (\underbrace{a_i + b_i}_{\in F}) x_i \in \text{span}\{x_1, \dots, x_n\}$$

$$c w_1 = \sum_{i=1}^n (\underbrace{c a_i}_{\in F}) x_i \in \text{span}\{x_1, \dots, x_n\}$$

Definition: Vectors  $x_1, \dots, x_n \in V$  are said to be linearly independent if

$$a_1 x_1 + a_2 x_2 + \dots + a_n x_n = 0$$

implies

$$a_1 = a_2 = \dots = a_n = 0$$

otherwise, they are called linearly dependent.

i.e. if  $\exists a_1, a_2, \dots, a_n$  not all zero

for which  $a_1 x_1 + a_2 x_2 + \dots + a_n x_n = 0$

then  $x_1, \dots, x_n$  are linearly dependent.

### EXAMPLES:

$$X_1 = \left\{ \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}$$

$$a_1 \begin{bmatrix} 0 \\ 1 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow a_1 = a_2 = 0$$

linear independence

$$X_2 = \left\{ \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}, \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} \right\}$$

$$a_1 = 1 \quad a_2 = -2 \quad a_3 = 1$$

$$\begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} = 2 \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$a_1 \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + a_2 \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} + a_3 \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} = 0$$

$X_2$  is linearly dependent

EXAMPLE: Consider linear space of polynomials with degree  $\leq 2$ .

Let  $P = \{P_1(t), P_2(t), P_3(t)\}$  be a set of polynomials

$$P_1(t) = 1$$

$$P_2(t) = t + 1$$

$$P_3(t) = t^2 + t + 1$$

Is  $P$  linearly independent?

$$a_1 \cdot 1 + a_2 (t+1) + a_3 (t^2 + t + 1) = 0(t)$$

$$= 0 + 0t + 0t^2 \quad \forall t$$

$$(a_1 + a_2 + a_3)1 + (a_2 + a_3)t + a_3 t^2 = 0$$

$$\Rightarrow a_3 = 0 \quad a_2 = 0 \quad a_1 = 0$$

linear independence

EXAMPLE:  $V$ : set of continuous functions

$$S = \{\cos t, \sin t, \cos(t - \pi/3)\}$$

Is  $S$  linearly ind?

$$a_1 \cos t + a_2 \sin t + a_3 \cos(t - \pi/3) = 0 \quad \forall t$$

$$\begin{aligned} \cos(t - \pi/3) &= \cos t \cos \pi/3 + \sin t \sin \pi/3 \\ &= \frac{1}{2} \cos t + \frac{\sqrt{3}}{2} \sin t \end{aligned}$$

$$\frac{1}{2} \cos t + \frac{\sqrt{3}}{2} \sin t - 1 \cos(t - \pi/3) = 0 \quad \forall t$$

linearly dependent

DEFINITION: Let  $V$  be a linear space and the set of vectors

$$B = \{x_1, \dots, x_n\} \text{ be a subset of } V.$$

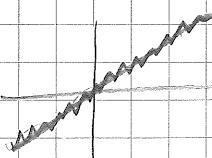
$B$  is said to be a basis for  $V$  iff

i)  $\text{span}\{B\} = V$

ii)  $B$  is a linearly independent set

EXAMPLE:  $V = \mathbb{R}^2$

$$B_1 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \quad q_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 0 \quad B_1 \neq \mathbb{R}^2$$



$$B_2 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

$B_2$  is a basis for  $\mathbb{R}^2$

$$B_3 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

not ind.

$$B_4 = \left\{ \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\} \checkmark$$

REMARK: There are infinitely many basis sets for a linear space  $V$ .

All of these basis sets have the same number of elements.

That number is called the dimension of the  $V$ .

If the dimension is finite,  $V$  is said to be finite dimensional.

Otherwise it is called infinite dimensional.

16.10.2015  
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$$x_1, x_2, \dots, x_n \in V$$

$$a_1, a_2, \dots, a_n \in F$$

$$\sum_{i=1}^n a_i x_i$$

$$\left\{ \sum_{i=1}^n a_i x_i \mid a_i \in F, i=1, \dots, n \right\}$$

$$\underbrace{\quad}_{\text{span } \{x_1, \dots, x_n\}}$$

$$\sum_{i=1}^n a_i x_i = 0_F \Rightarrow a_i = 0_F \quad \forall i$$

$$B = \left\{ \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}$$

$$a_1 \begin{bmatrix} 0 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\downarrow \quad \downarrow$$

$$1 \quad 0$$

$\Rightarrow B$  is linearly dependent

\* If it contains zero vector, it cannot be independent!

$$B = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}$$

$$a_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} a_1 + a_2 \\ a_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow a_1 = 0 \Rightarrow a_2 = 0$$

$B$  is linearly independent

$V$

$$B = \{x_1, \dots, x_n\}$$

$$- V = \text{span } \{B\}$$

-  $B$  is lin. ind.

If we satisfy these two condition, then we can say that " $B$  is a basis for  $V$ "

$$V = \mathbb{R}^2$$

$$B_1 = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

Both are basis for  $V$

$$B_2 = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

# of elements in  $B$  is called Dimension of  $V$

DEFINITION: If  $y \in V$  and  $B = \{x_1, \dots, x_n\}$  is a basis set for  $V$ , then

there is a unique  $n$ -tuple of scalars  $(a_1, \dots, a_n)$  such that

$$y = \sum_{i=1}^n a_i x_i$$

The scalars  $(a_1, \dots, a_n)$  are called the components/coordinates/representations of  $y$  with respect the basis  $B$ . We show the representation of  $y$  wrt  $B$  as vector denoted as  $[y]_B$ .

$$[y]_B = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

EXAMPLE:  $V = \mathbb{R}^2$   $F = \mathbb{R}$

$$B = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$$

$$y = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad [y]_B = ?$$

$$a_1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + a_2 \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \Rightarrow \begin{array}{l} a_1 + a_2 = 2 \\ a_2 = 3 \end{array} \Rightarrow a_1 = -1$$

$$[y]_B = \begin{bmatrix} -1 \\ 3 \end{bmatrix}$$

EXAMPLE:

$$V = \text{span} \{ \cos t, \sin t \}$$

$$B = \{ \cos t, \sin t \}$$

$$y \triangleq \cos(t - \pi/3)$$

$$y = \frac{1}{2} \cos t + \frac{\sqrt{3}}{2} \sin t$$

$$[y]_B = \begin{bmatrix} 1/2 \\ \sqrt{3}/2 \end{bmatrix}$$

$$\left[ \cos(t - \pi/3) \right]_B = \begin{bmatrix} 1/2 \\ \sqrt{3}/2 \end{bmatrix}$$

\*  ~~$V = \mathbb{R}^2$~~  -> because scalar mult. gives me complex vector space which is not inside of  $\mathbb{R}^2$ . So, it is NOT possible such combination.

Claim: For a given basis  $B$ , the representation  $[y]_B$  of a vector  $y$  is unique.

Proof: Proof by contradiction.

$$p \Rightarrow q$$

If  $A$  is a car  $\Rightarrow A$  has doors

$$\bar{q} \Rightarrow \bar{p}$$

If  $A$  has no doors  $\Rightarrow A$  is NOT a car

$p \rightarrow$  your assumption

$q \rightarrow$  conclusion in the theorem

Let us assume that  $[y]_B$  is not unique ( $\bar{q}$ )

$\Rightarrow$  There exists

$$[y]_B = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \quad [y]_B = \begin{bmatrix} a'_1 \\ a'_2 \\ \vdots \\ a'_n \end{bmatrix}$$

and  $\exists i$  s.t.  $a_i \neq a'_i$

$$\left. \begin{array}{l} y = \sum_{i=1}^n a_i x_i \\ y = \sum_{i=1}^n a'_i x_i \end{array} \right\} \quad 0 = \sum_{i=0}^n (a_i - a'_i) x_i$$

$\exists i$  s.t.  $a_i - a'_i \neq 0$

$\Rightarrow x_1, \dots, x_n$  is NOT linearly independent.

$\Rightarrow B$  is NOT a basis  $\Rightarrow$  CONTRADICTION!

EXAMPLE: Let  $\mathbb{R}^{2 \times 2}$  denote the linear space of real valued  $2 \times 2$  matrices with the standard matrix addition and scalar multiplication operations.

$$\mathbb{R}^{2 \times 2}$$

Let the canonical basis be :

$$B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

$$x_1 \quad x_2 \quad x_3 \quad x_4$$

Hence if we have a matrix  $v = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$

$$[v]_B = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}$$

$$v = ax_1 + bx_2 + cx_3 + dx_4$$

Theorem:  $V = \mathbb{R}^2$

$$v = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad B_1 = \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$$

$$B_2 = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \right\}$$

$$[v]_{B_1} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$[v]_{B_2} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$[v]_{B_1} = P [v]_{B_2} \quad \forall v$$

Theorem: Let  $V$  be an  $n$ -dimensional linear space over  $\mathbb{R}$ . Let  $B_1$  and  $B_2$  be two basis sets for  $V$ . Then there exists an  $n \times n$  real invertible matrix  $P$  such that

$$[v]_{B_1} = P [v]_{B_2} \quad \forall v \in V$$

Proof: Proof by construction (directly showing)

$$p \Rightarrow q$$

we call the coefficient as  $p_{ij}$

$$B_1 = \{v_1, \dots, v_n\}$$

$$w_j \in V$$

$$B_2 = \{w_1, \dots, w_n\}$$

$$w_j = \sum_{i=1}^n p_{ij} v_i \text{ for } j=1, \dots, n$$

Consider an arbitrary vector  $v \in V$

$$v = \sum_{j=1}^n \alpha_j w_j \Rightarrow [v]_{B_2} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$$

$$v = \sum_{j=1}^n \alpha_j \sum_{i=1}^n p_{ij} v_i = \sum_{j=1}^n \sum_{i=1}^n \alpha_j p_{ij} v_i$$

$$= \sum_{i=1}^n \left( \sum_{j=1}^n \alpha_j p_{ij} \right) v_i = \sum_{i=1}^n \alpha'_i v_i$$

$\underbrace{\alpha'_i}_{\alpha'_i}$

$$\Rightarrow [v]_{B_1} = \begin{bmatrix} \alpha'_1 \\ \alpha'_2 \\ \vdots \\ \alpha'_n \end{bmatrix}$$

$$\Rightarrow \alpha'_i \triangleq \sum_{j=1}^n p_{ij} \alpha_j$$

$$\alpha^1 = \sum_{j=1}^n p_{1j} \alpha_j$$

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$$

EXAMPLE: Consider  $V = \text{polynomials with degree } \leq 2$ .

$$B_1 = \{1, 1+t, 1+t+t^2\}$$

$$B_2 = \{1, t, t^2\}$$

Find the matrix  $P$  which converts representations wrt  $B_2$  into rep. wrt  $B_1$ .

$$[v]_{B_1} = P [v]_{B_2}$$

$$P = ?$$

Choose  $v = w_1$

$$[w_1]_{B_1} = \begin{bmatrix} \text{for } w_1 \\ \text{for } w_2 \\ \text{for } w_3 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$1 = 1(1) + 0(1+t) + 0(1+t+t^2)$$

$$t = -1(1) + 1(1+t) + 0(1+t+t^2)$$

$$t^2 = 0(1) + -1(1+t) + 1(1+t+t^2)$$

$$P = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix}$$

## NORMED SPACES

DEFINITION: Let  $(V, F)$  be a vector space. A norm on  $V$  is a function

$$\| \cdot \| : V \rightarrow \mathbb{R} \geq 0$$

$\underbrace{\phantom{\text{non-negative}}}_{\text{non-negative}}$   
real numbers

satisfying the following properties:

$$(P1) \|v\| \geq 0 \quad \forall v \in V$$

$$\|v\| = 0 \iff v = 0_V$$

$$(P2) \|\alpha v\| = |\alpha| \|v\| \quad \forall \alpha \in \mathbb{R} \quad \forall v \in V$$

$$(P3) \|v_1 + v_2\| \leq \|v_1\| + \|v_2\| \quad \left. \begin{array}{l} \text{triangular inequality} \\ \text{inequality} \end{array} \right\}$$

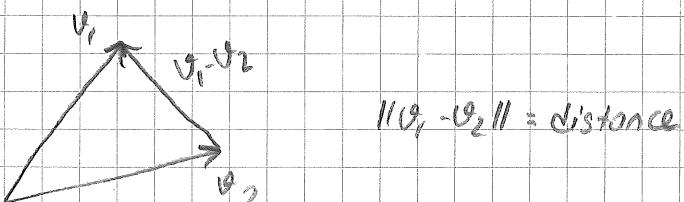
The triplet  $(V, F, \|\cdot\|)$  is called a normed space.

### REMARK:

1) The vector space is an algebraic structure and with the norm, we start introducing geometry into a linear space.

2) Norm defined a distance between two vectors  $v_1, v_2 \in V$  with the expression  $\|v_1 - v_2\|$

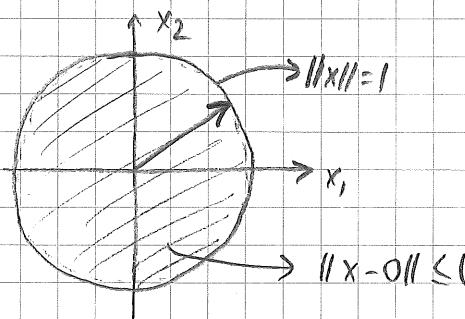
Since  $\|v\| = \|v - 0_V\|$ ,  $\|v\|$  is the distance of  $v$  to the origin.



$$V = \mathbb{R}^2$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\|x\| = \sqrt{x_1^2 + x_2^2}$$

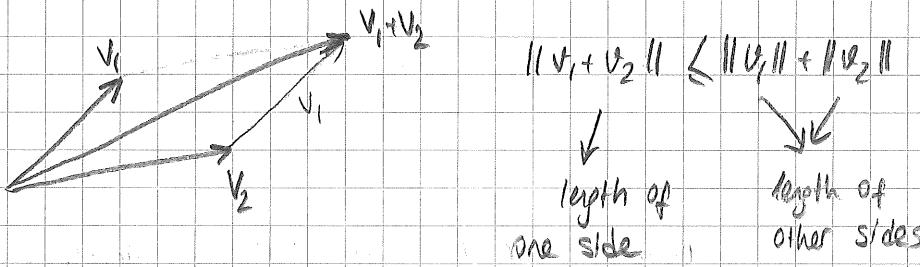


3) We can define a "sphere" in  $V$  using the norm concept.

$$S = \{ v \in V \mid \|v - v_0\| \leq r \}$$

$S$  is a sphere with center  $v_0$  and radius  $r$ .

4) Interpretation of the triangle inequality



20.10.2015  
Tuesday

$$x \in V \quad B = \{x_1, \dots, x_n\}$$

$$x = \sum_{i=1}^n q_i x_i \quad q_i \in F$$

unique  
coefficients

$$[x]_B = \begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_n \end{bmatrix}$$

$$x \in V \quad B_1 = \{x_1, \dots, x_n\}$$

$$B_2 = \{y_1, \dots, y_n\}$$

$$[x]_{B_1} = P [x]_{B_2}$$

↓  
is an  
invertible

$$\|\cdot\| : V \rightarrow \mathbb{R} \geq 0$$

$$1) \|x\| \geq 0 \quad \forall x \in V$$

$$\|x\| = 0 \iff x = 0_V$$

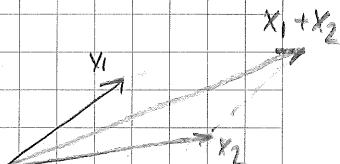
$$2) \|\alpha x\| = |\alpha| \|x\| \quad \forall x \in V \quad \forall \alpha \in \mathbb{F}$$

$$3) \|x_1 + x_2\| \leq \|x_1\| + \|x_2\| \quad \forall x_1, x_2 \in V$$

\* With addition of norm function  $\|\cdot\|$ , two algebraic structures  $V \oplus F$  becomes geometric also.

$$(V, F, \|\cdot\|), \quad \|x_1 - x_2\|, \quad \|x - x_0\| \leq r$$

↙  
sphere in  $V$   
center  $x_0$   
radius  $r$



EXAMPLE:  $V = \mathbb{R}^2$   $F = \mathbb{R}$

$$x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \quad \alpha_1, \alpha_2 \in \mathbb{R}$$

$$\|x\|_1 \triangleq |\alpha_1| + |\alpha_2|$$

Is this function  $\|\cdot\|_1$  a norm?

Check the properties.

1)  $\|x\|_1 \geq 0 \quad \forall x \in V \quad \checkmark$

Let  $x = 0_V = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \alpha_1 = 0 \quad \alpha_2 = 0 \Rightarrow \|x\|_1 = |0| + |0| = 0$  (backward)  $\checkmark$

Let  $\|x\|_1 = 0 = |\alpha_1| + |\alpha_2| \Rightarrow \alpha_1 = 0 \quad \alpha_2 = 0 \Rightarrow x = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0_V$  (forward)  $\checkmark$

2)  $\alpha x = \alpha \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \alpha \alpha_1 \\ \alpha \alpha_2 \end{bmatrix} \quad \|\alpha x\|_1 \triangleq |\alpha \alpha_1| + |\alpha \alpha_2| = |\alpha| |\alpha_1| + |\alpha| |\alpha_2| = |\alpha| \underbrace{(|\alpha_1| + |\alpha_2|)}_{\|x\|_1}$

3)  $x_1 = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \quad x_2 = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$

$$x_1 + x_2 = \begin{bmatrix} \alpha_1 + \beta_1 \\ \alpha_2 + \beta_2 \end{bmatrix}$$

$\| \cdot \|_2$

$$\|x_1 + x_2\|_1 = |\alpha_1 + \beta_1| + |\alpha_2 + \beta_2| \leq \underbrace{|\alpha_1| + |\alpha_2|}_{\|x_1\|_1} + \underbrace{|\beta_1| + |\beta_2|}_{\|x_2\|_1}$$

$$\Rightarrow \|x_1 + x_2\|_1 \leq \|x_1\|_1 + \|x_2\|_1 \quad \checkmark$$

$\Rightarrow \|\cdot\|_1$  is actually a norm.

1, norm

EXAMPLE:

$$\|x\|_2 = \left[ |\alpha_1|^2 + |\alpha_2|^2 \right]^{1/2}$$

2-norm

$\ell_2$ -norm

Euclidean Norm

EXAMPLE:

$$\|x\|_\infty = \max \{ |\alpha_1|, |\alpha_2| \} \quad \ell_\infty\text{-norm}$$

$$x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$$

$$\|x\|_1 = \sum_{i=1}^n |\alpha_i|$$

$$\|x\|_2 = \sqrt{\sum_{i=1}^n |\alpha_i|^2}$$

$$\|x\|_\infty = \max \{ |\alpha_1|, |\alpha_2|, \dots, |\alpha_n| \}$$

Those three norms can be generalized into  $p$ -norm.

$$\|x\|_p = \left( |\alpha_1|^p + |\alpha_2|^p \right)^{1/p}$$

$$x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} \Rightarrow \|x\|_p = \left( \sum_{i=1}^n |\alpha_i|^p \right)^{1/p} \quad \text{for } 1 \leq p \leq \infty$$

$$x = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad \|x\|_p = (2^p + 3^p)^{1/p}$$

$$p=1 \quad 2+3$$

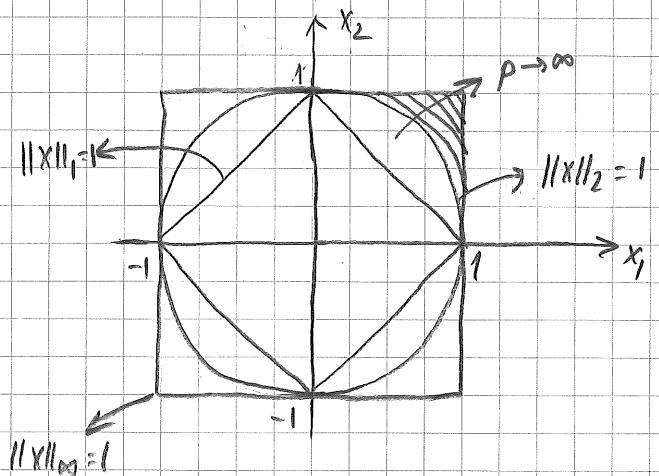
$$p=2 \quad 4+9$$

$$p=3 \quad 8+27$$

$$p \rightarrow \infty \quad 2^\infty + 3^\infty$$

$$\lim_{p \rightarrow \infty} \|x\|_p = \|x\|_\infty$$

Consider the unit spheres  $\|x\|_p \leq 1$



$$\|x\|_1 = |x_1| + |x_2| = 1$$

$$x_1 + x_2 = 1$$

$$-x_1 + x_2 = 1$$

$$\|x\|_\infty = 1$$

$$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$$

$$\begin{bmatrix} -1 \\ -1/2 \end{bmatrix} \quad \begin{bmatrix} -0.5 \\ 1 \end{bmatrix} \quad \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

EXAMPLE:  $\|x\|_{1/2} = \left( |x_1|^{1/2} + |x_2|^{1/2} \right)^2 \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

Is  $\|x\|_{1/2}$  a norm?

Check 3<sup>rd</sup> property  $\|x_1 + x_2\| \leq \|x_1\| + \|x_2\|$

$$x_1 = \begin{bmatrix} 4 \\ 0 \end{bmatrix} \quad x_2 = \begin{bmatrix} 9 \\ 0 \end{bmatrix}$$

$$\|x_1 + x_2\|_{1/2} = \left\| \begin{bmatrix} 4 \\ 9 \end{bmatrix} \right\|_{1/2} = 25$$

$$\|x_1\|_{1/2} = 4$$

$$\|x_2\|_{1/2} = 9$$

Violation in 3<sup>rd</sup> property

$\|\cdot\|_{1/2}$  is NOT a norm!

EXAMPLES: Norms on function spaces.

$$V = \left\{ f(\cdot) \mid f: [0, 1] \rightarrow \mathbb{R} \text{ such that } \int_0^1 |f(t)|^p dt < \infty \quad 1 \leq p \leq \infty \right\}$$

We can define norms as follows:

$$\|f\|_p \triangleq \left[ \int_0^1 |f(t)|^p dt \right]^{1/p}$$

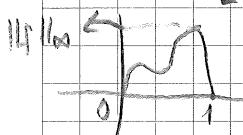
Specific Cases

$$\|f\|_1 = \int_0^1 |f(t)| dt \quad L_1\text{-norm}$$

$$\|f\|_2 = \sqrt{\int_0^1 |f(t)|^2 dt} \quad L_2\text{-norm}$$

RMS  
value of  
 $f(t)$

$$\|f\|_{\infty} = \max_{0 \leq t \leq 1} |f(t)| \quad L_{\infty}\text{-norm}$$



→ If there is negative value, take the absolute value of it!

23.10.2015

We defined norms on  $\mathbb{R}^n$

$$\|x\|_p = \left( \sum_{i=1}^n |x_i|^p \right)^{1/p}$$

$$\left( |x_1|^p + |x_2|^p \right)^{1/p} = |x_2| \quad \|x\|_{\infty} = \max |x_i|$$

Function Norms

$$\|g\|_p = \left( \int_0^1 |g(t)|^p dt \right)^{1/p}$$

$$\|g\|_{\infty} = \max |g(t)|$$

## MATRIX NORMS

There are two ways to define matrix norms.

The first way is to consider the matrix as a vector.

EXAMPLE.

$$A = \begin{bmatrix} 1 & -2 \\ 3 & -6 \end{bmatrix} \Rightarrow a = \begin{bmatrix} 1 \\ -2 \\ 3 \\ -6 \end{bmatrix}$$

$$\|A\|_{\infty} = 4$$

$$\|A\|_1 = 10$$

$$A = [a_{ij}]$$

$$\|A\|_{\infty} = \max_{i,j} |a_{ij}|$$

$$\|A\|_1 = \sum_i \sum_j |a_{ij}|$$

$$\|A\|_2 = \left( \sum_i \sum_j |a_{ij}|^2 \right)^{1/2} = \sqrt{\text{trace}(A^T A)}$$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \rightarrow \text{Tr}(B) = b_{11} + b_{22}$$

$$A^T = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \Rightarrow A^T A = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} a_{11}^2 + a_{21}^2 & * \\ * & a_{12}^2 + a_{22}^2 \end{bmatrix}$$

$$\text{tr} A^T A = a_{11}^2 + a_{21}^2 + a_{12}^2 + a_{22}^2$$

Frobenius Norm

$$\|A\|_p = \left( \sum_i \sum_j |a_{ij}|^p \right)^{1/p} \quad 1 \leq p \leq \infty$$

The second way to define a matrix norm is called as "induced norm".

DEFINITION: Let  $A: \mathbb{R}^n \rightarrow \mathbb{R}^m$  be an  $m \times n$  matrix. Let  $\|\cdot\|_{\mathbb{R}^n}$  &  $\|\cdot\|_{\mathbb{R}^m}$  denote the norms in  $\mathbb{R}^n$  and  $\mathbb{R}^m$  respectively.

The induced matrix norm is defined as

$$\|A\| \triangleq \max_{\substack{x \in \mathbb{R}^n \\ x \neq 0}} \frac{\|Ax\|_{\mathbb{R}^m}}{\|x\|_{\mathbb{R}^n}}$$

$$m \left[ \begin{array}{c} \\ A \\ \end{array} \right] \left[ \begin{array}{c} x_1 \\ x_2 \\ \vdots \\ x_n \\ \hline x \end{array} \right] = \left[ \begin{array}{c} y_1 \\ y_2 \\ \vdots \\ y_m \\ \hline y \end{array} \right]$$

$$\max_{\substack{x \in \mathbb{R}^n \\ x \neq 0}} \frac{\|y\|_{\mathbb{R}^m}}{\|x\|_{\mathbb{R}^n}}$$

$$\|Ax\| = |\alpha| \|x\|$$

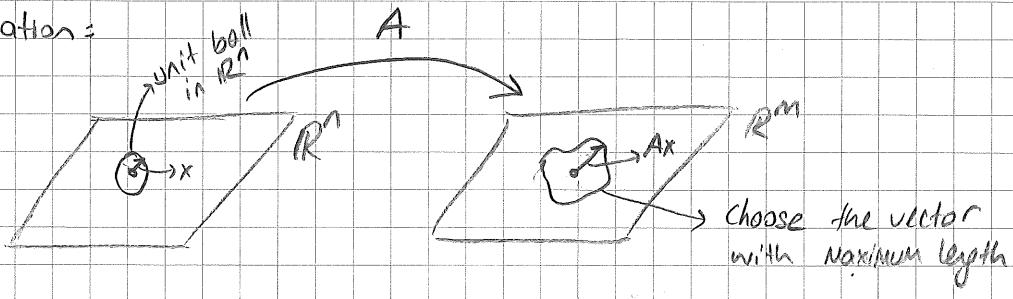
Remark: An equivalent definition is

$$\|A\| \triangleq \max_{\substack{\|x\|_{\mathbb{R}^n}=1}} \|Ax\|_{\mathbb{R}^m}$$

$$\frac{\|Ax\|_{\mathbb{R}^m}}{\|x\|_{\mathbb{R}^n}} = \left\| A \underbrace{\frac{x}{\|x\|_{\mathbb{R}^n}}}_{\text{A vector with unit norm}} \right\|_{\mathbb{R}^m}$$

$$\frac{\|x\|}{\alpha} = \left\| \frac{x}{\alpha} \right\| \quad \alpha > 0$$

Visulation:



EXAMPLE: Consider an  $m \times n$  matrix with real elements. Choose the  $\infty$ -norm  $\| \cdot \|_\infty$  for both  $\mathbb{R}^n$  &  $\mathbb{R}^m$ .

$$A = \begin{bmatrix} 1 & -2 \\ -3 & 4 \\ -2 & 2 \end{bmatrix} \quad 3 \times 2$$

$$\mathbb{R}^3 \quad \mathbb{R}^2$$

$$\|A\| = \max_{\|x\|_\infty=1} \|Ax\|_\infty$$

~~First row~~

$$\bar{A} = [1 \ -2] \quad \| \bar{A} \| = \max_{\|x\|_\infty=1} \| \bar{A}x \|_\infty$$

$$\begin{bmatrix} 1 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\| \bar{A}x \|_\infty = |x_1 - 2x_2|$$

$$\|x\|_\infty = 1 \rightarrow \max(|x_1|, |x_2|) = 1 \rightarrow x = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \Rightarrow \|\bar{A}\| = 3$$

$$\begin{bmatrix} 1 & -2 \\ -3 & 4 \\ -2 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} =$$

$$\max(|x_1|, |x_2|) = 1$$

$$\|Ax\|_\infty = \max_i |y_i|$$

$$y = Ax$$

$$\|A\|_\infty = 7 \quad x^* = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$\|A\| = \max_i \left( \sum_{j=1}^n |a_{ij}| \right) = \alpha$$

\* Prove this! (our aim)

$$\begin{cases} (I) \|A\| \leq \alpha \\ (II) \|A\| \geq \alpha \end{cases} \quad \left. \begin{array}{l} \\ \|A\| = \alpha \end{array} \right\}$$

$$y = Ax \quad y_i = \sum_{j=1}^n a_{ij} x_j$$

Part I:  $\|x\|_\infty = 1$

$$\|A\| = \max_{\|x\|_\infty = 1} \|Ax\|_\infty = \max_i |y_i|$$

$$= \max_i \left| \sum_{j=1}^n a_{ij} x_j \right| \leq \max_i \sum_{j=1}^n |a_{ij} x_j| = \max_i \sum_{j=1}^n |a_{ij}| x_j$$

$$\max_j |x_j| = 1 \quad \leq \max_i \sum_{j=1}^n |a_{ij}| = \alpha$$

$$\Rightarrow \|A\| \leq \alpha$$

Part II: Prove that  $\|A\| \geq \alpha$

$$\|A\| = \max_{\|x\|_\infty = 1} \|Ax\|_\infty$$

$$\|\bar{z}_1\|_\infty = 1$$

$$\geq \|A\bar{z}_1\|_\infty$$

$$\text{Choose } \bar{z}_1 \text{ s.t. } y_1 = \sum_{j=1}^n a_{1j} \bar{z}_1(j)$$

$$\vec{z}_1 \triangleq \begin{bmatrix} \text{sign}(a_{11}) & \text{sign}(a_{12}) & \dots & \text{sign}(a_{1n}) \end{bmatrix}^T$$

$$A\vec{z}_1 = \begin{bmatrix} \sum_{j=1}^n |a_{1j}| \\ x \\ x \\ \vdots \\ x \end{bmatrix}$$

$$A\vec{z}_1 = \begin{bmatrix} \sum_{j=1}^n |a_{1j}| \\ x \\ \vdots \\ x \end{bmatrix} \quad z = \begin{bmatrix} 3 \\ x \\ \vdots \\ x \end{bmatrix} \quad \|z\|_\infty \geq 3$$

$$\|A\| \geq \sum_{j=1}^n |a_{0j}|$$

$$\text{Choose } \vec{z}_2 = \begin{bmatrix} \text{sign } a_{21} & \text{sign } a_{22} & \dots & \text{sign } a_{2n} \end{bmatrix}^T$$

$$\|\vec{z}_2\|_\infty = 1$$

$$\|A\|_\infty = \max_{\|x\|_\infty=1} \|Ax\|_\infty \geq \|A\vec{z}_2\|_\infty$$

$$A\vec{z}_2 = \begin{bmatrix} x \\ \sum_{j=1}^n |a_{2j}| \\ x \\ \vdots \\ x \end{bmatrix} \geq \sum_{j=1}^n |a_{2j}|$$

$$\|A\vec{z}_2\|_\infty \geq \sum_{j=1}^n |a_{2j}|$$

$$\|A\| \geq \sum_{j=1}^n |a_{2j}|$$

I continue in this manner

$$\|A\| \geq \sum_{j=1}^n |a_{ij}| \quad \forall i$$

$$\|A\| \geq \max_i \sum_{j=1}^n |a_{ij}| = \alpha$$

QED

EXAMPLE: Choose  $\|\cdot\|_1$ , norm for both  $\mathbb{R}^n$  &  $\mathbb{R}^m$ .

$$A = \begin{bmatrix} 1 & -2 \\ -3 & 4 \\ -2 & 2 \end{bmatrix}$$

$$\|A\|_1 = \max_{\|x\|_1=1} \|Ax\|$$

$$\|\bar{A}\|_1 = \left| \begin{bmatrix} 1 & -2 \\ -3 & 4 \\ -2 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right|$$

$$\max_{\|x\|_1=1} |x_1 - 2x_2|$$

$$|x_1| + |x_2| = 1$$

$$\|\bar{A}\|_1 = 2$$

$$\begin{bmatrix} 1 & -2 \\ -3 & 4 \\ -2 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\|A\| = 8$$

$$\|A\| = \max_j \sum_{i=1}^m |a_{ij}| \quad \text{Prove this!}$$

Proof

## CONVERGENCE

DEFINITION: Let  $(V, F, \|\cdot\|)$  be a normed space. Let  $\{v_n\}_{n=1}^{\infty}$  be

a sequence of vectors in  $V$  i.e.,  $v_n \in V$  for  $n=1, 2, \dots$

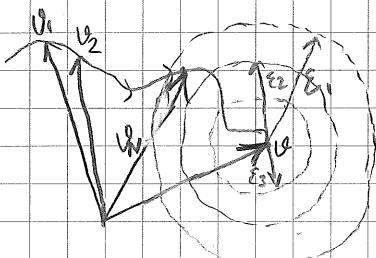
The sequence  $\{v_n\}_{n=1}^{\infty}$  is said to converge to the limit

$$v \in V \text{ iff } \|v_n - v\| \rightarrow 0 \text{ as } n \rightarrow \infty$$

OR

If given any  $\epsilon > 0$ ,  $\exists N$  ( $N$  can depend on  $\epsilon$ ) such that  $\|v_n - v\| < \epsilon \forall n \geq N$ .

$\downarrow$   
find  $N$ , then sequence can converge



Usually as  $\epsilon$  gets smaller,  $N$  gets larger.

$\epsilon \downarrow N \uparrow$

Remark: A sequence is called divergent if it is NOT convergent. If  $\exists \epsilon$  st we cannot find an  $N$  value, then the sequence is divergent.

EXAMPLE:  $V = \mathbb{R}$   $\|v\| = |v|$

Consider the sequence

$$\left\{ \left( \frac{1}{2} \right)^n \right\}_{n=1}^{\infty}$$

Prove that the sequence is convergent to ZERO.

$$\begin{array}{c} \| \\ v = 0 \end{array}$$

Let  $\varepsilon > 0$  be an arbitrary number. We have to find a  $N$   
 s.t.  $\|v_n - 0\| \leq \varepsilon \quad \forall n \geq N$

$$\|v_n\| = \left\| \left(\frac{1}{2}\right)^n \right\| = 2^{-n} \leq \varepsilon$$

$$-n \leq \log_2 \varepsilon \Rightarrow n \geq -\log_2 \varepsilon$$

$$N = \text{ceiling}(-\log_2 \varepsilon)$$



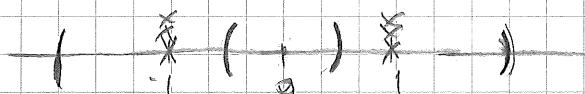
smallest integer  
greater than  $-\log_2 \varepsilon$ .

$$\Rightarrow \forall n \geq N \quad \|v_n\| \leq \varepsilon$$

EXAMPLE:  $V = \mathbb{R}$   $\|v\| = |v|$

Consider the sequence  $\left\{ (-1)^n \right\}_{n=1}^{\infty} = \{-1, 1, -1, 1, \dots\}$

Is the sequence convergent?



Suppose we want to check

if  $v_n \rightarrow 0$

$$\varepsilon = 2 \rightarrow N = 1 \rightarrow \text{our } N \text{ must be hold}$$

$\varepsilon = 1/2$  Nb  $N$   
can be  
found

$\Rightarrow$  The sequence is NOT convergent to ZERO.

Is the sequence convergent to  $v = 1$ ?

$$\varepsilon = 3 \quad N = 1$$

$\varepsilon = 1$  We cannot find  $N$ .

$\Rightarrow$  The sequence is NOT convergent to 1.

$\Rightarrow$  The sequence is NOT convergent to any point in  $\mathbb{R}$ .

$\Rightarrow$  Sequence is divergent.

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## CONVERGENCE

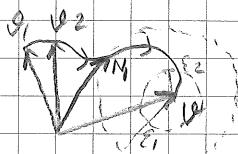
(V, F,  $\|\cdot\|$ )

$$\{v_n\}_{n=1}^{\infty}, v_n \in V$$

converges to  $v \in V$  iff  $\lim_{n \rightarrow \infty} \|v_n - v\| = 0$

OR

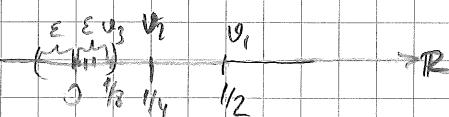
$\forall \epsilon > 0 \exists N \text{ s.t. } \|v_n - v\| < \epsilon \quad \forall n \geq N$



## EXAMPLES

$$V = \mathbb{R} \quad \|v\| = |v|$$

$$\left\{ \left( \frac{1}{2} \right)^n \right\}_{n=1}^{\infty}$$



$$\|v_n - v\| = \left| \left( \frac{1}{2} \right)^n \right| \leq \epsilon$$

$$n = -\log_2 \epsilon \quad N = \text{ceiling}(-\log_2 \epsilon)$$

## EXAMPLES

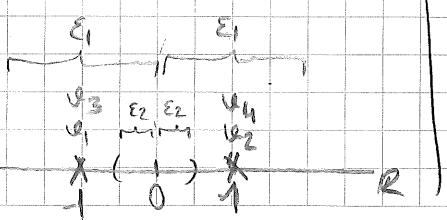
$$\left\{ (-1)^n \right\}_{n=1}^{\infty}, \|v\| = 1$$

$$v_n = (-1)^n$$

Is the sequence convergent to  $v = 0$

$$\epsilon_1 = 2, N_1 = 1$$

$\epsilon_2 = 1/2$  No  $N$  can be found!



Sequence is NOT convergent to 0.  
to any number.

NOTE: In many engineering applications, we are interested in the convergence of an iterative algorithm. But the problem is that we don't know where! Hence we cannot use the standard way to prove convergence. To avoid this problem, we define the concept of a "Cauchy Sequence".

DEFINITION: Let  $(V, F, \|\cdot\|)$  be a normed space. A sequence

$\{v_n\}_{n=1}^{\infty}$  is set to be a Cauchy Sequence if

$$\|v_n - v_m\| \rightarrow 0 \text{ as } n, m \rightarrow \infty$$

OR

$\forall \epsilon > 0 \exists N$  (depending on  $\epsilon$ ) such that  $\|v_n - v_m\| \leq \epsilon \quad \forall n, m \geq N$

REMARK: Every convergent sequence is a Cauchy Sequence. The reverse is NOT true.

Proof: Suppose the sequence  $\{v_n\}_{n=1}^{\infty}$  is convergent and it converges to  $v \in V$

$$\begin{aligned} 0 &\leq \|v_n - v_m\| = \|v_n - v + v - v_m\| \leq \|v_n - v\| + \|v - v_m\| \\ &= \|v_n - v\| + \|v_m - v\| \xrightarrow[n \rightarrow \infty]{m \rightarrow \infty} 0 = 0 \end{aligned}$$

$$0 \leq \|v_n - v_m\| \xrightarrow[n \rightarrow \infty]{m \rightarrow \infty} 0 \quad \Rightarrow \quad \|v_n - v_m\| \rightarrow 0 \quad \xrightarrow[n \rightarrow \infty]{m \rightarrow \infty}$$

EXAMPLE: A norm space that is defined as

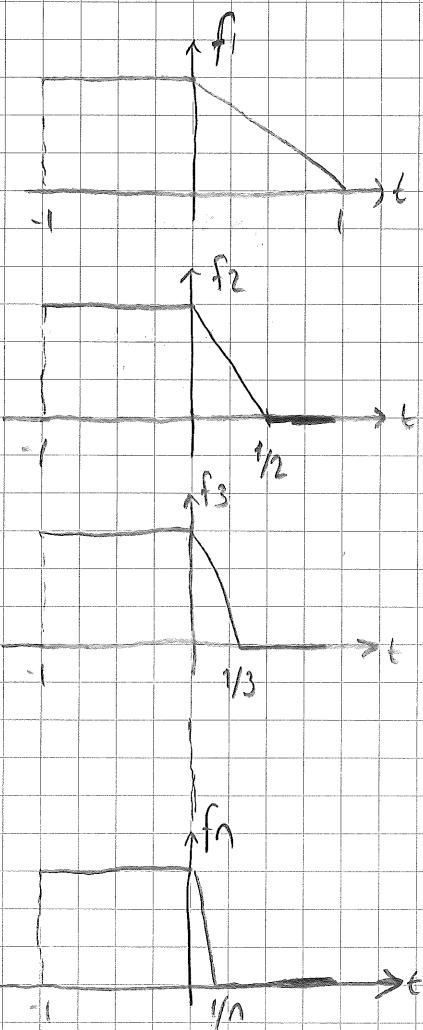
NOT COMPLETE SPACE

$$V = \left\{ f \mid f: [-1, 1] \rightarrow \mathbb{R}, f \text{ is continuous and } \int_{-1}^1 |f(t)| dt < \infty \right\}$$

Define the norm as

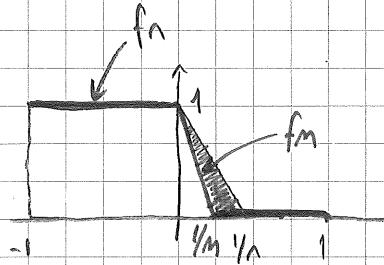
$$\|f\|_1 \triangleq \int_{-1}^1 |f(t)| dt$$

Consider sequence :  $\{f_n\}_{n=1}^{\infty}$



Is the sequence Cauchy?

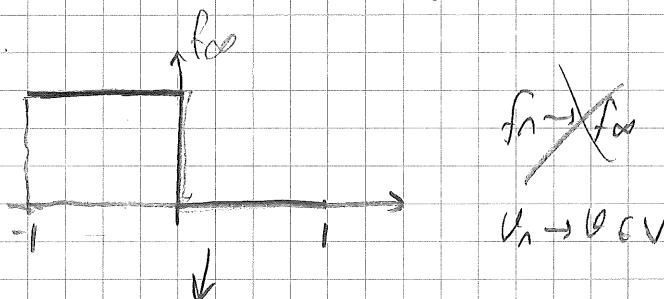
$$\|f_n - f_m\| = \int_{-1}^1 |f_n(t) - f_m(t)| dt$$



$$\|f_n - f_m\| = \frac{1}{2} \left| \frac{1}{n} - \frac{1}{m} \right| \rightarrow 0 \text{ as } n, m \rightarrow \infty$$

The sequence  $\{f_n\}_{n=1}^{\infty}$  is Cauchy!

Where does the function go to:



It is NOT cont.  $\Rightarrow$  it is not converges.

DEFINITION: A normed space is said to be complete if every Cauchy sequence is convergent.

For ex., this esp is NOT complete. If we don't think cont. requirement, it will be.

A complete normed space is called as "BANACH SPACE".

$$\{v_n\}_{n=1}^{\infty}, v_n \in V$$

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$v_n$  converges to  $v \in V$  if  $\|v_n - v\| \rightarrow 0$  as  $n \rightarrow \infty$

OR

$\forall \epsilon > 0 \exists N$  s.t.  $\|v_n - v\| \leq \epsilon \quad \forall n \geq N$

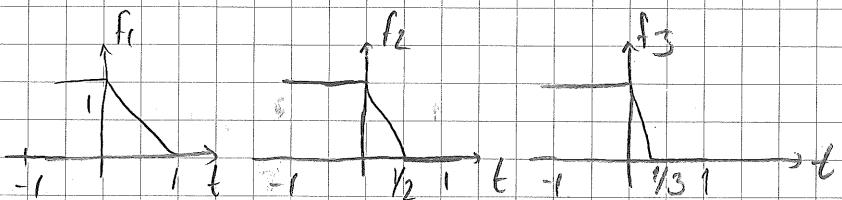
Cauchy Sequence

$$\|v_n - v_m\| \rightarrow 0 \quad n, m \rightarrow \infty$$

OR

$\forall \epsilon > 0 \exists N$  s.t.  $\|v_n - v_m\| \leq \epsilon \quad \forall n, m \geq N$

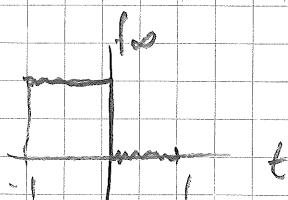
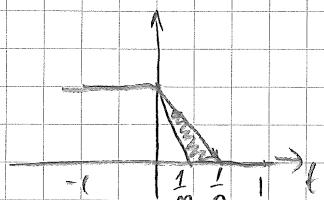
If a Seq. is convergent  $\Rightarrow$  It is Cauchy



$$V = \left\{ f : [-1, 1] \rightarrow \mathbb{R}, f \text{ is cont.}, \int_{-1}^1 |f(t)| dt < \infty \right\}$$

$$f_n \in V \quad \|f_n\| = \int_{-1}^1 |f_n(t)| dt$$

$$\|f_n - f_m\| = \int_{-1}^1 |f_n(t) - f_m(t)| dt \rightarrow 0 \rightarrow \text{This is Cauchy sequence}$$



$f_n$  converges to  $f_\infty$

$f_\infty$

because  $f_\infty$  is NOT cont  
NOT inside  $V$ .

Spaces where all Cauchy sequences are convergent are called Complete Normed Spaces. (Banach Spaces)

## INNER PRODUCT SPACES

An inner product space is a linear space with an additional function called an inner product.

DEFINITION: Let  $(V, \mathbb{C})$  be a vector space. (ie, the field is complex)

An inner product is a function from  $(V \times V)$  into  $\mathbb{C}$

$$\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{C}$$

Inner product satisfies the following properties;

1)  $\langle x, y \rangle = \overline{\langle y, x \rangle} \quad \forall x, y \in V$  (conjugate symmetry)

2) Linearity w.r.t the first argument:

a)  $\langle x+y, z \rangle = \langle x, z \rangle + \langle y, z \rangle \quad \forall x, y, z \in V$  (additivity)

b)  $\langle \alpha x, y \rangle = \alpha \langle x, y \rangle \quad \forall x, y \in V \quad \forall \alpha \in \mathbb{C}$  (homogeneity)

3)  $\langle x, x \rangle$  is real & nonnegative

$$\langle x, x \rangle \geq 0 \quad \forall x \in V$$

Equality hold iff  $x = 0_V$

$$\langle x, x \rangle = 0 \iff x = 0_V$$

(positive definiteness)

Linearity wrt second argument:

$$\langle x, y+z \rangle = \overline{\langle y+z, x \rangle} = \overline{\langle y, x \rangle + \langle z, x \rangle} = \langle x, y \rangle + \langle x, z \rangle$$

$$\sum x_i \bar{y}_i$$

$$\sum y_i \bar{x}_i$$

additivity wrt 2<sup>nd</sup> argument holds

$$\langle x, \alpha y \rangle = \overline{\langle \alpha y, x \rangle} = \overline{d \langle y, x \rangle} = \overline{d} \langle x, y \rangle$$

↓  
homogeneity holds with  $\overline{d}$ .

EXAMPLE:  $V = \mathbb{C}^n \quad x = [x_1 \ x_2 \ \dots \ x_n]^T$   
 $y = [y_1 \ y_2 \ \dots \ y_n]^T$

$$\langle x, y \rangle \stackrel{\Delta}{=} \sum_{i=1}^n x_i \bar{y}_i$$

Check the properties:

✓ \* 1)  $\langle x, y \rangle = \sum_{i=1}^n x_i \bar{y}_i = \sum_{i=1}^n \bar{x}_i \bar{\bar{y}}_i = \sum_{i=1}^n \bar{x}_i \bar{y}_i = \sum_{i=1}^n \bar{x}_i y_i = \langle y, x \rangle$

✓ \* 2) a)  $\langle x+y, z \rangle = \sum_{i=1}^n (x_i + y_i) \bar{z}_i = \sum_{i=1}^n x_i \bar{z}_i + \sum_{i=1}^n y_i \bar{z}_i = \langle x, z \rangle + \langle y, z \rangle$

b)  $\langle \alpha x, y \rangle = \sum_{i=1}^n (\alpha x_i) \bar{y}_i = \alpha \sum_{i=1}^n x_i \bar{y}_i = \alpha \langle x, y \rangle$

✓ \* 3)  $\langle x, x \rangle = \sum_{i=1}^n x_i \bar{x}_i = \sum_{i=1}^n |x_i|^2$  is always real

If  $x=0 \Rightarrow x_i=0 \Rightarrow |x_i|=0 \Rightarrow \langle x, x \rangle = 0$

If  $\langle x, x \rangle = 0 \Rightarrow |x_i|=0 \Rightarrow x_i=0 \Rightarrow x=0$

EXAMPLE:  $V = \mathbb{C}^{n \times n}$

$$\langle A, B \rangle = \sum_{i=1}^n \sum_{j=1}^n a_{ij} \bar{b}_{ij} = \text{trace}(A \bar{B}^T) \\ \in \mathbb{C}^{n \times n} \quad \in \mathbb{C}^{n \times n} \\ a_{ij}, b_{ij}$$
$$= \text{trace}(A^T \bar{B})$$

EXAMPLE:  $V = \left\{ f \mid [0, 1] \rightarrow \mathbb{C} \text{ such that } \int_0^1 |f(t)|^2 dt < \infty \right\}$

$V$ : square integrable functions.

$$\langle f_1, f_2 \rangle = \int_0^1 f_1(t) \overline{f_2(t)} dt$$

$(V, \langle \cdot, \cdot \rangle)$  is called  $L_2$  inner product space

THEOREM: (Cauchy - Schwarz Inequality)

Let  $V$  be an inner product space. Let  $x, y \in V$

$$|\langle x, y \rangle|^2 \leq \langle x, x \rangle \langle y, y \rangle$$

Proof: Part (I) Case  $y = 0_V$

$$\langle x, y \rangle = \langle x, 0_V \rangle = \langle x, \underset{\alpha}{0} \underset{\beta}{.} 0_V \rangle = \overline{0} \langle x, 0_V \rangle = 0$$

$$\langle y, y \rangle = 0$$

$$0 \leq \langle x, x \rangle, 0 = 0$$

$0 \leq 0$  Inequality is correct for  $y = 0_V$

Part (II) Case  $y \neq 0_V$

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(Part II) : Case  $y \neq 0$

$$\lambda = \frac{\langle x, y \rangle}{\langle y, y \rangle}$$

Let  $\tilde{\lambda}$  be arbitrary

$$0 \leq \langle x - \tilde{\lambda}y, x - \tilde{\lambda}y \rangle$$

$$= \langle x, x \rangle - \langle \tilde{\lambda}y, x \rangle - \langle x, \tilde{\lambda}y \rangle + (\tilde{\lambda}y, \tilde{\lambda}y)$$

$$= \langle x, x \rangle - \tilde{\lambda} \langle y, x \rangle - \tilde{\lambda} \langle x, y \rangle + |\tilde{\lambda}|^2 \langle y, y \rangle$$

$$= \langle x, x \rangle - \lambda \overline{\langle x, y \rangle} - \bar{\lambda} \langle x, y \rangle + |\lambda|^2 \langle y, y \rangle$$

choose specific  $\lambda = \frac{\langle x, y \rangle}{\langle y, y \rangle}$

$$= \langle x, x \rangle - \frac{\langle x, y \rangle \overline{\langle x, y \rangle}}{\langle y, y \rangle} - \frac{\langle x, y \rangle \langle x, y \rangle}{\langle y, y \rangle} + \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle}$$

$$= \langle x, x \rangle - \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle} - \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle} + \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle}$$

$$= \langle x, x \rangle - \frac{|\langle x, y \rangle|^2}{\langle y, y \rangle} \geq 0$$

$$\Rightarrow |\langle x, y \rangle|^2 \leq \langle x, x \rangle \langle y, y \rangle$$

Remark: An inner product induces a norm defined as

$$\|x\|^2 \triangleq \langle x, x \rangle$$

OR

$$\|x\| \triangleq \sqrt{\langle x, x \rangle}$$



induced norm

Proof:

$$1) \|x\| \geq 0$$

$\|x\| = 0$  iff  $x = 0_v$  by the properties of the inner product

$$\begin{aligned} 2) \|\alpha x\| &= \sqrt{\langle \alpha x, \alpha x \rangle} = \sqrt{|\alpha|^2 \langle x, x \rangle} \\ &= |\alpha| \sqrt{\langle x, x \rangle} \\ &= |\alpha| \|x\| \end{aligned}$$

$$3) \|x+y\|^2 \triangleq \langle x+y, x+y \rangle$$

$$= \langle x, x \rangle + \langle x, y \rangle + \langle y, x \rangle + \langle y, y \rangle$$

$$= \langle x, x \rangle + \langle x, y \rangle + \langle \overline{x}, \overline{y} \rangle + \langle y, y \rangle$$

$$= \langle x, x \rangle + 2 \operatorname{Re} \{ \langle x, y \rangle \} + \langle y, y \rangle$$

$$\leq \langle x, x \rangle + 2 \underbrace{|\langle x, y \rangle|}_{\leq \sqrt{\langle x, x \rangle} \sqrt{\langle y, y \rangle}} + \langle y, y \rangle$$

$$\leq \sqrt{\langle x, x \rangle} \sqrt{\langle y, y \rangle}$$

$$\leq \langle x, x \rangle + 2 \sqrt{\langle x, x \rangle} \sqrt{\langle y, y \rangle} + \langle y, y \rangle$$

$$= (\sqrt{\langle x, x \rangle} + \sqrt{\langle y, y \rangle})^2$$

$$a + b\bar{z}$$

$$a \leq \sqrt{a^2 + b^2}$$

$$\|x+y\|^2 \leq (\sqrt{\langle x, x \rangle} + \sqrt{\langle y, y \rangle})^2 = (\|x\| + \|y\|)^2$$

$$\|x+y\|^2 \leq (\|x\| + \|y\|)^2 \quad (\text{like triangular equality})$$

Remark: Every inner product space is also a normed space, converse is not true.

Definition: Inner product space that is complete wrt the norm induced by the inner product is called a complete inner product space.

Completeness  $\Rightarrow$  Cauchy  $\Rightarrow$  Convergent  
wrt induced norm  
wrt induced norm

Definition: Two vectors  $x, y \in V$  are said to be orthogonal if  $\langle x, y \rangle = 0$

Similarly two subsets  $S_1, S_2 \subset V$  are orthogonal

if  $\langle x, y \rangle = 0 \quad \forall x \in S_1 \quad \forall y \in S_2$

Ex:

$$1) V = \mathbb{R}^n \quad \langle x, y \rangle = \sum_{i=1}^n x_i y_i = x^T y = y^T x$$

Consider the canonical basic set

$$B = \{e_1, e_2, \dots, e_n\}$$

$$e_1 = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$e_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$e_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

$$\langle e_i, e_j \rangle = \begin{cases} 0 & , i \neq j \\ 1 & , i = j \end{cases} = \delta_{ij} \rightarrow \text{Kronecker Delta Function}$$

$$2) V = \left\{ f \mid f: [-\pi, \pi] \rightarrow \mathbb{C} \text{ such that } \int_{-\pi}^{\pi} |f(t)|^2 dt < \infty \right\}$$

Consider the set  $\{e^{int}\}_{n=-\infty}^{\infty}$

$$\langle f_1, f_2 \rangle \triangleq \int_{-\pi}^{\pi} f_1(t) \overline{f_2(t)} dt$$

complex conjugate in complex plane

$$\langle e^{int}, e^{jmt} \rangle = \int_{-\pi}^{\pi} e^{int} \overline{e^{jmt}} dt$$

$$= \int_{-\pi}^{\pi} \cos((n-m)t) + j \sin((n+m)t) dt$$

$$\langle e^{int}, e^{jmt} \rangle = \begin{cases} 0 & , n+m \\ 2\pi & , n=m \end{cases} \rightarrow \cos \text{ and } \sin \text{ are periodic when } n \neq m$$

$$= 2\pi \delta_{nm}$$

FABER CASTELL

$$3) S_1 = \left\{ \sin nt \right\}_{n=1}^{\infty}$$

$$S_2 = \left\{ \cos mt \right\}_{m=1}^{\infty}$$

Are  $S_1$  &  $S_2$  orthogonal?

(We have some  $V$  & inner product as the previous example)

$$\begin{aligned} \langle \sin(nt), \cos(mt) \rangle &= \int_{-\pi}^{\pi} \sin nt \cos mt dt \\ &= \frac{1}{2} \int_{-\pi}^{\pi} (\sin((n+m)t) + \sin((n-m)t)) dt \\ &= \begin{cases} 0, & n=m \\ 0, & n \neq m \end{cases} = 0 \end{aligned}$$

Yes,  $S_1$  &  $S_2$  are orthogonal

$$V=\mathbb{R}^n \quad \langle x, y \rangle = x_1 y_1 + x_2 y_2$$

$$\begin{bmatrix} 2 \\ 3 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 3 \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$? \begin{bmatrix} 1 \\ 2 \end{bmatrix} + ? \begin{bmatrix} 1 \\ 1 \end{bmatrix} \rightarrow \text{Bunu bulanayız}$$

$$\begin{bmatrix} 2 \\ 3 \end{bmatrix} = \alpha_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \alpha_2 \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$\underbrace{z}_z$        $\underbrace{z_1}_z$        $\underbrace{z_2}_z$

$$z = \alpha_1 z_1 + \alpha_2 z_2$$

$$\langle z, z_1 \rangle = \alpha_1 \langle z_1, z_1 \rangle + \alpha_2 \langle z_2, z_1 \rangle$$

$\rightarrow 0$  because  $z_1, z_2$  are orthogonal

$$\alpha_1 = \frac{\langle z, z_1 \rangle}{\langle z_1, z_1 \rangle}$$

$$\alpha_1 = \frac{5}{2} \quad \alpha_2 = -\frac{1}{2}$$

$$f(t) = \sum_{n=-\infty}^{\infty} \alpha_n e^{jnt}$$

$$\alpha_n = \frac{\langle f(t), e^{jnt} \rangle}{\langle e^{jnt}, e^{jnt} \rangle} = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(t) e^{-jnt} dt$$

Fourier Series

$$\int_{-\pi}^{\pi} e^{jnt} e^{-jnt} dt$$

Let  $V$  be an inner product space.

Let  $S_1 = \{v_1, v_2, \dots, v_n\}$  be an linearly independent set

Can we obtain another set  $S_2 = \{w_1, w_2, \dots, w_n\}$  such that

i)  $w_i \perp w_j$  when  $i \neq j$  s.t.

$$\langle w_i, w_j \rangle = 0 \text{ for } i \neq j$$

ii)  $\text{Span } S_1 = \text{Span } S_2$

### Gram Schmidt Orthogonalization Algorithm

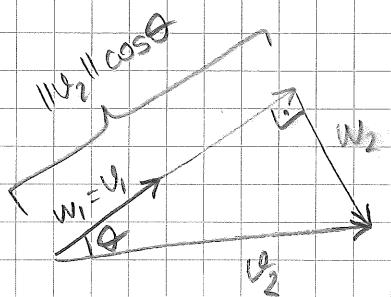
Step 1:  $w_1 = v_1$

$$\text{Step 2: } w_2 = v_2 - \frac{\langle v_2, w_1 \rangle}{\langle w_1, w_1 \rangle} w_1$$

$$\langle w_2, w_1 \rangle = \left\langle v_2 - \frac{\langle v_2, w_1 \rangle}{\langle w_1, w_1 \rangle} w_1, w_1 \right\rangle$$

$$= \langle v_2, w_1 \rangle - \frac{\langle v_2, w_1 \rangle}{\langle w_1, w_1 \rangle} \langle w_1, w_1 \rangle$$

$$= \langle v_2, w_1 \rangle - \langle v_2, w_1 \rangle = 0$$



$$\frac{\langle v_2, w_1 \rangle}{\underbrace{\langle w_1, w_1 \rangle}_{\|w_1\|^2}} w_1 = \frac{\langle v_2, w_1 \rangle}{\|w_1\|^2} w_1$$

$$\langle x, y \rangle = \|x\| \|y\| \cos \theta$$

$$= \left\langle v_2, \frac{w_1}{\|w_1\|} \right\rangle \underbrace{\frac{w_1}{\|w_1\|}}_{\|w_1\| \cos \theta}$$

$\frac{\langle v_2, w_1 \rangle}{\|w_1\|^2} w_1 \rightarrow \text{projection of } v_2 \text{ onto } w_1$

Step 3:  $w_3 = v_3 - \text{projection}_{w_1}(v_3) - \text{projection}_{w_2}(v_3)$

$$= v_3 - \frac{\langle v_3, w_1 \rangle}{\langle w_1, w_1 \rangle} w_1 - \frac{\langle v_3, w_2 \rangle}{\langle w_2, w_2 \rangle} w_2$$

Step n:  $w_n = v_n - \sum_{i=1}^{n-1} \frac{\langle v_n, w_i \rangle}{\langle w_i, w_i \rangle} w_i$

Proof:

Claim 1:  $\langle w_i, w_j \rangle = 0 \quad i \neq j \quad w_i \perp w_j$

i.e., we are going to prove that  $\{w_1, \dots, w_n\}$  is a pairwise orthogonal set.

Proof of Claim 1: Proof by induction (univariable)

Step 1: Prove the statement for some small n

Step 2: Assume that a claim is true for  $n=k$

Step 3: Prove that claim is true for  $n=k+1$

Step 1: Show that  $\{w_1, w_2\}$  is an orthogonal set (we have already done this)

Step 2: Assume that the set  $\{w_1, w_2, \dots, w_k\}$  is an orthogonal set

Step 3: Show that  $\{w_1, w_2, \dots, w_{k+1}\}$  is an orthogonal set.

We assume that

$$\langle w_i, w_j \rangle = 0 \quad i \neq j \quad 1 \leq i, j \leq k$$

We need to show  $\{w_1, w_2, \dots, w_k, w_{k+1}\}$  is an orthogonal set.

We only have to show that

$$\langle w_{k+1}, w_j \rangle = 0 \quad 1 \leq j \leq k$$

$$\left\langle v_{k+1} - \sum_{i=1}^k \frac{\langle v_{k+1}, w_i \rangle}{\langle w_i, w_i \rangle} w_i, w_j \right\rangle = 0$$

$$\langle v_{k+1}, w_j \rangle - \sum_{i=1}^k \frac{\langle v_{k+1}, w_i \rangle}{\langle w_i, w_i \rangle} \langle w_i, w_j \rangle$$

Assumption is  $\{w_1, w_2, \dots, w_k\}$  is orthogonal so  $\langle w_i, w_j \rangle = 0$

for  $i \neq j$

$$\langle v_{k+1}, w_j \rangle - \frac{\langle v_{k+1}, w_j \rangle}{\langle w_j, w_j \rangle} \langle w_j, w_j \rangle = 0$$

Claim 1 is proven

Claim 2:  $\text{Span } \{w_1, w_2, \dots, w_n\} = \text{Span } \{v_1, v_2, \dots, v_n\}$

Prove by induction

Step 1: Let us choose  $n=1$

$$\text{Span } \{w_1\} = \text{Span } \{v_1\}$$

$$w_1 = v_1$$

The statement is trivially correct because  $w_1 = v_1$

Step 2: Assume that

$$\text{span} \{w_1, w_2, \dots, w_k\} = \text{span} \{v_1, \dots, v_k\}$$

Step 3: Prove that

$$\text{span} \{w_1, \dots, w_k, w_{k+1}\} = \text{span} \{v_1, \dots, v_k, v_{k+1}\}$$

$\underbrace{\qquad\qquad\qquad}_{M_1} \qquad\qquad\qquad \underbrace{\qquad\qquad\qquad}_{M_2}$

$$M_1 = M_2$$

$$\begin{array}{c} M_1 \subset M_2 \\ M_2 \subset M_1 \end{array} \quad \left. \begin{array}{c} \\ M_1 = M_2 \end{array} \right.$$

06.11.2015  
Friday

$$\{v_1, \dots, v_k\} \quad \{w_1, \dots, w_k\}$$

$v_i \in V$ : inner product space  $w_i \perp w_j \quad i \neq j$

$v_i$ 's are li.  $\text{span} \{w_1, \dots, w_k\} = \text{span} \{v_1, v_2, \dots, v_k\}$

Proof of Claim 2:

Step 1: Choose  $n=1$   $\text{span} \{w_1\} = \text{span} \{v_1\}$

This is trivially correct since  $w_1 = v_1$

Step 2: Assume that  $\text{span} \{w_1, \dots, w_k\} = \text{span} \{v_1, \dots, v_k\}$

Prove that  $\text{span} \{w_1, \dots, w_{k+1}\} = \text{span} \{v_1, \dots, v_{k+1}\}$

$$\text{span} \{w_1, \dots, w_{k+1}\} = \text{span} \{v_1, \dots, v_{k+1}\}$$

$\underbrace{\qquad\qquad\qquad}_{M_1} \qquad\qquad\qquad \underbrace{\qquad\qquad\qquad}_{M_2}$

$$M_1 = M_2$$

$$\text{Prove: } M_1 \subset M_2 \quad \left. \begin{array}{l} \\ M_2 \subset M_1 \end{array} \right\} M_1 = M_2$$

Part 1: Prove  $M_1 \subset M_2$

Take an arbitrary element  $x$  in  $M_1 \Rightarrow$  show that  $x$  is also an element of  $M_2$ .

Let  $x$  be an arbitrary element in  $M_1$ .

$$x \in \text{span}\{w_1, \dots, w_{k+1}\}$$

$$x = \sum_{i=1}^{k+1} \alpha_i w_i = \alpha_1 w_1 + \alpha_2 w_2 + \dots + \alpha_{k+1} w_{k+1}$$

$\downarrow$                                    $\downarrow$                                    $\downarrow$   
 $\in \text{span}\{v_1\}$                        $\in \text{span}\{v_1, v_2\}$                        $\in \text{span}\{v_1, \dots, v_{k+1}\}$

$$\Rightarrow x \in \text{span}\{v_1, v_2, \dots, v_{k+1}\} \Rightarrow [M_1 \subset M_2]$$

Part 2: Prove  $M_2 \subset M_1 = \text{span}\{w_1, \dots, w_{k+1}\}$

Let  $x$  be arbitrary in  $M_2 \Rightarrow x \in M_2$

$$x \in \text{span}\{v_1, \dots, v_{k+1}\}$$

$$x = \sum_{i=1}^{k+1} \beta_i v_i = \sum_{i=1}^k \beta_i v_i + \beta_{k+1} v_{k+1}$$

$$= \underbrace{\sum_{i=1}^k \beta_i v_i}_{\in \text{span}\{v_1, \dots, v_k\}} + \beta_{k+1} \left( w_{k+1} + \underbrace{\sum_{j=1}^k \frac{\langle v_k, w_j \rangle}{\langle v_j, w_j \rangle} w_j}_{\in \text{span}\{w_1, \dots, w_{k+1}\}} \right)$$

$$= \text{span}\{w_1, \dots, w_k\}$$

$$x \in \text{span}\{w_1, \dots, w_{k+1}\} \Rightarrow x \in M_1 \Rightarrow [M_2 \subset M_1]$$

Ex: Let  $V = \{f \mid f: [-1, 1] \rightarrow \mathbb{R}, f \text{ is continuous, } \int_{-1}^1 |f(t)|^2 dt < \infty\}$

Define the inner product

$$\langle f, g \rangle = \int_{-1}^1 f(t) g(t) dt$$

$$\{v_1, v_2, v_3\} \quad v_1 = 1(t) \quad v_2 = t \quad v_3 = t^2 \rightarrow \text{Legendre Polynomials}$$

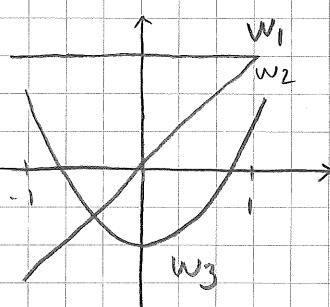
Find  $\{w_1, w_2, w_3\}$  such that  $w_i \perp w_j \quad i \neq j$

$$\text{span}\{v_1, v_2, v_3\} = \text{span}\{w_1, w_2, w_3\}$$

$$w_1 = v_1 = 1(t)$$

$$w_2 = t - \frac{\int_{-1}^t t dt}{\int_{-1}^1 dt} 1(t) = t$$

$$w_3 = t^2 - \frac{\int_{-1}^t t^2 dt}{\int_{-1}^1 dt} 1(t) - \frac{\int_{-1}^t t^3 dt}{\int_{-1}^1 t^2 dt} t = t^2 - \frac{\frac{2}{3}}{2} 1(t) \\ = t^2 - \frac{1}{3}$$



## GRAM-SCHMIDT ORTHONORMALIZATION

$$\{v_1, \dots, v_n\} \rightarrow \{w_1, \dots, w_n\} \quad w_i \perp w_j \quad i \neq j$$

$$\text{span}\{v_1, \dots, v_n\} = \text{span}\{w_1, \dots, w_n\}$$

- Apply Gram-Schmidt Orthogonalization

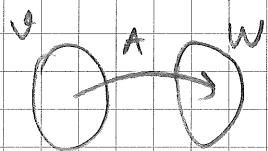
- Normalize the resulting vectors

$$\underline{\text{Step 1:}} \quad \bar{w}_1 = v_1 \quad w_1 = \frac{\bar{w}_1}{\|\bar{w}_1\|}$$

$$\underline{\text{Step 2:}} \quad \bar{w}_2 = v_2 - \langle v_2, w_1 \rangle w_1, \quad w_2 = \frac{\bar{w}_2}{\|\bar{w}_2\|}$$

$$\underline{\text{Step 3:}} \quad \bar{w}_3 = v_3 - \langle v_3, w_1 \rangle w_1 - \langle v_3, w_2 \rangle w_2, \quad w_3 = \frac{\bar{w}_3}{\|\bar{w}_3\|}$$

$$\underline{\text{Step } n:} \quad \bar{w}_n = v_n - \sum_{i=1}^{n-1} \langle v_n, w_i \rangle w_i \quad w_n = \frac{\bar{w}_n}{\|\bar{w}_n\|}$$



## LINEAR TRANSFORMATION

DEFINITION: Let  $V$  and  $W$  be vector spaces over the same field  $F$ .

A linear transformation  $A$  is a mapping from  $V$  into  $W$  shown as  $A: V \rightarrow W$  such that

$$A(\alpha_1 v_1 + \alpha_2 v_2) = \alpha_1 A v_1 + \alpha_2 A v_2 \quad \forall \alpha_1, \alpha_2 \in F$$



$$A\left(\sum_{i=1}^n \alpha_i v_i\right) = \sum_{i=1}^n \alpha_i A v_i$$

Ex

$V=W$  = polynomials degree  $\leq n$

$$A = \frac{d}{dt} \quad V = \text{domain of the L.T}$$

$W = \mathbb{C}$ -domain of the transformation

$$x_1 = \sum_{i=1}^n c_i t^i \quad x_2 = \sum_{i=1}^n d_i t^i$$

$$A(\alpha_1 x_1 + \alpha_2 x_2) = \frac{d}{dt} \left[ \alpha_1 \left( \sum_{i=1}^n c_i t^i \right) + \alpha_2 \left( \sum_{i=1}^n d_i t^i \right) \right]$$

$$= \alpha_1 \frac{d}{dt} \left( \sum_{i=1}^n c_i t^i \right) + \alpha_2 \frac{d}{dt} \left( \sum_{i=1}^n d_i t^i \right) = \alpha_1 A x_1 + \alpha_2 A x_2$$

$A = \frac{d}{dt}$  is a linear transformation

Ex:

$$V = W = \mathbb{R}^2$$

Let  $A$  be defined as

$$Ax = \begin{bmatrix} \alpha_1 \\ \alpha_1 + \alpha_2 \end{bmatrix} \quad \text{where} \quad x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}$$

$$x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \quad y = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$$

$$\alpha x + b y = \begin{bmatrix} \alpha \alpha_1 + b \beta_1 \\ \alpha \alpha_2 + b \beta_2 \end{bmatrix}$$

$$A(\alpha x + b y) = \begin{bmatrix} \alpha \alpha_1 + b \beta_1 \\ \alpha \alpha_1 + b \beta_1 + \alpha \alpha_2 + b \beta_2 \end{bmatrix}$$

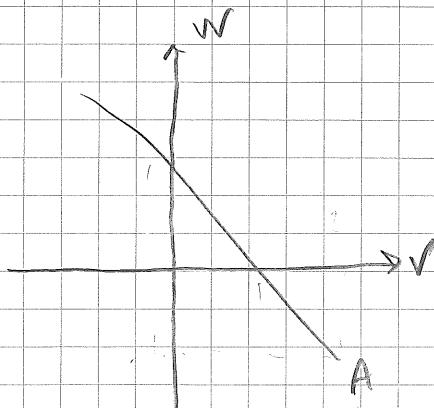
$$= a \begin{bmatrix} \alpha_1 \\ \alpha_1 + \alpha_2 \end{bmatrix} + b \begin{bmatrix} \beta_1 \\ \beta_1 + \beta_2 \end{bmatrix}$$

$$= a Ax + b Ay$$

$A$  is a linear transformation

Ex:

$$V = W = \mathbb{R}$$



$$y = 1 - x$$

$$Ax = 1 - x$$

$$x_1 = 0 \rightarrow y_1 = 1$$

$$x_2 = 2 \rightarrow y_2 = -1$$

$$A(\underbrace{ax_1 + bx_2}_{x_1 + x_2}) = a Ax_1 + b Ax_2$$

$$A2 = A0 + A2$$

$$-1 = 1 + (-1)$$

$$A(ax_1 + bx_2) = a Ax_1 + b Ax_2$$

$$a, b \in \mathbb{R}$$

$$a = b = 0$$

$$A0 = 0$$

$$A0_v = 0_w$$

Ex:

$$V = \{f \mid f: [0,1] \rightarrow \mathbb{R}, f \text{ is integrable}\}$$

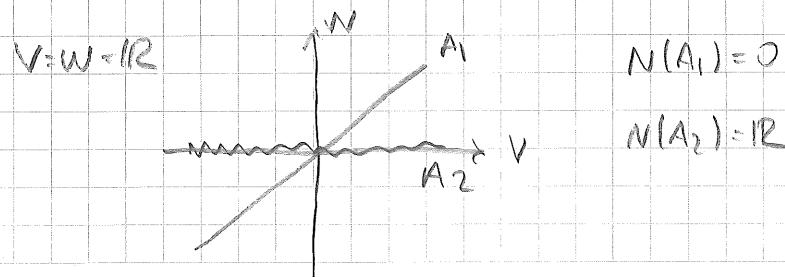
$$W = \mathbb{R}$$

$$\text{Define } A \text{ as } A(f) := \int_0^1 f(t) dt$$

$A$  is a linear transformation thanks to the properties of the integral operation.

**DEFINITION:** Let  $A: V \rightarrow W$  be a linear transformation. The null-space of  $A$  is defined as

$$N(A) \triangleq \{v \in V \mid Av = 0_w\}$$



Theorem:  $N(A)$  is a subspace of  $V$

Let  $x_1, x_2 \in N(A)$

$x_1 + x_2 \in N(A)$

$a x_1 \in N(A)$

$$Ax_1 = 0$$

$$Ax_2 = 0$$

$$A(x_1 + x_2) = Ax_1 + Ax_2 = 0_w$$

$\underbrace{w}_{0_w} \quad \underbrace{w}_{0_w}$

$$\Rightarrow x_1 + x_2 \in N(A)$$

$$A(ax_1) = a Ax_1 = 0_w \quad ax_1 \in N(A)$$

$\underbrace{w}_{0_w}$

$N(A)$  is a subspace of  $V$ .

DEFINITION: A linear transformation  $A$  is called one to one if

$$Av_1 = Av_2 \text{ implies } v_1 = v_2$$

Proposition: A linear transformation  $A: V \rightarrow W$  is one-to-one

$$\text{iff } N(A) = \{0_v\}$$

$$A \text{ is one-to-one} \Leftrightarrow N(A) = \{0_v\}$$

$$P \Leftrightarrow q$$

$$\text{Part 1: } A \text{ is one to one} \Rightarrow N(A) = \{0_v\}$$

$$P \Rightarrow q$$

Proof by contradiction:  $\bar{q} \Rightarrow \bar{p}$

Suppose the  $N(A) \neq \{0_v\}$

$\exists x \in N(A)$  such that  $x \neq 0_v$

$$Ax = 0_w$$

Suppose  $v_1 \in V$

Consider  $v_1$  &  $v_2 = v_1 + x$

$$v_1 \neq v_2$$

$$Av_1$$

$$Av_2 = A(v_1 + x) = Av_1 + Ax \underset{0_w}{=} Av_1$$

$$Av_1 = Av_2$$

$\Rightarrow A$  is NOT one-to-one }  $\bar{p}$

Part 2:  $q \Rightarrow p$

$N(A) = \{0_v\} \Rightarrow A$  is one-to-one

$\Rightarrow p$

Proof by Contradiction:  $\bar{p} \Rightarrow \bar{q}$

Suppose that  $A$  is NOT one-to-one

$\exists v_1, v_2$  such that  $v_1 \neq v_2$  and  $Av_1 = Av_2$

$$A(v_1 - v_2) = 0_w$$

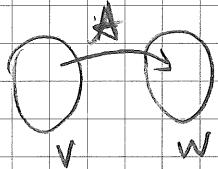
$v_1 - v_2 \in N(A)$  and  $v_1 - v_2 \neq 0_v$

$$\Rightarrow N(A) = \{0_v\} \quad \bar{q}$$

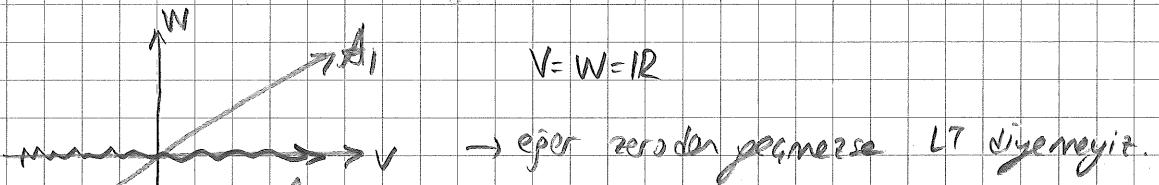
10.11.2015  
Tuesday

## Linear Transformation

$V, W$ : Fields are the same



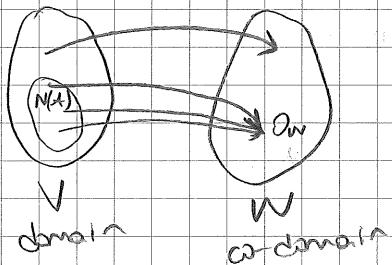
$$A(a_1v_1 + a_2v_2) = a_1 A(v_1) + a_2 A(v_2)$$



→ eger zero dan gecmezse LT dijeneriyit.

$$N(A_1) = 0_V$$

$$N(A_2) = V = \mathbb{R}$$



null space  $\rightarrow N(A) \stackrel{\text{def}}{=} \{ v \in V \mid Av = 0_W \}$

One to one

$$Av_1 = Av_2 \Rightarrow v_1 = v_2$$

$$\text{one to one} \Leftrightarrow N(A) = \{ 0_V \}$$

EXAMPLE:

$$V = W = \{\text{polynomials with degree } \leq 2\}$$

$$A = \frac{d}{dt} \quad \text{Is A one-to-one?}$$

$$v = at^2 + bt + c \quad \begin{cases} u_1 = t+1 \\ u_2 = t-1 \end{cases} \quad \left. \begin{array}{l} u_1 \neq u_2 \text{ while } Au_1 = Au_2 \\ A \text{ is NOT one-to-one!} \end{array} \right.$$

$$N(A) = \{\text{constant polynomials}\} = \{0_v\} = D_{1,1}$$

EXAMPLE:

$$V = \{f \mid f \text{ is integrable } f: [0, 1] \rightarrow \mathbb{R}\}$$

$$W = \mathbb{R}$$

$$Af = \int_0^1 f(t) dt \quad \text{Is A one-to-one?}$$

$$v = 2t - 1 \rightarrow \int_0^1 (2t-1) dt = t^2 - t \Big|_0^1 = 0$$

$$f = 2t - 1 \in N(A)$$

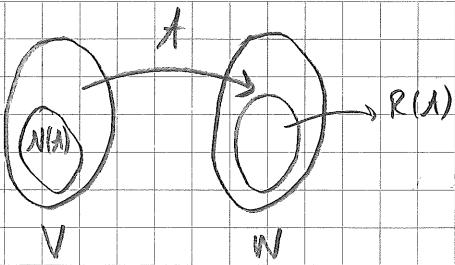
$$N(A) \neq \{0_v\} \Rightarrow A \text{ is NOT one-to-one}$$

EXAMPLE:  $V = W = \mathbb{R}^2$

$$A x = \begin{bmatrix} x_1 \\ x_1 + x_2 \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \text{Is A one-to-one?}$$

$$v = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \quad Av = 0 = \begin{bmatrix} v_1 \\ v_1 + v_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{cases} v_1 = 0 \\ v_2 = 0 \end{cases} \Rightarrow N(A) = \{0_v\}$$

A is one-to-one.



**DEFINITION:** Let  $A: V \rightarrow W$  be a linear transformation. The range space of  $A$  is defined as

$$R(A) \triangleq \{ w \in W \mid \exists v \in V \text{ st. } Av = w \}$$

**Theorem:**  $R(A)$  is a subspace of  $W$ .

**Proof:** Let  $w_1, w_2 \in R(A)$   $\exists v_1, v_2 \in V$  st.  $Av_1 = w_1$ ,  $Av_2 = w_2$

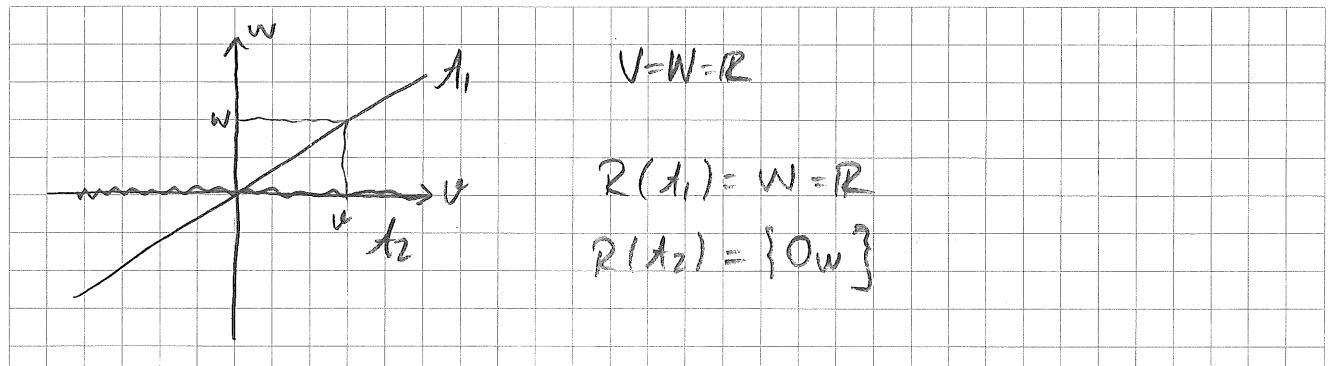
$$\rightarrow w_1 + w_2 \stackrel{?}{\in} R(A)$$

$$v_1 + v_2 \in V$$

$$\begin{aligned} A(v_1 + v_2) &= Av_1 + Av_2 = w_1 + w_2 \\ \Rightarrow w_1 + w_2 &\in R(A) \end{aligned}$$

$$\begin{aligned} \rightarrow \alpha w_1 &\in R(A) \quad \alpha v_1 \in V \quad A\alpha v_1 = \alpha Av_1 = \alpha w_1 \\ \Rightarrow \alpha w_1 &\in R(A) \end{aligned}$$

$\therefore R(A)$  is a subspace of  $W$ .



DEFINITION: A linear transformation  $A: V \rightarrow W$  is called onto if  $R(A) = W$ .

Otherwise if  $R(A) \subsetneq W$ ,  $A$  is called into.

In previous example,  $A_1$  is onto &  $A_2$  is into.

EXAMPLE:  $V = W = \{\text{polynomials with degree } \leq 2\}$

$$A = \frac{d}{dt} \quad \text{Is } A \text{ is onto?}$$

$$W = t^2 \quad \forall v \in V \text{ st } Av = t^2$$

$\Rightarrow A$  is NOT onto.

EXAMPLE:  $V = \{f: [0, 1] \rightarrow \mathbb{R} \mid f \text{ is integrable}\}$

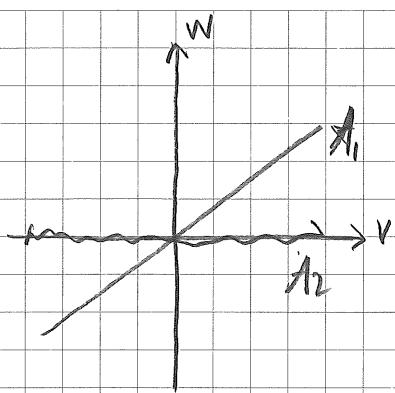
$$W = \mathbb{R}$$

$$Af = \int_0^1 f(t) dt \quad \text{Is } A \text{ is onto?}$$

$$a \in \mathbb{R}$$

$$f(t) = a \quad \forall t \in [0, 1] \rightarrow \int_0^1 f(t) dt = a$$

$A$  is onto.



$$V = W = \mathbb{R}$$

$$N(A_2) = \{0\} \quad \dim = 0$$

$$N(A_1) = \mathbb{R} \quad \dim = 1$$

$$R(A_1) = \mathbb{R} \quad \dim = 1$$

$$R(A_2) = \{0\} \quad \dim = 1$$

$$\boxed{\dim N(A) + \dim R(A) = \dim V}$$

Theorem: If  $V$  is finite dimensional  $\Rightarrow t$  is linear transformation from  $V$  to  $W$ . Then  $R(t)$  is a finite dimensional subspace of  $W$  and

$$\dim N(A) + \dim R(A) = \dim V.$$

$$v = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \in \mathbb{R}^2 \xrightarrow{t} Av = a_1 t + a_2 t^2$$

Proof: Part (i) Let  $V$  be  $n$ -dimensional

Since  $N(A) \subset V$

Suppose  $\dim N(A) = m$

Part (i) Suppose  $m = n$



$$N(A) \subset V$$

$$\dim N(A) = \dim V$$

$$N(A) = V$$

What about the range space?

$$A\varphi = 0_W \Rightarrow R[A] = 0_W$$

$\Downarrow$   
 $\varphi \in V$

$$\dim N(A) = n$$

$$\dim R(A) = 0$$

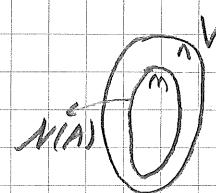
$$\dim N(A) + \dim R(A) = n = \dim V$$

Part 2) Suppose  $m < n$

Suppose  $\{v_1, \dots, v_m\}$  be a basis for  $N(A)$

$$\text{span} \{v_1, \dots, v_m\} = N(A)$$

$$N(A) \not\subseteq V$$

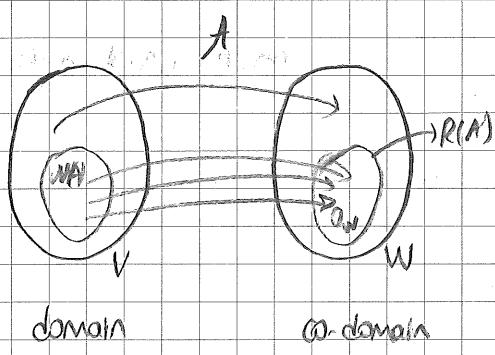


We can add vectors in to basis  $\{v_1, \dots, v_m\}$  such that the resulting set is a basis for  $V$ .

$$\{v_1, v_2, \dots, v_m, w_1, w_2, \dots, w_{n-m}\}$$

Let  $v$  be an arbitrary element in  $V$

$$v = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_m v_m + \beta_1 w_1 + \beta_2 w_2 + \dots + \beta_{n-m} w_{n-m}$$



13.11.2015  
Friday

$$N(A) \triangleq \{x \in V \mid Ax = 0_w\}$$

$$R(A) \triangleq \{y \in W \mid \exists x \in V \text{ s.t. } Ax = y\}$$

$$\dim N(A) + \dim R(A) = \dim V$$

Proof:  $\dim V = n$     $\dim N(A) = m$     $m \leq n$

Part 1) Case  $m = n$

$$\begin{aligned} \dim N(A) &= n \\ N(A) &\subset V \\ &\quad \left. \begin{array}{l} \{v : 0_w \\ v \in V \\ \forall v \end{array} \right\} \\ &\quad \dim R(A) = 0 \end{aligned}$$

Equality  $\dim N(A) + \dim R(A) = n$  is satisfied.

Part 2)  $m < n$

Let  $\{v_1, v_2, \dots, v_m\}_{cv}$  be a basis for  $N(A)$

We can find  $n-m$  vectors in  $V$  s.t. the new set is a basis for  $V$ .

$\{v_1, v_2, \dots, v_m, w_1, w_2, \dots, w_{n-m}\}$  : A basis for  $V$ .

We can write an arbitrary vector  $\mathbf{v} \in V$  as a linear combination of these vectors.

$$\mathbf{v} = \alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_m \mathbf{v}_m + \beta_1 \mathbf{w}_1 + \dots + \beta_{n-m} \mathbf{w}_{n-m}$$

Apply  $A$  to both sides of this equation.

$$A\mathbf{v} = \underbrace{\beta_1 A\mathbf{w}_1 + \beta_2 A\mathbf{w}_2 + \dots + \beta_{n-m} A\mathbf{w}_{n-m}}_{\text{An arbitrary element of } R(A)} + \underbrace{\alpha_1 Aw_1 + \alpha_2 Aw_2 + \dots + \alpha_m Aw_m}_{\text{EW}}$$

We can write an arbitrary element of  $R(A)$  as a linear combination of  $n-m$  vectors.

$$\text{sp}\{Aw_1, Aw_2, \dots, Aw_{n-m}\} \Rightarrow \dim R(A) \leq n-m$$

$R(A)$  is finite dimensional!

Check if these vectors are li or not.

$$c_1 Aw_1 + c_2 Aw_2 + \dots + c_{n-m} Aw_{n-m} = \mathbf{0}_w$$

$$A(c_1 w_1 + c_2 w_2 + \dots + c_{n-m} w_{n-m}) = \mathbf{0}_w$$

$$c_1 w_1 + c_2 w_2 + \dots + c_{n-m} w_{n-m} \in N(A)$$

$$c_1 w_1 + c_2 w_2 + \dots + c_{n-m} w_{n-m} = d_1 \mathbf{v}_1 + d_2 \mathbf{v}_2 + \dots + d_m \mathbf{v}_m$$

$$d_1 \mathbf{v}_1 + d_2 \mathbf{v}_2 + \dots + d_m \mathbf{v}_m - c_1 w_1 - c_2 w_2 - \dots - c_{n-m} w_{n-m} = \mathbf{0}_V$$

$$d_1 = d_2 = \dots = d_m = c_1 = c_2 = \dots = c_{n-m} = 0$$

$\underbrace{\{Aw_1, Aw_2, \dots, Aw_{n-m}\}}_{\text{A basis for } R(A)}$  is a li set

$$\dim R(A) = n - m$$

$$\underbrace{\dim N(A)}_{=m} + \underbrace{\dim R(A)}_{=n-m} = n$$

### Rank Nullity Theorem

Suppose  $V$  is an  $n$ -dimensional vector space  $v \in V$

Suppose  $\{v_1, \dots, v_n\}$  is a basis for  $V$

$$v = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n \Rightarrow [v]_B = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} \in \mathbb{R}^n$$

$$\begin{array}{ccc} & \xrightarrow{A} & \\ V & & W \\ \dim = n & & \dim = m \\ B & & C \\ & \xrightarrow{R^n} & \xrightarrow{R^m} \end{array}$$
$$[v]_B \in \mathbb{R}^n \quad [w]_C \in \mathbb{R}^m$$

$$[w]_C = A [v]_B \quad \text{if} \quad w = Av$$

## MATRIX REPRESENTATIONS OF LINEAR TRANSFORMATIONS

DEFINITION: Let  $V$  ( $\dim V = n$ ) and  $W$  ( $\dim W = m$ ) be two linear spaces over the same field  $F$ .

Let  $A : V \rightarrow W$  be a linear transformation. Given the basis  $B = \{v_1, \dots, v_n\}$  and  $C = \{w_1, \dots, w_m\}$  for  $V$  &  $W$ , the transformation  $A$  can be represented by an  $m \times n$  matrix  $A = [a_{ij}]$  ( $a_{ij} \in F$ ) such that for  $v \in V$  &  $w \in W$  satisfying  $w = Av$

$$\text{Then we have } [w]_C = A [v]_B$$

$m$   
 $m \times n$

Let us have  $w = Av$  & suppose that

$$[w]_C = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix} \quad [v]_B = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$$

$$w = \sum_{i=1}^m \beta_i w_i = Av = A \sum_{j=1}^n a_{ij} v_j = \sum_{j=1}^n a_{ij} Av_j$$

$V$   
 $\in V$        $W$   
 $\in W$

$$= \sum_{j=1}^n a_{ij} \sum_{i=1}^m a_{ij} w_i$$

$$= \sum_{i=1}^m \left( \sum_{j=1}^n a_{ij} a_{ij} \right) w_i$$

$$= \sum_{i=1}^m \beta_i w_i$$

$$\boxed{\beta_i = \sum_{j=1}^n a_{ij} \alpha_j} \quad i = 1, \dots, m$$

$$\begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_m \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$$

Procedure to find A:

- 1) Take each vector  $v_j$  in B
- 2) Take the transform of  $v_j$ :  $A v_j$
- 3) Express  $A v_j$  in terms of  $a_{ij}$  in C.
- 4) Set the  $j^{\text{th}}$  column of A to the resulting coefficients

$$[w]_c = A[v]_b$$

$$B = \{v_1, \dots, v_n\} \quad C = \{w_1, \dots, w_m\}$$

$$[Av_1]_c = A[v_1]_b$$

$$[Av_1]_c = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \text{First column of } A \text{ is } [Av_1]_c$$

Take  $v_2$

$$[Av_2]_c = A[v_2]_b = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \Rightarrow$$

$\Downarrow$   
2<sup>nd</sup> column of A is  $[Av_2]_c$

EXAMPLE:  $V = \{ \text{polynomials with degree } \leq 3 \}$

$$W = \{ \quad " \quad " \quad " \quad \leq 2 \} \subset W$$

$$A: V \rightarrow W \quad Af = \frac{df}{dt}$$

$$B = \{ v_1, v_2, v_3, v_4 \}$$

$$v_1 = 1, \quad v_2 = 1+t, \quad v_3 = 1+t+t^2, \quad v_4 = 1+t+t^2+t^3$$

$$C = \{ w_1, w_2, w_3 \}$$

$$w_1 = 1, \quad w_2 = 1+t, \quad w_3 = 1+t+t^2$$

$$[w]_c = A[v]_B$$

$$A = \begin{bmatrix} 0 & 1 & -1 & -1 \\ 0 & 0 & 2 & -1 \\ 0 & 0 & 0 & 3 \end{bmatrix} \quad 3 \times 4$$

$$Av_1 = 0 = 0 \cdot 1 + 0 \cdot (1+t) + 0 \cdot (1+t+t^2)$$

$$Av_2 = 1 = 1 \cdot 1 + 0 \cdot (1+t) + 0 \cdot (1+t+t^2)$$

$$Av_3 = 2t+1 = -1 \cdot 1 + 2 \cdot (1+t) + 0 \cdot (1+t+t^2)$$

$$Av_4 = 3t^2+4t+1 = -1 \cdot 1 + 1 \cdot (1+t) + 3 \cdot (1+t+t^2)$$

$$v = t^3 + 2t^2 + 3t + 1$$

$$\begin{array}{ccc} \uparrow & \downarrow & \\ [v]_B = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} & \rightarrow & [w]_c = \begin{bmatrix} -1 \\ 1 \\ 3 \end{bmatrix} \end{array}$$

$$\begin{aligned} w &= -1(1) + 1(1+t) + 3(1+t+t^2) \\ &= 3t^2 + 6t + 3 \end{aligned}$$

Ex

Let  $V = \mathbb{R}^{2 \times 2}$

$A: V \rightarrow V$

$$Ax = Sx + xs^T \quad \text{where} \quad s = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

$$B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} \cup$$

$$C = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\} \cup$$

$$[w]_c = A[v]_B$$

$$A \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 \\ -1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$$

$$= w_1 + 0w_2 + (-1)w_3 + 0w_4$$

$$A \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = -w_4 - (w_3 - w_1)$$

$$A \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} = -w_4 + w_3 - w_1$$

$$A \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = w_3 - w_1$$

$$\begin{array}{ccc}
 V & \xrightarrow{A} & W \\
 \downarrow & & \downarrow \\
 \mathbb{R}^n & & \mathbb{R}^m \\
 B & & C \\
 [v]_B & \xrightarrow{\quad} & [w]_C \\
 \\ 
 \bar{V} & \xrightarrow{\bar{A}} & \bar{C} \\
 [\bar{v}]_{\bar{B}} & \xrightarrow{\quad} & [\bar{w}]_{\bar{C}}
 \end{array}$$

### EFFECT OF BASIS CHANGE ON THE MATRIX REPRESENTATION

1) Basis change in the Domain

Suppose that we change the basis in the domain & select  $\bar{B}$  instead of  $B$ .

$$[w]_C = A [v]_B$$

$$\begin{matrix}
 [w]_C = \bar{A} [\bar{v}]_{\bar{B}} \\
 \text{or} \\
 [w]_C = \bar{A} P [v]_B
 \end{matrix}$$

$$[v]_B = P [\bar{v}]_{\bar{B}} \quad \text{we already know this}$$

$$[w]_C = \underbrace{AP}_{\bar{A}} [\bar{v}]_{\bar{B}}$$

$$\bar{A} = AP$$

2) Basis change in Co-domain (Range)

We use  $\bar{C}$  instead of  $C$

$$[w]_C = A [v]_B$$

$$[w]_{\bar{C}} = \bar{A} [\bar{v}]_{\bar{B}}$$

$$[w]_C = Q [w]_{\bar{C}}$$

$$Q(w)_{\bar{C}} = A [v]_B$$

$$[w]_{\bar{C}} = \underbrace{Q^T}_{\bar{A}} A [v]_B$$

$$\bar{A} = Q^T A$$

3) Basis Change in Both Domain & Co-domain

$$\left. \begin{array}{l} [w]_C = A [v]_B \\ [w]_{\bar{C}} = \bar{A} [v]_{\bar{B}} \end{array} \right\} \bar{A} = Q^T A P$$

**SPECIAL CASE:** If  $w=v$ ,  $A$  is a linear transformation from  $V$  to itself,  
then the basis  $B$  can be taken to be the same as  $C$ .  
Then a basis change in both domain & co-domain would  
give

$$\bar{A} = P^T A P \text{ since } Q = P$$

**EXAMPLE:**  $V = \{ \text{polynomials with degree } \leq 3 \}$

$W = \{ \text{polynomials with degree } \leq 2 \}$

$$B = \{ 1, 1+t, 1+t+t^2, 1+t+t^2+t^3 \}$$

$$C = \{ 1, 1+t, 1+t+t^2 \}$$

$$A = \begin{bmatrix} 0 & 1 & -1 & -1 \\ 0 & 0 & 2 & -1 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

Change the basis in domain as  $\bar{B} = \{1, t, t^2, t^3\}$

$$\bar{A} = AP \quad [v]_{\bar{B}} = P[v]_B$$

↓  
?

$$[v]_B = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix} [v]_{\bar{B}}$$

$$\Rightarrow \bar{A} = AP = \begin{bmatrix} 0 & 1 & -1 & -1 \\ 0 & 0 & 2 & -1 \\ 0 & 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & -2 & 0 \\ 0 & 0 & 2 & -3 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

Change the basis in the co-domain to canonical basis while keeping the basis of the domain as the canonical basis.

$$\bar{C} = \{1, t, t^2\}$$

$$[w]_C = \bar{A} [v]_{\bar{B}}$$

$$[w]_{\bar{C}} = \bar{A} [v]_{\bar{B}}$$

$$\bar{A} = Q^{-1} A \quad \text{which} \quad [w]_C = Q [w]_{\bar{C}}$$

$$Q^{-1} = R \quad \bar{A} = RA$$

$$Q^{-1} [w]_C = [w]_{\bar{C}}$$

$$[w]_{\bar{C}} = R [w]_C$$

$$\bar{C} = \{1, t, t^2\}$$

$$C = \{1, 1+t, 1+t+t^2\}$$

$$R = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\Rightarrow \bar{A} = R\bar{A} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & -2 & 0 \\ 0 & 0 & 2 & -3 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

$$[W]_{\bar{C}} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix} [U]_{\bar{B}}$$

17.11.2015  
Tuesday

$$\begin{array}{ccc}
 \overset{\wedge}{V} & \xrightarrow{A} & \overset{\wedge}{W} \\
 \overset{\text{II}}{P} & \xrightarrow{A} & \overset{\text{III}}{R}^M \\
 [V]_B & & [W]_{\bar{C}} \\
 P \downarrow & \bar{A} & \downarrow Q \\
 [V]_{\bar{B}} & \xrightarrow{\quad} & [W]_{\bar{C}}
 \end{array}
 \quad \boxed{\bar{A} = Q^{-1}AP}$$

$$[V]_B = P [V]_{\bar{B}}$$

$$[W]_{\bar{C}} = Q [W]_{\bar{B}}$$

REMARK: In general, a basis for  $N(A) \& R(A)$  can be found by finding the sets for the  $N(\bar{A}) \& R(\bar{A})$

EXAMPLE:  $N = \mathbb{R}^{2 \times 2}$   $W = N$

$$Ax = Sx + xS^T \quad S = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \\ -1 & 1 & 1 & 1 \\ 0 & -1 & -1 & 0 \end{bmatrix}$$

$$B = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

$$C = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \right\}$$

Task 1: Find a basis for  $R(A)$

$$R(A) \triangleq \{ w \in W \mid \exists v \in V \quad Av = w \}$$

$$R(A) = \{ y \in \mathbb{R}^4 \mid \exists x \in \mathbb{R}^4 \quad Ax = y \}$$

- Find a basis for  $R(A)$

- Convert the vectors in the basis into matrices using the basis  $C$ .

$$y = \begin{bmatrix} c_1 & c_2 & c_3 & c_4 \\ | & | & | & | \\ x_1 & x_2 & x_3 & x_4 \end{bmatrix} \quad R(A) = \left\{ \begin{array}{l} \text{column space} \\ \text{of } A \end{array} \right\}$$

$$y = x_1 c_1 + x_2 c_2 + x_3 c_3 + x_4 c_4$$

Procedure: Make elementary column operations.

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

$\Rightarrow$  Basis for  $R(A)$

$$\left\{ \begin{bmatrix} 1 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 2 \\ 1 \end{bmatrix} \right\}$$

$$\begin{bmatrix} 1 \\ 0 \\ -1 \\ 0 \end{bmatrix} = [w_1]_c \Rightarrow w_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 0 \\ 2 \\ -1 \end{bmatrix} = [w_2]_c \Rightarrow w_2 = \begin{bmatrix} 2 & 2 \\ 2 & 0 \end{bmatrix} - \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

Basis for  $R(A) = \left\{ \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \right\}$

$$\dim R(A) = 2 \Rightarrow \dim N(A) = \dim V - \dim R(A) = 2$$

Task 2: Find a basis for  $N(A)$

Solution 1:  $N(A) = \{ v \in V \mid Av = 0_V \}$

$$Ax = 0_{2 \times 2}$$

$$x = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

$$Ax = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 0 & b \\ c & d \end{bmatrix} + \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} c & d \\ a & b \end{bmatrix} + \begin{bmatrix} b & -a \\ a & -c \end{bmatrix} = \begin{bmatrix} c+b & d+a \\ a+d & b-c \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\left. \begin{array}{l} b+c=0 \\ a-d=0 \\ c-a=0 \\ b-a=0 \end{array} \right\} \quad \begin{array}{l} c=-b \\ d=a \end{array}$$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} = a \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + b \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

Basis for  $N(A) = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \right\}$

Solution 2: Use the matrix representation

- Find a basis for  $N(A)$

- Convert the vectors into matrices using the basis  $B$ .

$$N(A) = \{ \mathbf{x} \in \mathbb{R}^4 \mid A\mathbf{x} = \mathbf{0} \}$$

$$\begin{bmatrix} 1 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \\ -1 & 1 & 1 & 1 \\ 0 & -1 & -1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Elementary row operation to simplify  
the matrix.

$$\begin{bmatrix} 1 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \\ 0 & 2 & 2 & 0 \\ 0 & -1 & -1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & 1 & -1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$x_1 - x_4 = 0 \quad x_4 = x_1$$

$$x_2 + x_3 = 0 \quad x_3 = -x_2$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}$$

Basis for  $N(A)$  =  $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \right\}$

Basis for  $N(A)$  =  $\left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \right\}$

## DIRECT SUMS

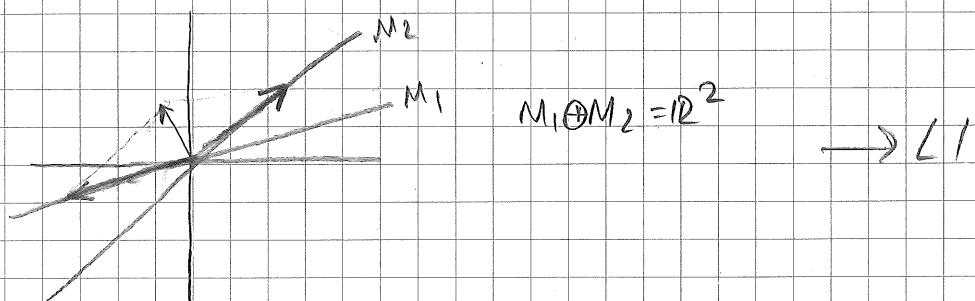
Remember the definition for the sum of subspaces

DEFINITION: Let  $V$  be a vector space and let  $M_1, M_2, \dots, M_k$  be subspaces of  $V$ . The sum of these subspaces is defined as

$$M = \{m \in V \mid m = m_1 + m_2 + \dots + m_k \text{ where } m_i \in M_i \forall i\}$$

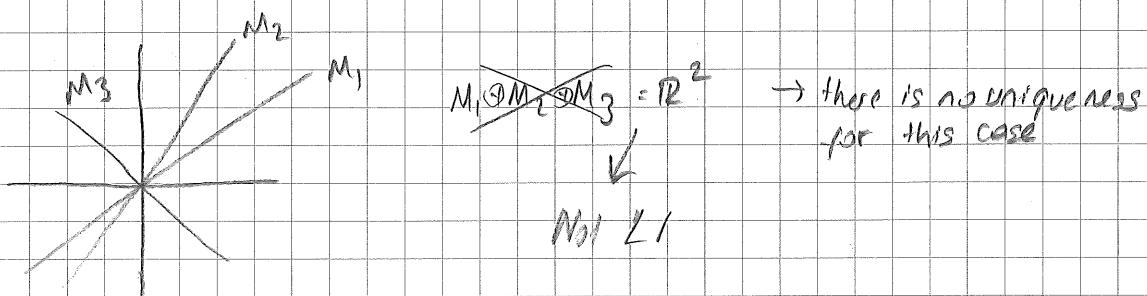
$$M = M_1 + M_2 + \dots + M_k$$

$$V = \mathbb{R}^2$$



$$M_1 \oplus M_2 = \mathbb{R}^2$$

$$\rightarrow L1$$



$$M_1 \oplus M_2 \oplus M_3 = \mathbb{R}^2$$

$\rightarrow$  there is no uniqueness for this case

$$M_1 \cap L1$$

$\oplus \rightarrow$  to use this symbol,  $M_i$  must be linearly indep & span all  $V$ .

so  $M_1 \oplus M_2$  but not  $M_1 \oplus M_2 \oplus M_3$

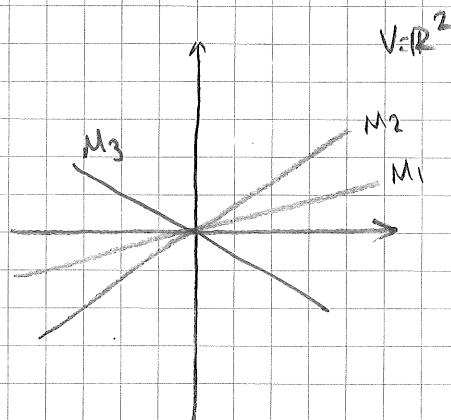
## DIRECT SUM

20. 11. 2015  
Friday

$V, M_1, M_2, \dots, M_k$   
 subspaces

$$M = M_1 + M_2 + \dots + M_k$$

$$M = \{ m \in V \mid m = m_1 + m_2 + \dots + m_k, m_i \in M_i \forall i \}$$



$$M_1 + M_2 = \mathbb{R}^2 \rightarrow \text{there is uniqueness}$$

$$M_1 + M_2 + M_3 = \mathbb{R}^2 \rightarrow \text{but for this case, it is NOT unique}$$

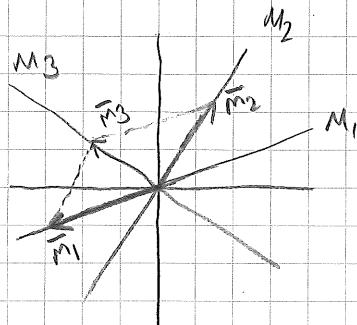
**DEFINITION:** Let  $M_1, M_2, \dots, M_k$  be subspaces of  $V$ . The subspaces are said to be linearly independent if

$$m_1 + m_2 + \dots + m_k = 0_V \text{ where } m_i \in M_i \quad i=1, 2, \dots, k$$

implies

$$m_1 = m_2 = \dots = m_k = 0_V$$

$$a_1 x_1 + a_2 x_2 + \dots + a_k x_k = 0_V \Rightarrow a_1 = a_2 = \dots = a_k = 0$$



$$0_V = m_1 + m_2 + m_3$$

$$0_V = \underbrace{m_1}_{\in M_1} + \underbrace{m_2}_{\in M_2} + \underbrace{m_3}_{\in M_3}$$

$$0_V = m_1 + m_2 + m_3$$

$$\bar{m}_3 = \bar{m}_1 + \bar{m}_2 \Rightarrow \bar{m}_1 + \bar{m}_2 - \bar{m}_3 = 0 \rightarrow \text{not linearly ind.}$$

REMARK: Let  $V = M_1 + M_2 + \dots + M_k$  and let  $M_1, M_2, \dots, M_k$  are linearly independent. Let  $x \in V$

$$x = m_1 + m_2 + \dots + m_k \quad m_i \in M_i \quad \forall i$$

$m_1, m_2, \dots, m_k$  are unique

Proof: Assume that  $m_1, \dots, m_k$  are not unique.

$$\Rightarrow x = m_1 + \dots + m_k \quad m_i \in M_i \quad \forall i$$

$$x = \bar{m}_1 + \dots + \bar{m}_k \quad \bar{m}_i \in M_i \quad \forall i \quad \exists i \text{ where } m_i \neq \bar{m}_i$$

$$0_V = \underbrace{(m_1 - \bar{m}_1)}_{\substack{\text{Or} \\ \in M_1}} + \underbrace{(m_2 - \bar{m}_2)}_{\substack{\text{Or} \\ \in M_2}} + \dots + \underbrace{(m_k - \bar{m}_k)}_{\substack{\text{Or} \\ \in M_k}}$$

$$\left. \begin{array}{l} \left. \begin{array}{l} m_1 - \bar{m}_1 = 0_V \\ m_2 - \bar{m}_2 = 0_V \\ \vdots \\ m_k - \bar{m}_k = 0_V \end{array} \right\} \begin{array}{l} m_1 = \bar{m}_1 \\ m_2 = \bar{m}_2 \\ \vdots \\ m_k = \bar{m}_k \end{array} \right\} \begin{array}{l} \text{Contradiction} \\ \text{Decomposition} \end{array}$$

$x = m_1 + m_2 + \dots + m_k$   
is unique.

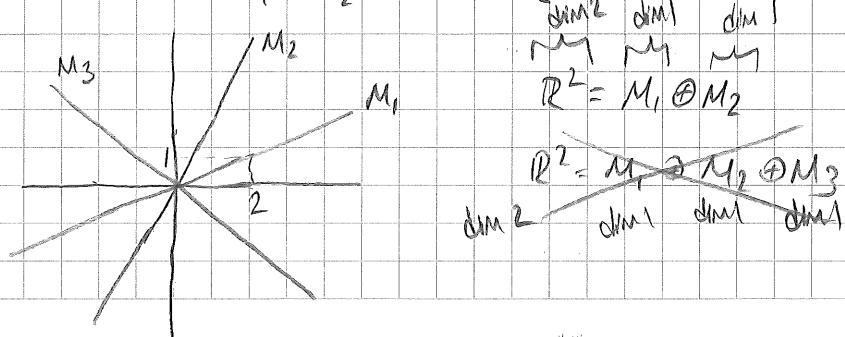
DEFINITION: Let  $M_1, M_2, \dots, M_k$  be subspaces of  $V$ . Let

$$i) M = M_1 + M_2 + \dots + M_k$$

ii)  $M_1, \dots, M_k$  are linearly independent

Then  $M$  is said to be direct sum of  $M_1, \dots, M_k$ . This is

shown as  $M = M_1 \oplus M_2 \oplus \dots \oplus M_k$



$$\begin{bmatrix} 2 \\ 1 \end{bmatrix} \in M_1, \quad \left\{ \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 2 \end{bmatrix} \right\} \quad B = \left\{ \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right\} \quad \rightarrow \dim M_1 = 1$$

$$\dim M_2 = 1$$

When we have a direct sum, summation of dimension of  $M_i$  is equal to dimension of direct sum.

Ex:

$$V = \mathbb{R}^4$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \in \mathbb{R}^4$$

$$M_1 \triangleq \left\{ x \in \mathbb{R}^4 \mid x_3 = x_4 = 0 \right\} \quad \begin{bmatrix} x_1 \\ x_2 \\ 0 \\ 0 \end{bmatrix} \quad \dim M_1 = 2$$

$$M_2 \triangleq \left\{ x \in \mathbb{R}^4 \mid x_1 = x_2 = 0 \right\} \quad \begin{bmatrix} 0 \\ 0 \\ x_3 \\ x_4 \end{bmatrix} \quad \dim M_2 = 2$$

$$M_3 \triangleq \left\{ x \in \mathbb{R}^4 \mid x_1 = 0 \right\} \quad \begin{bmatrix} 0 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \quad \dim M_3 = 3$$

$M_2 \subset M_3$

$$M_1 + M_2 = \mathbb{R}^4 \quad \rightarrow \quad \begin{bmatrix} x_1 \\ x_2 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \quad x_1 = x_2 = x_3 = x_4 = 0 \rightarrow \text{Direct Sum}$$

$$M_1 + M_3 \neq \mathbb{R}^4$$

$$M_2 + M_3 \neq M_3$$

$M_1, M_2, M_3$  are not l.i.

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad M_1 + M_3 \neq \mathbb{R}^4$$

$$\begin{bmatrix} 0 \\ 0 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ x_2 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \quad M_2 \text{ & } M_3 \text{ are not l.i.}$$

$$\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \\ 0 \end{bmatrix} \quad M_2 + M_3 = M_3$$

DEFINITION: Let  $V$  be a inner product space. Two subspaces are said to be orthogonal if

$$\langle M_1, M_2 \rangle = 0 \quad \begin{array}{l} \forall m_1 \in M_1 \\ \forall m_2 \in M_2 \end{array}$$

We denote this as  $M_1 \perp M_2$

DEFINITION: Let  $M$  is equal to  $M_1 + M_2 + \dots + M_k$  and  $M_i \perp M_j$  for  $i \neq j$ , then  $M$  is said to be an orthogonal direct sum of  $M_1, \dots, M_k$ .

We show this as

$$M = M_1 \overset{\perp}{\oplus} M_2 \overset{\perp}{\oplus} \dots \overset{\perp}{\oplus} M_k$$

DEFINITION: If  $M = V$

$V = M_1 \oplus M_2 \oplus \dots \oplus M_k$  is called to be a direct sum decomposition of  $V$ .

$V = M_1 \overset{\perp}{\oplus} M_2 \overset{\perp}{\oplus} \dots \overset{\perp}{\oplus} M_k$  is called an orthogonal direct sum decomposition of  $V$ .

$M \subset V$

$M^\perp \rightarrow \text{perp}$

DEFINITION: Let  $M$  be a subspace of an inner product space  $V$ . The orthogonal complement  $M^\perp$  of the subspace  $M$  is defined as

$$M^\perp \triangleq \{ x \in V \mid \langle x, m \rangle = 0 \quad \forall m \in M \}$$

THEOREM:  $M^\perp$  is a subspace of  $V$ .

Proof: Take two elements  $x, y \in M^\perp$

$$\langle y, m \rangle = 0 \quad \forall m \in M$$

$$\langle x, m \rangle = 0 \quad \forall m \in M$$

$$\langle x+y, m \rangle = \underbrace{\langle x, m \rangle}_{=0} + \underbrace{\langle y, m \rangle}_{=0} = 0 \quad \forall m \in M \Rightarrow x+y \in M^\perp$$

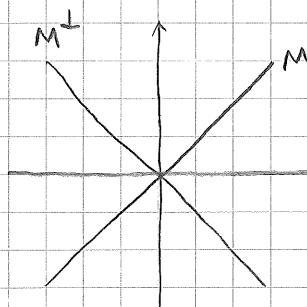
$$\langle \alpha x, m \rangle = \alpha \langle x, m \rangle = 0 \quad \forall m \in M \Rightarrow \alpha x \in M^\perp$$

$\Rightarrow M^\perp$  is subspace.

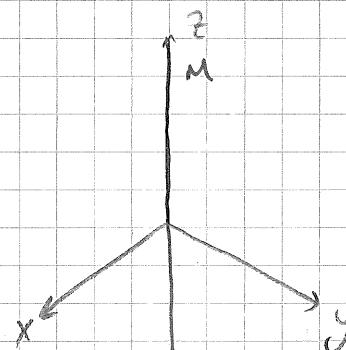
Theorem: Let  $V$  be an inner product space and  $M$  be a subspace of  $V$ .

Then,

$$V = M \overset{\perp}{\oplus} M^\perp$$



$$V = \mathbb{R}^2 = M \overset{\perp}{\oplus} M^\perp$$



$$M^\perp = xy\text{-plane}$$

$$\mathbb{R}^3 = \underset{\text{axis}}{z} \overset{\perp}{\oplus} \underset{\text{x-y plane}}{xy}$$

Proof:

$$\left. \begin{array}{l} V = M \oplus M^\perp \\ V = M + M^\perp \end{array} \right\} \text{linear independence} \quad \left. \begin{array}{l} V = M + M^\perp \\ M \perp M^\perp \end{array} \right\} \begin{array}{l} \text{needs to be proved} \\ \text{by definition} \end{array}$$

linear Independence:

$$\begin{array}{ll} x \in M & \\ y \in M^\perp & x+y = 0_V \end{array}$$

$$\underbrace{\langle x+y, x \rangle}_\text{Or} = 0 = \langle x, x \rangle + \cancel{\langle y, x \rangle}$$

$$\begin{matrix} \downarrow \\ 0 \end{matrix} \xrightarrow{y \in M^\perp} \begin{matrix} \downarrow \\ x \in M \end{matrix}$$

$$\Rightarrow \langle x, x \rangle = 0 \Rightarrow x = 0_V$$

$$\langle x+y, y \rangle = 0 = \cancel{\langle x, y \rangle} + \langle y, y \rangle$$

$$\Rightarrow \langle y, y \rangle = 0 \Rightarrow y = 0_V$$

$M$  &  $M^\perp$  are 1;

Proof:  $V = M + M^\perp$

We have to show that every  $x \in V$  can be written as the sum of  $x_1 \in M$  &  $x_2 \in M^\perp$

$$\begin{array}{c} x = x_1 + x_2 \\ \text{and} \\ x_1 \in M \quad x_2 \in M^\perp \end{array}$$

$$\dim V = n$$

Part-I:  $\dim M = n \quad M \subset V$

$$\dim M = \dim V$$

$$\Rightarrow M = V$$

Let  $x \in V$  be arbitrary

$$M^\perp = \{0_V\}$$

$$x = \underbrace{x}_{\in V} + \underbrace{0_V}_{\in M^\perp}$$

!  $0_V \in M^\perp$  does not violate linearly ind. case !

Part II:  $\dim M < n$   
 $\underbrace{n}_k < n$

Let  $B = \{m_1, m_2, \dots, m_k\}$  be a basis for  $M$ .

Let  $C = \{m_1, m_2, \dots, m_k, v_1, v_2, \dots, v_{n-k}\}$  be a basis for  $V$

Apply Gram-Schmidt orthonormalization process to  $C$ . Suppose we obtain

$$\bar{C} = \{e_1, e_2, \dots, e_k, f_1, f_2, \dots, f_{n-k}\}$$

$\bar{C}$  is a basis for  $V$ .

$\bar{B} = \{e_1, e_2, \dots, e_k\}$  is basis for  $M$ .

Let  $x$  be an arbitrary element of  $V$ .

$$x = \sum_{i=1}^k \alpha_i e_i + \sum_{j=1}^{n-k} \beta_j f_j = x_1 + x_2$$

$\underbrace{\qquad}_{=x_1} \quad \underbrace{\qquad}_{=x_2}$

$x_1 \in M$  & if we show  $x_2 \in M^\perp$ , we are done!

$$\langle x_2, m \rangle = 0 \quad \forall m \in M$$

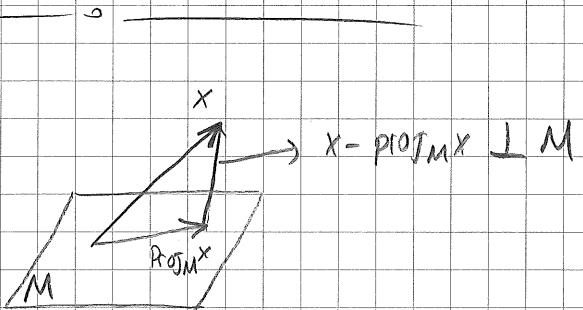
$\sum_{i \in M}$

$$\left( \sum_{j=1}^{n-k} \beta_j f_j, \sum_{i=1}^k \gamma_i e_i \right) = \sum_{j=1}^{n-1} \sum_{i=1}^k \underbrace{\beta_j \bar{\gamma}_i}_{=0 \forall i,j} \langle f_j, e_i \rangle = 0$$

(E is orthonormal)

$$\Rightarrow x_2 \in M^\perp$$

$$\Rightarrow V = M + M^\perp \\ = M \oplus M^\perp$$



**THEOREM: (Projection Theorem)**

Let H be a Hilbert space and let M a finite dimensional subspace of H. For any  $x \in H$ , the following minimization problem has a solution.

$$\min_{m \in M} \|x - m\|$$

$$\underbrace{c \in M^*}_{\text{co } M^*}$$

In other words, we can find the closest vector to x lying in the subspace M. If  $m^* \in M$  is a solution, then  $x - m^*$  is orthogonal to M. Furthermore, the solution  $m^*$  is unique and it is the orthogonal

projection of  $x$  onto  $M$ .

$$m^* = \text{Proj}_M x$$

Proof:  $H = M \overset{\perp}{\oplus} M^\perp$

Any  $x \in H$  can be written as  $x = x_1 + x_2$

$$\|x - m\|^2 = \|x_1 + x_2 - m\|^2 = \underbrace{\|x_1 - m\|}_{\in M}^2 + \underbrace{\|x_2\|}_{\in M^\perp}^2$$

$$= \langle x_1 - m + x_2, x_1 - m + x_2 \rangle$$

$$= \langle x_1 - m, x_1 - m \rangle + \cancel{\langle x_1 - m, x_2 \rangle} + \cancel{\langle x_2, x_1 - m \rangle} - \cancel{\langle x_2, x_2 \rangle}$$

$$= \langle x_1 - m, x_1 - m \rangle + \langle x_2, x_2 \rangle$$

$$\Rightarrow \|x - m\|^2 = \|x_1 - m\|^2 + \|x_2\|^2 \geq \|x_2\|^2$$

$$m^* = x_1$$

→ Decomp. is unique if  $m^*$  is unique  
( $H = M \overset{\perp}{\oplus} M^\perp$  is a  
direct sum decomp.)

$$x - m^* = x - x_1 = x_2 \perp M$$

26. 11. 2015  
Tuesday

$M_1, M_2, \dots, M_k \subset V$

$$M_1 \oplus M_2 \oplus \dots \oplus M_k = M$$

$M_1, M_2, \dots, M_k$  are linearly ind.



$$m_1 + m_2 + \dots + m_k = 0_V \Rightarrow m_i = 0 \quad \forall i$$

If we have a direct sum, any element  $m \in M$

$$m = m_1 + m_2 + \dots + m_k$$

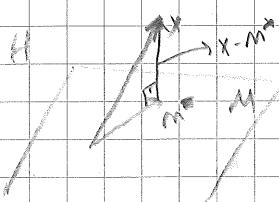
decomp. is unique

$$M_1 \perp M_2$$

$$\langle m_i, m_j \rangle = 0 \quad \forall i \neq j$$

$$M \subset V \quad M^\perp \triangleq \{x \in V \mid \langle x, m \rangle = 0 \quad \forall m \in M\}$$

$$V = M \oplus M^\perp$$



$$\min_{m \in M} \|x - m\|$$

$m^*$  | always exists  
| is unique

$$x - m^* \perp M$$

This is true for any inner product space.  
(Convergence of sequence)

Proof:  $H = M \oplus M^\perp$  Any vector  $x \in H$   $x = x_1 + x_2$   
 $x_1 \in M$   $x_2 \in M^\perp$

$$\|x - m\|^2 = \|x_1 + x_2 - m\|^2 = \|x_1 - m + x_2\|^2 = \langle x_1 - m + x_2, x_1 - m + x_2 \rangle$$

$$= \underbrace{\langle x_1 - m, x_1 - m \rangle}_{=0} + \underbrace{\langle x_1 - m, x_2 \rangle}_{=0} + \underbrace{\langle x_2, x_1 - m \rangle}_{=0} + \langle x_2, x_2 \rangle$$

$$= \|x_1 - m\|^2 + \|x_2\|^2 \geq \|x_2\|^2$$

$$\boxed{m^* = x_1}$$

$x_1$  is unique  $\Rightarrow m^*$  is unique.

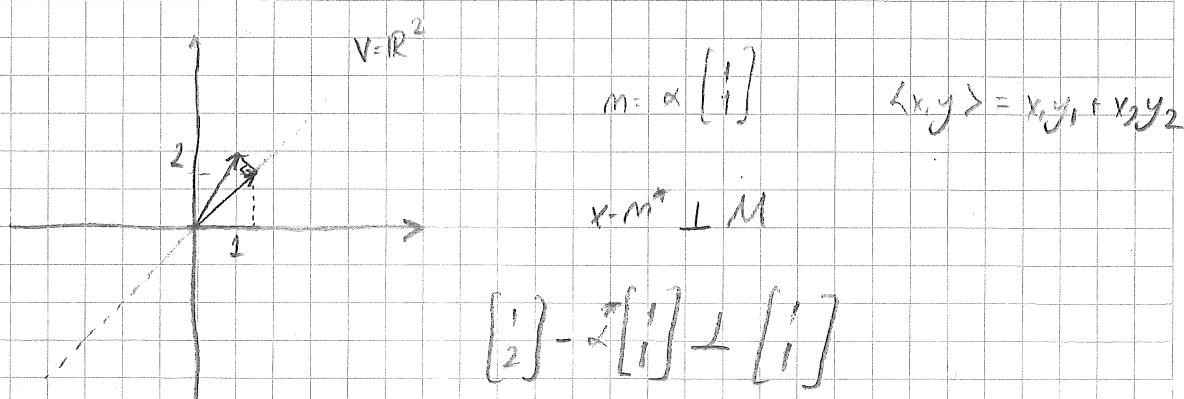
$$x - m^* = x - x_1 = x_1 + x_2 - x_1 = x_2$$

$$\overbrace{x - m^*} \perp M$$

Orthogonality Condition

EXAMPLE:  $V = \mathbb{R}^2$   $M = \{ \text{span} \{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \} \}$

$$x = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \text{Find } m^* \text{ which minimizes } \|x - m\|$$



$$\begin{bmatrix} 1 \\ 2 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \perp \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 - \alpha^* \\ 2 - \alpha^* \end{bmatrix} \perp \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$1 - \alpha^* + 2 - \alpha^* = 0$$

$$\Rightarrow \alpha^* = \frac{3}{2}$$

$$m^* = \frac{3}{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

EXAMPLE:  $M = \text{span} \{v_1\}$ ,  $x$ , find  $m^* \in M$  minimizing  $\|x - m\|$

$$m = \alpha v_1$$

$$x - \alpha^* v_1 \perp v_1$$

$$\langle x - \alpha^* v_1, v_1 \rangle = 0$$

$$\langle x, v_1 \rangle - \alpha^* \langle v_1, v_1 \rangle = 0$$

$$\alpha^* = \frac{\langle x, v_1 \rangle}{\langle v_1, v_1 \rangle} \Rightarrow m^* = \frac{\langle x, v_1 \rangle}{\langle v_1, v_1 \rangle} v_1$$

EXAMPLE:  $M = \text{span} \{v_1, v_2\}$ ,  $x$

$$m = \alpha_1 v_1 + \alpha_2 v_2$$

$$x - \alpha_1 v_1 - \alpha_2 v_2 \perp v_1$$

$$x - \alpha_1 v_1 - \alpha_2 v_2 \perp v_2$$

$$\langle x - \alpha_1 v_1 - \alpha_2 v_2, v_1 \rangle = 0$$

$$\langle x, v_1 \rangle - \alpha_1 \langle v_1, v_1 \rangle - \alpha_2 \langle v_2, v_1 \rangle = 0$$

$$\alpha_1 \langle v_1, v_1 \rangle + \alpha_2 \langle v_2, v_1 \rangle = \langle x, v_1 \rangle$$

$$\alpha_1 \langle v_1, v_2 \rangle + \alpha_2 \langle v_2, v_2 \rangle = \langle x, v_2 \rangle$$

$$\begin{bmatrix} \langle v_1, v_1 \rangle & \langle v_2, v_1 \rangle \\ \langle v_1, v_2 \rangle & \langle v_2, v_2 \rangle \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} \langle x, v_1 \rangle \\ \langle x, v_2 \rangle \end{bmatrix}$$

$G$ : Gramian Matrix

$$d = G^{-1} b$$

$$v_1 = v_2 \rightarrow G = \begin{bmatrix} \langle v_1, v_1 \rangle & \langle v_1, v_1 \rangle \\ \langle v_1, v_1 \rangle & \langle v_1, v_1 \rangle \end{bmatrix} \rightarrow G \text{ is not invertible!}$$

$$\text{span}\{[1], [1]\} = \text{span}\{[1]\}$$

$G$  is invertible iff  $v_1$  &  $v_2$  are linearly independent. Other case, we cannot apply this process.

GENERAL CASE:

$$M = \text{span} \{ \underbrace{v_1, v_2, \dots, v_k}_m \}$$

a basis for  $M$

$$m = \sum_{i=1}^k d_i v_i \quad x = \sum_{i=1}^k a_i v_i \perp v_j \forall j$$

$$\left\langle x - \sum_{i=1}^k d_i v_i, v_j \right\rangle = 0 \quad \forall j$$

$$\langle x, v_j \rangle = \sum_{i=1}^k \langle v_i, v_j \rangle d_i \quad \forall j$$

$$\begin{bmatrix} \langle v_1, v_1 \rangle & \dots & \langle v_k, v_1 \rangle \\ \vdots & \ddots & \vdots \\ \langle v_1, v_k \rangle & \dots & \langle v_k, v_k \rangle \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} \langle x, v_1 \rangle \\ \langle x, v_2 \rangle \\ \vdots \\ \langle x, v_k \rangle \end{bmatrix}$$

$\underbrace{\qquad\qquad\qquad}_{G} \quad \underbrace{\qquad\qquad\qquad}_{\alpha} \quad \underbrace{\qquad\qquad\qquad}_{b}$

$G$  is invertible iff  $v_1, v_2, \dots, v_k$  are l.l.

$$\boxed{\alpha = G^{-1}b}$$

SPECIAL CASE  $\{v_1, v_2, \dots, v_k\}$  is an orthonormal basis.

$$\langle v_i, v_j \rangle = 0 \text{ for } i \neq j$$

$$\langle v_i, v_i \rangle = 1$$

$$\begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} \langle x, v_1 \rangle \\ \langle x, v_2 \rangle \\ \vdots \\ \langle x, v_k \rangle \end{bmatrix}$$

$\underbrace{\qquad\qquad\qquad}_{k \times k}$

$$a_i^* = \langle x, v_i \rangle$$

$$m^* = \sum_{i=1}^k a_i^* v_i = \sum_{i=1}^k \langle x, v_i \rangle v_i$$

EXAMPLE:  $H$ : space of square integrable functions defined over  $[-\pi, \pi]$   
with the inner product

$$\langle f_1, f_2 \rangle = \int_{-\pi}^{\pi} f_1(t) \overline{f_2(t)} dt$$

$$M = \text{span} \left\{ \frac{e^{int}}{\sqrt{2\pi}} \right\}_{n=-N}^{n=N}$$

$v_n$

$$\langle v_n, v_m \rangle = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{int} e^{-jmt} dt = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{j(n-m)t} dt = \delta_{nm} = \begin{cases} 1 & , n=m \\ 0 & , n \neq m \end{cases}$$

$$d_n = \langle x, v_n \rangle$$

$$d_n = \frac{1}{2\pi} \int_{-\pi}^{\pi} x(t) e^{-jnt} dt$$

Finite Fourier Series  
(coefficients for  $x$ )

$$\text{Proj}_M x = \sum_{n=-N}^N d_n^* x_n = \sum_{n=-N}^N \frac{1}{2\pi} \left( \int_{-\pi}^{\pi} x(t) e^{-jnt} dt \right) \frac{e^{jnt}}{\sqrt{2\pi}}$$

$N \rightarrow \infty$  we have Fourier Series Representation of  $x$ .

27.11.2015  
Friday

PROJ THM

$$V = M \overset{\perp}{\oplus} M^\perp$$

$$v = m_1 + m_2$$

$$\begin{matrix} \downarrow \\ v \in M^\perp \\ m \in M \end{matrix}$$

$m_1$  &  $m_2$  are unique

$$m_1 \perp m_2$$

$$\min_m \|x - m\| = x_1 = \text{Proj}_M x$$

$$M = \text{sp}\{v_1, v_2\}$$

$x \in V$

$$x - \alpha_1 v_1 - \alpha_2 v_2 \perp v_2$$

$$\langle x - \alpha_1 v_1 - \alpha_2 v_2, v_j \rangle = 0 \quad j: 1, 2$$

$$\left[ \begin{array}{cc} \langle v_1, v_1 \rangle & \langle v_1, v_2 \rangle \\ \langle v_2, v_1 \rangle & \langle v_2, v_2 \rangle \end{array} \right] \left[ \begin{array}{c} \alpha_1 \\ \alpha_2 \end{array} \right] = \left[ \begin{array}{c} \langle x, v_1 \rangle \\ \langle x, v_2 \rangle \end{array} \right]$$

$\underbrace{\phantom{0}}_G \quad \underbrace{\phantom{0}}_\alpha \quad \underbrace{\phantom{0}}_b \quad \Rightarrow \quad \alpha = G^{-1} b$

$$x_1 = \alpha_1 v_1 + \alpha_2 v_2$$

For  $v_2 = 2v_1$ ,

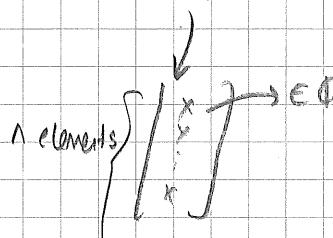
$$G = \begin{bmatrix} \langle v_1, v_1 \rangle & 2\langle v_1, v_2 \rangle \\ 2\langle v_2, v_1 \rangle & 4\langle v_2, v_2 \rangle \end{bmatrix} = \langle v_1, v_1 \rangle \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \rightarrow \text{not invertible}$$

## APPLICATION OF PROJ. THM TO $\mathbb{C}^N$

$$M = \text{span } \{m_1, m_2, \dots, m_k\}$$

$$m_i \in \mathbb{C}^n$$

$m_1, m_2, \dots, m_k$  are l.i.



$m_1, m_2, \dots, m_k$  is a basis for  $M$ .

$$\boxed{k < n}$$

$$\boxed{x \in \mathbb{C}^n}$$

$\left. \begin{array}{c} \uparrow \\ \text{So strictly} \\ \text{true!} \end{array} \right\}$

$\text{Proj}_{\mathbb{C}^n} x = x \rightarrow$  it's inside  $\mathbb{C}^n$  itself.

$$\text{Proj}_M x = ?$$

Assume  
that it  
 $\in M$   
is projection  
of  $x$ !

$$\rightarrow M = \alpha_1 m_1 + \alpha_2 m_2 + \dots + \alpha_k m_k = \underbrace{[m_1 \mid m_2 \mid \dots \mid m_k]}_{\triangleq B} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_k \end{bmatrix}$$

$$m = B\alpha$$

$$\langle x, y \rangle = y^H x$$

$$x, y \in \mathbb{C}^n$$

$$\langle x - m_i, m_i \rangle = 0 \quad i: 1, \dots, k$$

$$\langle x - B\alpha, m_i \rangle = 0 \quad i: 1, \dots, k$$

$$m_1^H (x - B\alpha) = 0$$

$$m_2^H (x - B\alpha) = 0$$

⋮

$$m_k^H (x - B\alpha) = 0$$

$$\left. \begin{array}{c} \\ \\ \\ \end{array} \right\}$$

$$\begin{bmatrix} m_1^H \\ m_2^H \\ \vdots \\ m_k^H \end{bmatrix} \underbrace{(x - B\alpha)}_{B^H} = 0$$

$$(x - B\alpha) = 0$$

$$B^H (x - B\alpha) = 0$$

$$\underbrace{B^H B}_{G} \alpha = \underbrace{B^H x}_{b}$$

$$\begin{bmatrix} \langle m_1, m_1 \rangle & \langle m_1, m_2 \rangle \\ \langle m_1, m_2 \rangle & \vdots \\ \vdots & \vdots \\ \langle m_k, m_1 \rangle & \langle m_k, m_k \rangle \end{bmatrix} \alpha = \begin{bmatrix} \langle x, m_1 \rangle \\ \langle x, m_2 \rangle \\ \vdots \\ \langle x, m_k \rangle \end{bmatrix}$$

$$\alpha^* = G^{-1} b = (B^H B)^{-1} B^H x$$

$$\text{Proj}_M x = B \alpha^* = \underbrace{B (B^H B)^{-1} B^H}_{P} x$$

$P$  is the projection matrix onto  $M$ .

$$x - \text{Proj}_M x = x - B (B^H B)^{-1} B^H x = \underbrace{(I - B (B^H B)^{-1} B^H)}_{\text{projection matrix onto } M^\perp} x$$

REMARK: An orthogonal projection matrix  $P \in \mathbb{C}^{k \times k}$  satisfies

$$i) P^H = P$$

$$ii) P^2 = P$$

$$x \in \mathbb{C}^n$$

$$\underbrace{P P x}_{\in \mathbb{C}^n} = P x$$

$$P = B (B^H B)^{-1} B^H$$

$$\begin{aligned} P^2 &= B (B^H B)^{-1} B^H B (B^H B)^{-1} B^H \\ &= \underbrace{B (B^H B)^{-1} B^H}_{= I} = P \end{aligned}$$

$$\begin{pmatrix} P^2 \\ \vdots \\ 0 \end{pmatrix} = P x$$

$$P^3 = \underbrace{P^2}_{P} P = P^2 = P$$

$$\rightarrow P^T = P \quad \forall t$$

EXAMPLE: Find the orthogonal projection of the vector  $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$  onto the subspace spanned by  $\left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} \right\}$

$\underbrace{\qquad\qquad\qquad}_{\text{1.i set}}$

$$B = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}$$

$$B^H B = B^T B = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$$

$$(B^T B)^{-1} = \frac{1}{8} \begin{bmatrix} 3 & -1 \\ -1 & 3 \end{bmatrix}$$

$$P = B (B^H B)^{-1} B^H = B (B^T B)^{-1} B^T = \frac{1}{8} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 3 & 1 \\ -1 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1/2 & 0 & 1/2 \\ 0 & 1 & 0 \\ 1/2 & 0 & 1/2 \end{bmatrix}$$

$$x_1 = \text{Proj}_M x = Px = \begin{bmatrix} 1/2 \\ 0 \\ 1/2 \end{bmatrix}$$

$$x - x_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1/2 \\ 0 \\ 1/2 \end{bmatrix} = \begin{bmatrix} 1/2 \\ 0 \\ -1/2 \end{bmatrix} \Rightarrow \begin{aligned} \langle \begin{bmatrix} 1/2 \\ 1/2 \\ -1/2 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix} \rangle &= 0 \\ \langle \begin{bmatrix} 1/2 \\ 0 \\ -1/2 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \rangle &= 0 \end{aligned}$$

## APPLICATION OF PROJ THEOREM TO SOLUTIONS OF LINEAR EQUATIONS

$$Ax = b$$

$\underbrace{A \in \mathbb{C}^{m \times n}}$

$a, b \in \mathbb{C}^m$   
 $x \in \mathbb{C}^n$  is unknown

- 1) Is there a solution?
- 2) If there is a solution, is it unique?

EXAMPLE:

$$A = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad b = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

$$\begin{array}{l} m=2 \\ n=1 \end{array}$$

$$\underbrace{\begin{bmatrix} 1 \\ 1 \end{bmatrix}}_A x = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \rightarrow \text{There is a solution.}$$

The solution is unique.

$$R(A) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \quad \dim = 1$$

$$N(A) = \text{span} \left\{ \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \quad \dim = 0$$

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} x = \begin{bmatrix} 3 \\ 1 \end{bmatrix} \rightarrow \text{Is there a solution? NO}$$

↙  
 some  $\in R(A)$   
 $\notin N(A)$

Is  $\begin{bmatrix} 3 \\ 1 \end{bmatrix}$  in  $R(A)$ ? NO

$$\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \underset{\text{A}}{\sim} \begin{bmatrix} 1 & 2 \\ 0 & 0 \end{bmatrix} \rightarrow x = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$R(A) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \quad \dim = 1$$

$$N(A) = \text{span} \left\{ \begin{bmatrix} -2 \\ 1 \end{bmatrix} \right\} \quad \dim = 1$$

$$\underbrace{\dim R(A)}_{=1} + \underbrace{\dim N(A)}_{=1} = \underbrace{\dim V}_{=2}$$

$$\text{There is a solution.} \rightarrow [3], [0], [1]$$

$$\begin{aligned} Ax &= b \\ x \&\& (x+g) \text{ are soln.} \\ A(x+g) &= Ax + Ag = b \\ &\downarrow \\ &\text{CN}(A) \end{aligned}$$

The solution is NOT unique. ( $\dim N(A)$  is diff. than 0, so solution is not unique)

## ANSWERS

1) Yes, iff  $b \in R(A)$

2) Yes, iff  $N(A) = \{0\}$

$$\dim N(A) = 0$$

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} \underset{\text{A}}{\sim} \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad b \notin R(A) \Rightarrow \text{There is no solution.}$$

If there is no exact solution, we go for a "best approximation"  
i.e., we look for an  $\hat{x}$  that would solve the following  
minimization problem

$$\min_{x \in \mathbb{C}^n} \|Ax - b\| \geq 0$$

↓  
equivalent  
problem

$$\min_{y \in R(A)} \|y - b\|$$

$\downarrow$   
 $b = b_1 + b_2$   
 $\downarrow$   
 $R(A)$        $\downarrow R(A)^\perp$

$$V = M \overset{\perp}{\oplus} M^\perp$$

$\text{co-domain}$

$$m \left[ \begin{array}{c} \\ \vdots \\ \end{array} \right] R(A) \subset \mathbb{C}^m$$

$$\mathbb{C}^m = R(A) \overset{\perp}{\oplus} R(A)^\perp$$

$$b \in \mathbb{C}^m$$

$$b = b_1 + b_2$$

$\downarrow$   
 $y \in R(A)$   
 $\in R(A)$

$$\|Ax - b\|^2 = \|Ax - b_1 - b_2\|^2 = \underbrace{\langle Ax - b_1 - b_2, Ax - b_1 - b_2 \rangle}_{R(A) \quad R(A)^\perp}$$

$$= \langle Ax - b_1, Ax - b_1 \rangle - \cancel{\langle Ax - b_1, b_2 \rangle} \cdot \cancel{\langle b_2, Ax - b_1 \rangle} + \langle b_2, b_2 \rangle$$

$$= \|Ax - b_1\|^2 + \|b_2\|^2 \geq \|b_2\|^2$$

We can always find one  $\hat{x}$  values which satisfies  $A\hat{x} = b_1$ , since

$$b_1 \in R(A)$$

The minimum value is obtained at  $x = \hat{x}$ .

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} x = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad b_1 = \text{Proj}_{R(A)} b$$

$$\text{Proj}_{R(A)} = B(B^H B)^{-1} B^H \quad \text{and } B = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$B^H B = 2 \Rightarrow \text{Proj}_{R(A)} = \frac{\begin{bmatrix} 1 & 1 \end{bmatrix}}{2} = \frac{1}{2} \begin{bmatrix} 1 & 1 \end{bmatrix}$$

$$b_1 = \text{Proj}_{R(A)} b = \frac{1}{2} \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix}$$

$$A \hat{x} = b_1 \rightarrow \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \hat{x} = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix} \Rightarrow \boxed{\hat{x} = 3/2} \rightarrow \text{The solution is unique}$$

EXAMPLE:  $A = \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \quad b = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$

$$\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$R(A) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \quad \& \quad b \notin R(A) \Rightarrow \text{There is NO exact solution!}$

$$b_1 = \text{Proj}_{R(A)} b = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix}$$

$$A \hat{x} = b_1 \Rightarrow \begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \end{bmatrix} = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix} \rightarrow \text{There is a solution but it is NOT unique!}$$

$$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}, \begin{bmatrix} 3/2 \\ 0 \end{bmatrix}$$

Because  $\dim N(A) \neq 0$

$$A(\hat{x} + a) = A\hat{x} + Aa = b, \quad a \in N(A)$$

$$A(\hat{x} + a) = b_1$$

$N(A) = \text{span} \left\{ \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\} \neq \{0\} \Rightarrow \hat{x} \text{ is NOT unique.}$

Suppose  $\hat{x}$  is a solution of  $A\hat{x} = b$ ,

Suppose that  $m$  is any vector in  $N(A)$

Then  $\hat{x} + m$  is another solution.

$$\begin{array}{l} A\hat{x} = b \\ m \in N(A) \end{array} \quad \left. \begin{array}{l} \\ \end{array} \right\} A(\hat{x} + m) = b,$$

In the case of non-uniqueness, we are going to look for the solution with min norm.

$$\min_{A\hat{x}=b} \|\hat{x}\|$$

$$N(A) \subset \mathbb{C}^n \Rightarrow \mathbb{C}^n = N(A) \oplus N^\perp(A)$$

Take an arbitrary solution  $\hat{x}$  satisfying  $A\hat{x} = b$ . We can decompose  $\hat{x}$  as,

$$\hat{x} = \hat{x}_1 + \hat{x}_2$$

$\downarrow$        $\downarrow$   
 $\in N(A)$        $\in N^\perp(A)$

We are going to find min norm of solution.

$$\|\hat{x} + m\|^2 = \|\hat{x}_1 + \hat{x}_2 + m\|^2 = \|\hat{x}_1\|^2 + \|\hat{x}_2 + m\|^2 \geq \|\hat{x}_1\|^2$$

$\downarrow$        $\downarrow$   
 $m \in N(A)$        $\in N^\perp(A)$

$$m = -\hat{x}_2$$

$$\hat{x} + m = \hat{x} + (-\hat{x}_2) = \hat{x}_1 \rightarrow \text{The minimum norm solution is } \hat{x}_1$$

$$\hat{x}_1 = \text{Proj}_{N^\perp(A)} \hat{x}$$

$$b_1 = \text{Proj}_{N^\perp(A)} b$$

01.12.2015  
Tuesday

$$MCV = \mathbb{C}^n$$

$$M = \text{span} \left\{ m_1, m_2, \dots, m_k \right\}$$

$\subseteq F^n$

$$x \in \mathbb{C}^n$$

$$\text{Proj}_{\mathcal{M}} x = B(B^H B)^{-1} B^H x$$

$$B = [m_1 | m_2 | \dots | m_k]$$

$B^H B$  is invertible iff  $\{m_1, \dots, m_6\}$  is li.

$$Ax = b \quad \begin{matrix} \leftarrow \\ \downarrow \\ \in \mathbb{C}^n \end{matrix} \quad \rightarrow \mathbb{C}^m$$

- There exist an exact solution iff  $b \in R(A)$

If  $b$  is not in  $R(A)$

$$\min_{x \in \mathbb{C}^n} \|Ax - b\|$$

$$\text{Solve : } A\hat{x} = b_1 \quad \& \quad b_1 = \text{Proj}_{(R(A))^\perp} b$$

- The solution is unique iff  $N(A) = \{0\}$

$$\dim N(A) = 0$$

$$A(\hat{x}+m) = b_1$$

$\downarrow \in N(A)$

$$\min \| \hat{x} \| \quad A\hat{x} = b_1 \quad \hat{x}_i = \text{Proj}_{N^{\perp}(A)} \hat{x}$$

It is difficult to make a projection onto  $N^{\perp}(A)$ . Therefore, we are going to use the following theorem

Theorem:  $N^{\perp}(A) = R(A^H)$

Proof: We are going to prove  $N(A) = R^{\perp}(A^H)$

Part - I: Prove  $N(A) \subset R^{\perp}(A^H)$

Let  $x \in N(A) \Rightarrow Ax=0$

$$\langle x, y \rangle = y^H x \Rightarrow \langle Ax, y \rangle = 0 \quad y \text{ is arbitrary}$$

$$y^H A x = 0$$

$$(A^H y)^H x = 0$$

$$\langle x, A^H y \rangle = 0$$

∴

$$x \perp A^H y \Rightarrow x \perp R(A^H) \Rightarrow x \in R^{\perp}(A^H)$$

Part - II: Prove  $R^{\perp}(A^H) \subset N(A)$

$$x \in R^{\perp}(A^H)$$

$$x \perp A^H y \quad y \text{ is arbitrary}$$

$$\langle x, A^H y \rangle = 0$$

$$(A^H y)^H x = y^H A x = 0$$

$$\langle Ax, y \rangle = 0 \Rightarrow Ax=0 \Rightarrow x \in N(A)$$

Example:

$$\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$R(A) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$$

$$\begin{bmatrix} 2 \\ 1 \end{bmatrix} \notin R(A)$$

$$b_1 = \text{Proj}_{R(A)} b = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix}$$

$$A\hat{x} = b_1$$

$$\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \hat{x} = \begin{bmatrix} 3/2 \\ 3/2 \end{bmatrix} \quad \hat{x} = \begin{bmatrix} 3/2 \\ 0 \end{bmatrix}$$

$$N(A) = \text{span} \left\{ \begin{bmatrix} -2 \\ 1 \end{bmatrix} \right\} \quad A^H = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$$

$$\begin{matrix} N^\perp(A) = \text{span} \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right\} \\ \parallel \\ R(A^H) \end{matrix} \Rightarrow R(A^H) = \text{span} \left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right\}$$

$$\hat{x}_1 = \underbrace{\text{Proj}_{R(A^H)}}_{B(B^H B)^{-1} B^H} \hat{x}$$

$$B = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad B^H B = 5 \quad \text{Proj}_{R(A^H)} = \frac{BB^H}{5} = \frac{1}{5} \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \quad \text{and } \hat{x} = \begin{bmatrix} 3/2 \\ 0 \end{bmatrix}$$

$$\hat{x}_1 = \frac{1}{5} \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} 3/2 \\ 0 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} 3/2 \\ 3 \end{bmatrix}$$

$$m \begin{bmatrix} n \\ \parallel \\ (n-k) + k \end{bmatrix} \quad \dim N(A) + \dim R(A) = \dim \mathbb{C}^n$$

$$N(A) \subset \mathbb{C}^n \quad \dim N^\perp(A) = k$$

$$\dim R(A^H) = k$$

$\dim R(A) = k$  # of linearly independent columns of  $A$

$\dim R(A^H) = k$  # of linearly independent rows of  $A$

$k$  is called  
to be the  
rank of matrix.

## Special Cases:

1) Columns of  $A$  are li

$A$  is full column rank

$$m \begin{bmatrix} A \end{bmatrix} x = \begin{bmatrix} \end{bmatrix} \quad m \geq n \quad \text{There are more equations than unknowns (Overdetermined)}$$

$$Ax = b$$

$$\dim R(A) = n \Rightarrow \underbrace{\dim N(A)}_n + \underbrace{\dim R(A)}_n = \dim V$$

$$\Rightarrow \dim N(A) = 0 \Rightarrow N(A) = \{0\}$$

If there exist a solution  $\Rightarrow$  It is unique.

$$b_1 = \underbrace{\text{Proj}_{R(A)}}_{B(B^H B)^{-1} B^H} b$$

$$B = A \Rightarrow b_1 = A(A^H A)^{-1} A^H b$$

$$A \hat{x} = b_1 = A(A^H A)^{-1} A^H b$$

$$\Rightarrow A(\hat{x} - (A^H A)^{-1} A^H b) = 0 \Rightarrow \hat{x} = (A^H A)^{-1} A^H b$$

$\hat{x}$  is unique

$$\text{Proj}_{N^\perp(A)} \hat{x} = \hat{x}$$

$(A^H A)^{-1} A^H$  is called to be Left Pseudo Inverse of  $A$ .

04.12.2015  
Friday

$$Ax = b$$

$\downarrow \quad \downarrow \quad \downarrow$

$m \times n \quad n \times 1 \quad m \times 1$

-  $\exists$  a solution iff  $b \in R(A)$   
in  
COLUMN  
space

- A solution is unique iff  $N(A) = \{0\}$   
 $\dim N(A) = 0$

$$Ax = b$$

There is no exact solution:

$$\min_{x \in \mathbb{C}^n} \|Ax - b\|$$

$$b_1 = \text{Proj}_{R(A)} b$$

$$A\hat{x} = b_1$$

If  $N(A) = \{0\}$ ,  $\hat{x}$  is unique

If not, solution is not unique

$$\min_{\hat{x}} \| \hat{x} \|$$
$$A\hat{x} = b_1$$

$$\hat{x}_1 = \text{Proj}_{N(A)^\perp} \hat{x} \quad \rightarrow \text{any solution}$$

$$N(A)^\perp = R(A^H)$$

$$\hat{x}_1 = \text{Proj}_{R(A^H)} \hat{x}$$

$$\dim R(A) = \dim R(A^H)$$

↓  
 column  
 space

↓  
 row space  
 of A.

$$m \begin{bmatrix} & \\ & n \end{bmatrix}$$

# of lin. columns of A = k = # of lin. rows of A.

k = Rank of the matrix A.

### SPECIAL CASE

1) Column of A are lin.

$$m \begin{bmatrix} & \\ & n \end{bmatrix}$$

$$m \geq n$$

} A is full  
column rank  
over determined

$$\dim R(A) = n$$

$$\dim N(A) \rightarrow \dim R(A) = n \Rightarrow N(A) = \{0\}$$

↓  
 = 0

↓  
 n

If we find a solution  $\Rightarrow$  it has to be unique

$$Ax = b$$

$$b_1 = \text{Proj}_{R(A)} b$$

↓  
 $B(B^H B)^{-1} B^H$

$$B = [m_1 | m_2 | \dots | m_k]$$

$$B = A$$

$$b_1 = A(A^H A)^{-1} A^H b$$

$$\begin{bmatrix} 1 & 1 \\ 2 & 2 \\ 3 & 1 \end{bmatrix}$$

$$A\hat{x} = A(A^H A)^{-1} A^H b$$

$$A \underbrace{(\hat{x} - (A^H A)^{-1} A^H b)}_{\in N(A)} = 0$$

$$\hat{x} = (A^H A)^{-1} A^H b$$

↓      ↓  
unique      left pseudo-inverse  
solution      of  $A$ .

$$\hat{x}_1 = \text{Proj}_{\frac{N(A)}{m \times n}} \hat{x} = \hat{x}$$

### SPECIAL CASE II

Row of  $A$  are l.i.

III

$A$  is full row rank

$$m \left[ \begin{array}{c|c|c|c} & & & \\ \hline & & & \\ \hline & & & \end{array} \right] = \left[ \begin{array}{c} \\ \hline \\ \hline \end{array} \right]$$

$$m \leq n$$

Underdetermined system of equations.

$$\dim R(A^H) = m$$

II,

$$\dim R(A) = m$$

$$R(A) \subset \mathbb{C}^m \rightarrow m \left[ \begin{array}{c|c|c|c} & & & \\ \hline & & & \\ \hline & & & \end{array} \right] \left[ \begin{array}{c} \\ \hline \\ \hline \end{array} \right]$$

$\downarrow$   
 $m$  dimensional

$$R(A) = \mathbb{C}^m$$

$$Ax = b$$

$\downarrow \mathbb{C}^m$

Solution always exists. Because  $b \in R(A)$

$$b_1 = \text{Proj}_{R(A)} b$$

$$= \text{Proj}_{\mathbb{C}^m} b = b$$

$$A\hat{x} = b$$

$$\hat{x}_1 = \text{Proj}_{N^\perp(A)} \hat{x} = \text{Proj}_{R(A^\perp)} \hat{x}$$

$\underbrace{B(B^\perp B)^{-1} B^\perp}$   $\rightarrow B = A^\perp$

$$= A^\perp (A A^\perp)^{-1} A \hat{x}$$

$$\hat{x}_1 = A^\perp (A A^\perp)^{-1} b$$

$\hookrightarrow$  Right-pseudo inverse of A.

### SPECIAL CASE III

A is both full column rank & full row rank. Columns are rows of A are l.i.

$$M \left[ \begin{array}{c} 1 \\ \vdots \end{array} \right] \quad M = n$$

We have square matrix

$$3 \left[ \begin{array}{c} 1 \\ \vdots \\ 3 \end{array} \right]$$

$\Rightarrow$  3rd min row  $\Rightarrow$  Rank = 3  $\Rightarrow$  # of ind col. = 3  $\Rightarrow$   $n = 3 \Rightarrow n = m$

$$Ax = b$$

$\nwarrow$

$$m \begin{bmatrix} n \end{bmatrix}$$

$$N(A) = \{0\}$$

$$R(A) = \mathbb{C}^m$$

$$x = A^{-1} b$$

solution always exists & it is unique.

$$\begin{aligned} x &= (A^H A)^{-1} A^H b \\ &= A^{-1} (A^H)^{-1} A^H b \\ &= A^{-1} b \end{aligned}$$

Left & right pseudo-inverse both turn into  $A^{-1}$ .

SPECIAL CASE IV (there is no short cut, we have to apply all procedure)

$A$  is neither full column rank nor full row rank

EXAMPLE:

$$\underbrace{\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 3 \\ 3 & 2 & 1 \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \quad \underbrace{b}_{\text{error}}$$

Obtain the unique minimum norm solution which minimize  $\|Ax-b\|$ .

$$\hat{x}_1 = ?$$

$$2 \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

Rank of  $A=2$

$b \notin R(A)$

$$b = \text{Proj}_{R(A)} b$$

$\downarrow$

$$B(B^H B)^{-1} B^H$$

$$B = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 3 & 1 \end{bmatrix}$$

$$B^H B = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 3 & 1 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 3 & 1 \end{bmatrix} = \begin{bmatrix} 11 & 7 \\ 7 & 11 \end{bmatrix}$$

$$(B^H B)^{-1} = \frac{1}{72} \begin{bmatrix} 11 & -7 \\ -7 & 11 \end{bmatrix}$$

$$\underbrace{B(B^H B)^{-1} B^H}_P = \begin{bmatrix} 1 \\ 1 \\ 3 \\ 3 \\ 1 \end{bmatrix} \frac{1}{72} \begin{bmatrix} 11 & -7 \\ -7 & 11 \end{bmatrix} \begin{bmatrix} 1 & 1 & 3 \\ 1 & 3 & 1 \end{bmatrix}$$

$$\Rightarrow P = \frac{1}{72} \begin{bmatrix} 8 & 16 & 16 \\ 16 & 64 & -4 \\ 16 & -4 & 68 \end{bmatrix} \rightarrow \text{Any proj matrix must be symmetric}$$

$$b_1 = Pb = P \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} = \frac{1}{72} \begin{bmatrix} 24 \\ 256 \\ -60 \end{bmatrix}$$

$$A\hat{x} = b$$

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 3 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \frac{1}{72} \begin{bmatrix} 24 \\ 256 \\ -60 \end{bmatrix}$$

$$\dim(RIA) = 2$$

$$x_2 = 0$$

$$\dim(NIA) = 1$$

$$x_1 + x_3 = \frac{1}{72} 24$$

$$3x_1 + x_3 = -\frac{60}{72}$$

$$x_3 = \frac{11}{12}$$

$$x_1 = -\frac{7}{12}$$

$$x = \begin{bmatrix} -7/12 \\ 0 \\ 11/12 \end{bmatrix}$$

$$\hat{x}_1 = \text{Proj}_{\mathcal{R}(A^H)} \hat{x}$$

$$A^H = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 2 & 2 \\ -1 & 3 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix}$$

$$B^H B = \begin{bmatrix} 3 & 6 \\ 6 & 14 \end{bmatrix}$$

$$P = \begin{bmatrix} 5/6 & 1/3 & -1/6 \\ 1/3 & 1/3 & 1/3 \\ -1/6 & 1/3 & 5/6 \end{bmatrix}$$

$$\hat{x}_1 = P \begin{bmatrix} -7/12 \\ 0 \\ 11/12 \end{bmatrix}$$

$$= \frac{1}{72} \begin{bmatrix} -46 \\ 8 \\ 62 \end{bmatrix}$$

} Unique  
minimum norm  
minimum error  
solution

$$A = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix}$$

$$A: V \rightarrow V$$

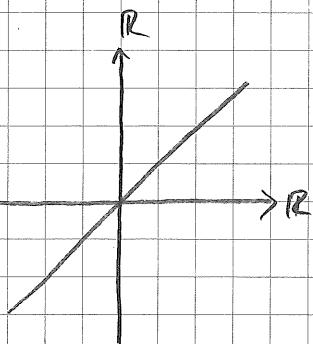
$$\left[ \begin{array}{cc|cc} * & * & 0 & 0 \\ * & * & 0 & 0 \\ \hline 0 & 0 & * & 0 \\ 0 & 0 & 0 & * \end{array} \right]$$

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

$$A: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$\begin{bmatrix} * & * \\ * & * \end{bmatrix} \quad \begin{bmatrix} * & * \\ * & * \end{bmatrix}$$

Invariance



$$M = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$$

$$A \alpha \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} 3 \\ 3 \end{bmatrix} = 3 \alpha \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

by  
span  
subspace

$M$  is invariant under  $A$

## SPECTRAL ANALYSIS OF LINEAR OPERATORS

DEFINITION: Let  $A: V \rightarrow V$

be a linear transformation defined over vector space  $V$ .

A subspace  $M$  of  $V$  is said to be invariant under  $A$  if

$$Ax \in M \text{ for all } x \in M.$$

EXAMPLE:  $R(A)$  is invariant under  $A$

Let  $x \in R(A)$  be an arbitrary vector in  $R(A)$

$Ax \in R(A) \Rightarrow R(A)$  is invariant under  $A$ .

EXAMPLE:  $N(A)$  is invariant under  $A$ .

$$x \in N(A)$$

$Ax = 0_V \in N(A) \Rightarrow N(A)$  is invariant under  $A$ .

DEFINITION: Powers of a linear transformation  $A$  are defined as

$$A^k x = \underbrace{A(A(\dots(Ax)\dots))}_{A \text{ is applied } k \text{ times}}$$

$A$  is applied  $k$  times

We define  $A: V \rightarrow V$ , otherwise  $V \rightarrow W$ , we cannot apply  $A$  more than one

In this way, polynomials of  $A$  can be constructed using linear combinations of powers of  $A$ .

$$p(s) = d_0 s^0 + d_1 s^1 + \dots + d_{n-1} s^{n-1} + d_n$$

$$p(A) = d_0 A^0 + d_1 A^1 + \dots + d_{n-1} A + d_n I$$

identity transformation

$$I(x) = x$$

Property:  $(\underbrace{A^2 + A + 2I}_{p(A)}) Ax = A^3 x + A^2 x + 2Ax$

$$= A(A^2 x + Ax + 2x)$$

$$= A(\underbrace{A^2 + A + 2I}_{p(A)} x)$$

$$p(A) \cdot Ax = A p(A)x \Rightarrow p(A) \text{ & } A \text{ commutes}$$

EXAMPLE:  $R(p(A))$  &  $N(p(A))$  are invariant under  $A$ .

-  $R(p(A)) \quad x \in R(p(A))$

$\exists y \text{ st } x = p(A)y$

$$Ax = A p(A)y = p(A) \underbrace{Ay}_{y'} = p(A)y' \in R(p(A))$$

$R(p(A))$  is invariant under  $A$ .

-  $N(p(A)) \quad x \in N(p(A))$

$$p(A)x = 0_r$$

$$p(A)Ax = A \underbrace{p(A)x}_{0_r} = 0_r \Rightarrow Ax \in N(p(A))$$

$\Rightarrow N(p(A))$  is invariant under  $A$ .

**DEFINITION:** Let  $A$  denote the matrix representation of a linear transformation from  $V$  to  $V$ . ( $A$  is a square matrix)

The eigenvalues of  $A$  denoted by  $\lambda_i$  are defined as the  $n$ -roots of the equation

$$\det(SI - A) = 0$$

where  $d(S) \stackrel{\Delta}{=} \det(SI - A)$  is called as the characteristic polynomials of  $A$ .

Vectors  $e_i \in \mathbb{C}^n$  satisfying  $e_i \neq 0$  and  $Ae_i = \lambda_i e_i$  are called as the eigenvectors of  $A$ .

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad SI - A = \begin{bmatrix} S & 0 \\ 0 & S \end{bmatrix} - \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} S-2 & -1 \\ -1 & S-2 \end{bmatrix}$$

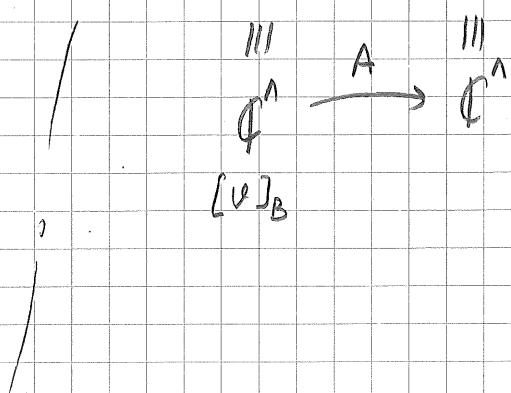
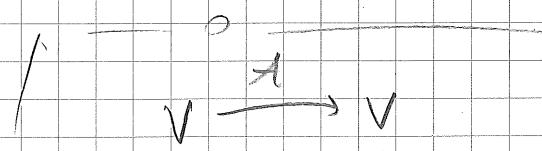
$$d(S) = \det(SI - A) = (S-2)^2 - 1 = S^2 - 4S + 3 = 0$$

$$\lambda_1 = 3 \quad \lambda_2 = 1$$

$$\begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} e_1 = 3e_1$$

We have to find non-zero vector.  $e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$\begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} e_2 = 1e_2 \rightarrow e_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



From this point on in this course, we are going to work on only the matrix representation of a linear transformation. However, we need to keep in mind that the matrix  $A$  represents a linear transformation and vectors we work with are representations wrt some basis sets.

$N(p(A))$  is invariant under  $A$ .

$N(p(A))$  is invariant under  $A$ .

$$y = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} x$$

$\underbrace{\qquad\qquad\qquad}_{A}$        $\mathbb{R}^2 = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix}}_{B} \right\}$

$$[y]_B = \bar{A} [x]_B$$

$$\begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \Rightarrow \bar{A} = \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}$$

$\underbrace{\qquad\qquad\qquad}_{A}$

$$Ae_1 = \lambda_1 e_1 \rightarrow (\lambda_1 I - A) e_1 = 0$$

$$e_1 \in N(\lambda_1 I - A)$$

$$e_2 \in N(\lambda_2 I - A)$$

$$\mathbb{R}^2 = N(\lambda_1 I - A) \oplus N(\lambda_2 I - A)$$

08.12.2015

Tuesday

$$A: V \rightarrow V$$

$$\downarrow \quad \downarrow$$

III

$$A: \mathbb{C}^n \rightarrow \mathbb{C}^n$$

MCV

$$x \in M \xrightarrow{A^n} Ax \in M$$

$$A: n \times n$$

$$\underbrace{\det(SI - A)}_{{\text{char. poly}}} = 0 \quad \left. \begin{array}{l} \text{char. eqn.} \\ \text{dis} \end{array} \right.$$

$$s^n + d_1 s^{n-1} + \dots + d_{n-1} s + d_n = 0$$

$$(s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n) = 0$$

$$Ae_i = \lambda_i e_i$$

$\sim$

$$e_i \neq 0$$

$\text{span}\{e_i\}$

$\mathbb{R}^2$

$$\text{span}\{(1)\} \quad e_i = \begin{pmatrix} 1 \\ i \end{pmatrix}$$

$$\left. \begin{array}{l} N(p(A)) \\ R(p(A)) \end{array} \right\} \text{invariant under } A$$

EX contd

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

$$\left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$

$$Ae_1 = \begin{bmatrix} 3 \\ 3 \end{bmatrix} = 3e_1$$

This means  
 $e_1$  is eigen vector

$$Ae_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} = 1e_2$$

$\text{span}\left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$  &  $\text{span}\left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$  are invariant under linear transf. A.

$e_1, e_2$  are linearly independent  $\Rightarrow \mathbb{R}^2 : \text{span}\left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\} \overset{M_1}{\perp} \text{span}\left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\} \overset{M_2}{\perp}$   
 $\Rightarrow$  spans are l. ind.

$$[y]_B = \bar{A} [x]_B$$

(choose  $B = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$ )

For  $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$\begin{bmatrix} 3 \\ 0 \end{bmatrix} = \bar{A} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

First column  
of  $\bar{A}$

$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \bar{A} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Second column  
of  $\bar{A}$

$$\Rightarrow \bar{A} = \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\bar{A} = f(A)$$

$$3e_1 = Ae_1$$
  
$$e_2 = Ae_2$$

$$[e_1 \ e_2] \underbrace{\begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}}_A = A \underbrace{[e_1 \ e_2]}_P$$

$$\Rightarrow \boxed{\bar{A} = P^{-1}AP}$$

Theorem: Consider the linear transformation  $y = Ax$  where  $A \in \mathbb{C}^{n \times n}$ ,  $x, y \in \mathbb{C}^n$

Suppose that

$$i) \mathbb{C}^n = M_1 \oplus M_2 \oplus \dots \oplus M_k$$

ii) Each subspace  $M_i$  is invariant under  $A$ .

Then, the transformation  $A$  has a block diagonal representation

$$\bar{A} = \begin{bmatrix} \bar{A}_1 & & & \\ & \bar{A}_2 & & \\ & & \ddots & \\ & & & \bar{A}_k \end{bmatrix}$$

$$\text{where } \bar{A} = P^{-1}AP$$

$$P = [P_1 | P_2 | \dots | P_k]$$

$$P_i = [b_i^1 \ b_i^2 \ \dots \ b_i^{n_i}]$$

$n_i$  is the dimension of  $M_i$  and  $b_i^1, \dots, b_i^{n_i} \in \mathbb{C}^n$  are basis vectors for  $M_i$ .  $\bar{A}_i$  is of size  $n_i \times n_i$ .

A specific case:

$$\mathbb{C}^n = M_1 + M_2 \quad M_1 = \text{span} \left\{ \underbrace{\overbrace{b_1^1, b_1^2}^{1,1}}_{\mathbb{C}^5} \right\}$$

$$n=5$$

$$M_2 = \text{span} \left\{ \underbrace{\overbrace{b_2^1, b_2^2, b_2^3}^{1,1}}_{\in \mathbb{C}^5} \right\}$$

$$n_1 = \dim M_1 = 2$$

$$n_2 = \dim M_2 = 3$$

$$A \in \mathbb{C}^{5 \times 5}$$

$M_1$  &  $M_2$  are both invariant under  $A$ .

$$P = [P_1 \mid P_2]$$

$$P_1 = [b_1^1 \mid b_1^2]$$

$$P_2 = [b_2^1 \mid b_2^2 \mid b_2^3]$$

$$P = [b_1^1 \mid b_1^2 \mid b_2^1 \mid b_2^2 \mid b_2^3]$$

$$\bar{A} = P^T A P \text{ or } P \bar{A} = A P$$

$$\begin{bmatrix} b_1^1 & b_1^2 & b_2^1 & b_2^2 & b_2^3 \end{bmatrix} \begin{pmatrix} \bar{A}_1 & \begin{matrix} b_1^1 \\ b_2^1 \end{matrix} & \begin{matrix} 0 & 0 & 0 \end{matrix} \\ \begin{matrix} 0 & 0 & b_1^2 \\ 0 & 0 & b_2^2 \end{matrix} & \begin{matrix} 0 & 0 & 0 \end{matrix} \\ \begin{matrix} 0 & 0 & b_1^2 \\ 0 & 0 & b_2^2 \end{matrix} & \begin{matrix} b_1^1 & b_1^2 & b_2^1 & b_2^2 & b_2^3 \end{matrix} \end{pmatrix} = A \begin{pmatrix} b_1^1 & b_1^2 & b_2^1 & b_2^2 & b_2^3 \end{pmatrix}$$

$\checkmark$

$\bar{A}_2$

$b_1^1$  must be  
written in terms of  
 $M_1$ , geom. (invariant  
under  $A$ )

### EXAMPLE:

$$A = \begin{bmatrix} 1 & 1 & -1 \\ -1 & 3 & -2 \\ 0 & 0 & 1 \end{bmatrix}$$

$$M_1 = \text{span} \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$M_2 = \text{span} \left\{ \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right\}$$

→ all vectors are  
l.i. so call these  
 $b_1^1, b_1^2, b_2^1$

i) Is  $M_1$  invariant under  $A$ ?

$$Ab_1^1 = \begin{bmatrix} 2 \\ 2 \\ 0 \end{bmatrix} = 2b_1^1 + 0b_1^2 \in M_1$$

$$Ab_1^2 = \begin{bmatrix} 1 \\ 3 \\ 0 \end{bmatrix} = 1b_1^1 + 2b_1^2 \in M_1$$

$M_1$  is invariant under  $A$ .

ii) Is  $M_2$  invariant under  $A$ ?

$$Ab_2^1 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = 1b_2^1 \in M_2 \Rightarrow M_2 \text{ is invariant under } A.$$

$$\mathbb{R}^3 = \underbrace{M_1}_{\dim=2} \oplus \underbrace{M_2}_{\dim=1}$$

iii) Change the basis in both domain & codomain to  $\{b_1, b_1^2, b_2\}$

$$\bar{A} = \left[ \begin{array}{cc|c} 2 & 1 & 0 \\ 0 & 2 & 0 \\ \hline 0 & 0 & 1 \end{array} \right]$$

EXAMPLE:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 2 & 1 \\ 0 & 0 & 3 \end{bmatrix}$$

- Find eigenvalues

$$(S\bar{I} - A) = \begin{bmatrix} s-1 & 0 & 0 \\ 1 & s-2 & -1 \\ 0 & 0 & s-3 \end{bmatrix}$$

$$\det(S\bar{I} - A) = (s-1)(s-2)(s-3) = 0$$

$$\lambda_1 = 1$$

$$\lambda_2 = 2$$

$$\lambda_3 = 3$$

$$Ae_1 = e_1$$

$$(A - I)e_1 = 0$$

$$(A - \lambda_1 I)e_1 = 0 \rightarrow A - \lambda_1 I = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 1 & 1 \\ 0 & 0 & 2 \end{bmatrix} \quad e_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$\begin{matrix} \text{Column} \\ \text{rank} \end{matrix} = 2$$

$$\dim R(A)$$

$$\Rightarrow \dim N(A) = 1 \quad \Rightarrow N(A - \lambda_1 I) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$(A - \lambda_2 I) = \begin{bmatrix} -1 & 0 & 0 \\ -1 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad e_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \Rightarrow N(A - \lambda_2 I) = \text{span} \left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$(A - \lambda_3 I) = \begin{bmatrix} -2 & 0 & 0 \\ -1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad e_3 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \Rightarrow N(A - \lambda_3 I) = \text{span} \left\{ \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \right\}$$

$$\mathbb{R}^3 = \underbrace{N(A - \lambda_1 I)}_1 \oplus \underbrace{N(A - \lambda_2 I)}_1 \oplus \underbrace{N(A - \lambda_3 I)}_1$$

$$\tilde{A} = \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \lambda_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \Rightarrow A \text{ is diagonalizable}$$

11.12.2015  
Friday

$$\mathbb{C}^7 = M_1 \oplus M_2 \oplus M_3$$

$$\frac{4}{\lambda_1} \quad \frac{2}{\lambda_2} \quad \frac{1}{\lambda_3}$$

$M_1, M_2 \text{ & } M_3$  are invariant under  $A$ .

$$\tilde{A} = \left[ \begin{array}{c|c|c} 0 & 0 & 0 \\ \hline A_1 & & \\ \hline & 2 \times 2 & \\ & A_2 & \\ \hline & & 1 \times 1 \\ & A_3 & \end{array} \right]$$

$$A = P^{-1} A' P$$

$$P = [P_1 \ P_2 \ P_3]$$

$$P_i = [b_i^1 \ b_i^2 \ \dots \ b_i^{n'}]$$

EXAMPLE:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 2 & 1 \\ 0 & 0 & 3 \end{bmatrix}$$

$$d(s) = \det(sI - A) = (s-1)(s-2)(s-3) = 0$$

$$\lambda_1 = 1$$

$$\lambda_2 = 2$$

$$\lambda_3 = 3$$

$$N(A - \lambda_1 I) = N\left(\begin{bmatrix} 0 & 0 & 0 \\ -1 & 1 & 1 \\ 0 & 0 & 2 \end{bmatrix}\right) = \text{span}\left\{\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}\right\}$$

$\sim \tilde{e}_1$

$$Ae_1 = \lambda_1 e_1$$

$$(A - \lambda_1 I)e_1 = 0$$

$$A - \lambda_2 I = \begin{bmatrix} -1 & 0 & 0 \\ -1 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow N(A - \lambda_2 I) = \text{span}\left\{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}\right\}$$

$\sim \tilde{e}_2$

$$A - \lambda_3 I = \begin{bmatrix} -2 & 0 & 0 \\ -1 & -1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow N(A - \lambda_3 I) = \text{span}\left\{\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}\right\}$$

$\sim \tilde{e}_3$

$$x = \alpha_1 \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + \alpha_2 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} + \alpha_3 \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

$\in \mathbb{R}^3$

$$\mathbb{R}^3 = \text{span}\{e_1\} \oplus \text{span}\{e_2\} \oplus \text{span}\{e_3\}$$

$$\mathbb{R}^3 = \underbrace{N(A - \lambda_1 I)}_{n_1=1} \oplus \underbrace{N(A - \lambda_2 I)}_{n_2=1} \oplus \underbrace{N(A - \lambda_3 I)}_{n_3=1}$$

$\sim M_1$        $\sim M_2$        $\sim M_3$

$$\bar{A} = \begin{bmatrix} \quad \end{bmatrix} \quad P = \begin{bmatrix} p_1 & p_2 & p_3 \end{bmatrix} \\ = \begin{bmatrix} e_1 & e_2 & e_3 \end{bmatrix}$$

$$\bar{A} = P^{-1}AP \Rightarrow P\bar{A} = AP$$

$$\begin{bmatrix} e_1 & e_2 & e_3 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} = A \begin{bmatrix} e_1 & e_2 & e_3 \end{bmatrix}$$

$A$  is diagonalizable.

**THEOREM:** Let  $A$  be an  $n \times n$  matrix with  $n$  distinct eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ .

$$\lambda_i \neq \lambda_j \text{ when } i \neq j$$

Then the set of eigenvectors  $\{e_1, \dots, e_n\}$  form a linearly independent set. Moreover,

$$\text{Span}\{e_i\} = N(A - \lambda_i I)$$

Hence

$$N(A - \lambda_1 I) \underset{d_1=1}{\oplus} N(A - \lambda_2 I) \underset{d_2=1}{\oplus} \dots \underset{d_n=1}{\oplus} N(A - \lambda_n I)$$

Since  $N(A - \lambda_i I)$  is invariant under  $A$ ,  $A$  has a diagonal representation.

$$\bar{A} = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

$$\bar{A} = E^{-1}AE \text{ where } E = [e_1 | e_2 | \dots | e_n]$$

Proof: We have to show that  $\{e_1, \dots, e_n\}$  is a li set

Consider e.g.  $A$  is  $3 \times 3$  and  $\{e_1, e_2, e_3\}$  are its eigen vectors

$$\alpha_1 e_1 + \alpha_2 e_2 + \alpha_3 e_3 = 0$$

Multiply both sides with  $A - \lambda_1 I$  from the left

$$\begin{aligned} (A - \lambda_1 I) e_j &= A e_j - \lambda_1 e_j \\ &\stackrel{\lambda_j e_j}{=} (\lambda_j - \lambda_1) e_j \end{aligned}$$

$$\cancel{\alpha_1 (\lambda_1 - \lambda_1) e_1} + \alpha_2 (\lambda_2 - \lambda_1) e_2 + \alpha_3 (\lambda_3 - \lambda_1) e_3 = 0$$

$$\alpha_2 (\lambda_2 - \lambda_1) e_2 + \alpha_3 (\lambda_3 - \lambda_1) e_3 = 0$$

Let us multiply both sides with  $A - \lambda_2 I$

$$\alpha_2 (\lambda_2 - \lambda_1) (\lambda_2 - \lambda_2) e_2 + \alpha_3 (\lambda_3 - \lambda_1) (\lambda_3 - \lambda_2) e_3 = 0$$

$$\underbrace{\alpha_2}_{\neq 0} (\lambda_2 - \lambda_1) (\lambda_3 - \lambda_2) e_3 = 0 \quad \Rightarrow \quad \alpha_3 = 0$$

✓  
distinct  
eigen  
values

$$\left. \begin{array}{l} \Rightarrow \alpha_3 = 0 \\ \alpha_2 = 0 \\ \alpha_1 = 0 \end{array} \right\} e_1, e_2, e_3 \text{ are li'}$$

$e_1, e_2, \dots, e_n$  are li &  $\{e_1, \dots, e_n\}$  is a basis for  $\mathbb{C}^n$ .

$\downarrow$

$\in \mathbb{C}^n$

$$\mathbb{C}^n = \underbrace{\text{span}\{e_i\}}_{N(A - \lambda_1 I)} \oplus \underbrace{\text{span}\{e_i\}}_{N(A - \lambda_2 I)}$$

Prove that

$$N(A - \lambda_1 I) = \text{span}\{e_i\} \rightarrow \text{to prove that first prove } \text{span}\{e_i\} \subseteq N(A - \lambda_1 I)$$

then  $N(A - \lambda_1 I) \subseteq \text{span}\{e_i\}$

Part I) Let  $x$  be arbitrary in  $\text{span}\{e_i\}$   $x \in \text{span}\{e_i\}$

$$\begin{aligned} x &= \alpha e_i & (A - \lambda_1 I)x &= (A - \lambda_1 I)\alpha e_i \\ && &= \alpha (A - \lambda_1 I)e_i = \alpha (\lambda_i - \lambda_1) e_i \underset{\approx 0}{=} 0 \end{aligned}$$

$$\Rightarrow \text{span}\{e_i\} \subseteq N(A - \lambda_1 I)$$

Part II)  $x \in N(A - \lambda_1 I)$

$\in \mathbb{C}^n$

$$x = \sum_{j=1}^n \alpha_j e_j$$

$$\begin{aligned} x - \alpha_i e_i &= \sum_{\substack{j=1 \\ j \neq i}}^n \alpha_j e_j \\ \in N(A - \lambda_1 I) &\quad \in N(A - \lambda_1 I) \end{aligned}$$

$$0 = \sum_{\substack{j=1 \\ j \neq i}}^n \alpha_j \underbrace{(A - \lambda_1 I)}_{(\lambda_j - \lambda_1)} e_j$$

$$\sum_{\substack{j=1 \\ j \neq i}}^n a_j (\lambda_j - \lambda_i) e_j = 0$$

$$a_j (\lambda_j - \lambda_i) = 0 \quad \forall j \neq i$$

$$\lambda_j = 0 \quad \forall j \neq i \Rightarrow x - a_i e_i = 0 \Rightarrow x = a_i e_i$$

$$\Rightarrow x \in \text{span} \{e_i\}$$

$$\Rightarrow N(A - \lambda_i I) \subset \text{span} \{e_i\}$$

$$\Rightarrow N(A - \lambda_i I) = \text{span} \{e_i\}$$

$$\underbrace{d^n = N(A - \lambda_1 I) \oplus \dots \oplus N(A - \lambda_n I)}_{\text{dim }=1}$$

$$d(s) = \det(sI - A)$$

$$d(s) = s^n + d_1 s^{n-1} + \dots + d_{n-1} s + d_n$$

$$\deg(d(s)) = n$$

Distinct eigenvalue case:

$$d(s) = (s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n)$$

General Case:

$$d(s) = (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \dots (s - \lambda_p)^{r_p} \quad r_i: \text{multiplicity of } \lambda_i \text{ in } d(s)$$

$$r_1 + r_2 + \dots + r_p = n$$

ALGEBRAIC MULTIPLICITY

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad d(s) = \det(sI - A)$$

$$= \det \left( \begin{bmatrix} s-2 & -1 \\ -1 & s-2 \end{bmatrix} \right)$$

$$= s^2 - 4s + 3.$$

$$d(A) = A^2 - 4A + 3I$$

$$= \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} - 4 \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} + 3 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 5 & 4 \\ 4 & 5 \end{bmatrix} - \begin{bmatrix} 8 & 4 \\ 4 & 8 \end{bmatrix} + \begin{bmatrix} 3 & 0 \\ 0 & 3 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$d(A) = 0_{n \times n}$$

Theorem: (Cayley Hamilton Theorem)

Every  $n \times n$  matrix satisfies its characteristic eqn.

$$d(A) = 0_{n \times n}$$

$$A^n + d_1 A^{n-1} + \dots + d_n I = 0_{n \times n}$$

REMARK: Cayley Hamilton Thm basically says that  $n^{\text{th}}$  and higher order powers of an  $n \times n$  matrix can be written as a linear combination of its lower powers.

$$A^n = -d_1 A^{n-1} - d_2 A^{n-2} - \dots - d_n I$$

For previous example,

$$A^2 - 4A + 3I = 0$$

$$A^2 = 4A - 3I$$

$$A^3 = AA^2 = 4A^2 - 3A$$

$$= 4(4A - 3I) - 3A$$

$$= 13A - 12I$$

$$A^n = \alpha A + \beta I$$

$\forall n \in \mathbb{N}$

$$\exp(s) = \sum_{n=0}^{\infty} \frac{s^n}{n!}$$

$$\exp(A) = \sum_{n=0}^{\infty} \frac{A^n}{n!}$$

$$= \alpha A + \beta I$$

$$A^{-1} = ?$$

$$A^2 - 4A + 3I = 0$$

$$A - 4I + 3A^{-1} = 0 \Rightarrow A^{-1} = \frac{-A + 4I}{3}$$

$$f(A) = \alpha A + \beta I$$

---

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad A^{100} = ?$$

$$A^{100} = \alpha A + \beta I$$

$$\lambda_1 = 3 \quad e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 1 \quad e_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

→ from earlier  
lectures

$$A^{100} = \alpha A + \beta I$$

$$\rightarrow A^{100} e_1 = \alpha A e_1 + \beta e_1 \rightarrow A e_1 = \lambda_1 e_1$$

$$3^{100} e_1 = 3\alpha e_1 + \beta e_1$$

$$A^2 e_1 = \lambda_1 A e_1 = \lambda_1^2 e_1$$

$$3^{100} e_1 = (3\alpha + \beta) e_1$$

$$A^n e_1 = \lambda_1^n e_1$$

$$\boxed{3^{100} = 3\alpha + \beta}$$

$$\rightarrow A^{100} e_2 = \alpha A e_2 + \beta e_2$$

$$e_2 = \alpha e_2 + \beta e_2$$

$$\boxed{\alpha + \beta = 1}$$

$$\Rightarrow \alpha = \frac{3^{100}-1}{2}$$

$$\beta = \frac{3 - 3^{100}}{2}$$

$$\Rightarrow A^{100} = \frac{3^{100}-1}{2} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} + \frac{3 - 3^{100}}{2} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$d(A) = 0_{n \times n}$$

$$A^n + d_1 A^{n-1} + \dots + d_n I = 0$$

$$M(A) = 0_{n \times n} \rightarrow \text{sometimes yes!}$$

EXAMPLE:

$$A = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad d(s) = (s-2)^2(s-1)$$

$$\begin{aligned} d(A) &= (A - 2I)^2 (A - I) \\ &= (A - 2I)(A - 2I)(A - I) \end{aligned}$$

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

$$= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$m(s) = (s-2)(s-1)$$

$$m(A) = (A - 2I)(A - I)$$

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

$$m(A) = 0_{n \times n}$$

$\downarrow$   
called minimal polynomial

## MINIMAL POLYNOMIAL

DEFINITION: A monic polynomial is a polynomial whose highest degree coefficient

is unity,  $= 1$

Ex

$$s^n + a_1 s^{n-1} + \dots \rightarrow \text{monic}$$

$$2s^n + a_1 s^{n-1} + \dots \rightarrow \text{not monic}$$

**DEFINITION:** For an  $n \times n$  matrix  $A$ , the minimal polynomial  $m(s)$  is the monic polynomial with the smallest degree such that

$$m(A) = 0_{n \times n}$$

**Theorem:** Given  $A \in \mathbb{C}^{n \times n}$ , let  $m(s)$  be its minimal polynomial

i)  $m(s)$  is unique.

ii)  $m(s)$  divides  $d(s)$  without any remainder.

$$\exists q(s) \text{ s.t. } d(s) = m(s)q(s)$$

iii) Every root of  $d(s)$  is also a root of  $m(s)$

$$d(s) = (s-2)^2(s-1)$$

~~$m(s) \neq (s-2)^2$~~   $\rightarrow$  Prop iii) is violated

$$m(s) = (s-2)(s-1) \checkmark$$

$$m(s) = (s-2)^2(s-1) \checkmark$$

$m(s) = (s-2)(s-1)(s-3) \rightarrow$  prop ii) is not satisfied

$$\begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad d(s) = (s-2)^2(s-1) \\ m(s) = (s-2)(s-1) \checkmark$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad d(s) = (s-2)^2(s-1) \\ \cancel{m(s) \neq (s-2)(s-1)} \quad m(s) = (s-2)^2(s-1) \checkmark$$

?

↓

check

$$(A-2I)(A-I)$$

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

Proof:

i) Suppose  $m(s)$  is not unique!

$$m_1(s) \text{ monic}$$

$$m_2(s) \text{ monic}$$

$$m_1(A) = 0_{n \times n}$$

$$m_2(A) = 0_{n \times n}$$

$$\Rightarrow \deg m_1 = \deg m_2 = k$$

$$m_1(s) = s^k + a_1 s^{k-1} + \dots + a_k$$

$$m_2(s) = s^k + b_1 s^{k-1} + \dots + b_k$$

$$a_i \neq b_i \text{ for some } i$$

$$m_1(s) - m_2(s) = (a_1 - b_1)s^{k-1} + (a_2 - b_2)s^{k-2} + \dots + (a_k - b_k)$$

$$\text{Suppose } a_1 - b_1 \neq 0$$

$$\frac{m_1(s) - m_2(s)}{a_1 - b_1} = s^{k-1} + \frac{a_2 - b_2}{a_1 - b_1} s^{k-2} + \dots + \frac{a_k - b_k}{a_1 - b_1}$$

$$\underbrace{\quad}_{\substack{a_1 - b_1}} \frac{m_1(A) - m_2(A)}{a_1 - b_1} = 0_{n \times n}$$

$$\left. \begin{array}{l} \deg \frac{m_1(s) - m_2(s)}{a_1 - b_1} < k \\ \text{monic} \end{array} \right\} \begin{array}{l} \text{contradiction} \\ \text{to the starting} \\ \text{assumption} \\ \text{that } m_1 \text{ & } m_2 \\ \text{are minimal.} \end{array}$$

ii)  $m(s)$  divide  $d(s)$  without a remainder

$$d(s) = m(s) q(s)$$

$$\begin{array}{r} s^3 + 2s^2 + 3s + 4 \\ - s^3 - 2s^2 - s \\ \hline 2s + 4 \end{array} \quad \left| \begin{array}{c} s^2 + 2s + 1 \\ s \end{array} \right.$$

$$(s^3 + 2s^2 + 3s + 4) = (s^2 + 2s + 1)s + (2s + 4)$$

$$d(s) = m(s) q(s) + \underline{r(s)}$$

$$\text{degree } (r(s)) < \text{degree } m(s)$$

Assume  $r(s) \neq 0$

$$d(s) = m(s) q(s) + r(s)$$

$$\tilde{d}(A) = m(A) q(A) + r(A)$$

$$\tilde{o}_{nn} = o_{nn} + r(A)$$

$$r(A) = o_{nn}$$

$$\deg(r(s)) < \deg(m(s))$$

$m(s)$  is not minimal  $\Rightarrow$  contradiction

$A \in \mathbb{C}^{n \times n}$   $\lambda_1, \lambda_2, \dots, \lambda_n$

15.12.2015

Tuesday

$\lambda_i \neq \lambda_j$  when  $i \neq j$

$$\mathbb{C}^n = \underbrace{N(A - \lambda_1 I)}_{\dim=1} \oplus \underbrace{N(A - \lambda_2 I)}_{\dim=1} \oplus \dots \oplus \underbrace{N(A - \lambda_n I)}_{\dim=1}$$

$$\left( \begin{array}{l} x \in N(A - \lambda_1 I) \\ (A - \lambda_1 I)x = 0 \\ \downarrow Ax = \lambda_1 x \end{array} \right) = \text{span}\{e_1\} \oplus \text{span}\{e_2\} \oplus \dots \oplus \text{span}\{e_n\}$$

$n$  linearly ind. eigenvector

$$Ax = \lambda_1 x \in N(A - \lambda_1 I) \quad \bar{A} = E^{-1} A E \quad E = [e_1 \ e_2 \ \dots \ e_n]$$

$$\bar{A} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & 0 \\ & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix} \text{ is diagonal}$$

$A$  is diagonalizable

How can we generalize this result to matrices with repeated eigen-values?

$$\begin{aligned} d(s) &= \det(sI - A) = s^n + a_1 s^{n-1} + \dots + a_n = 0 \\ &= (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \dots (s - \lambda_n)^{r_n} \end{aligned}$$

$$r_1 + r_2 + \dots + r_n = n$$

[In the distinct eigenvalue case:  $d(s) = (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \dots (s - \lambda_n)^{r_n}$ ]

Characteristic Polynomial =  $d(s)$

$d(s) = 0$  : char. eqn.

$d(A) = 0_{n \times n}$  (Cayley Hamilton Thm)

Minimal Polynomial : Monic polynomial with the least degree s.t  $m(s)$

$$m(A) = O_{n \times n}$$

Properties:

- 1)  $m(s)$  is unique
- 2)  $m(s)$  divides  $d(s)$  without any remainder  
 $\exists g(s)$  st  $d(s) = m(s)g(s)$
- 3) Every root of  $d(s)$  is a root of  $m(s)$ .

$$d(s) = (s-2)^4(s-u)^2$$

$$\cancel{m(s) = (s-3)} \quad (\text{Property #2})$$

$$\cancel{m(s) = (s-2)^5(s-u)} \quad (\text{Property #2})$$

$$\cancel{m(s) = (s-u)^2} \quad (\text{Property #3})$$

$$m(s) = s^l + c_1 s^{l-1} + \dots + c_l$$

$$m(A) = A^l + c_1 A^{l-1} + \dots + c_l I = O_{n \times n}$$

$$\lambda_i \quad i=1, \dots, 0$$

Consider the eigen vector  $e_i$

$$m(A) e_i = O_{n \times 1}$$

[ ] ↑  
Vector

$$A^l e_i + c_1 A^{l-1} e_i + \dots + c_l e_i = O_{n \times 1}$$

$$A e_i = \lambda_i e_i$$

$$A^2 e_i = A A e_i = A \lambda_i e_i = \lambda_i^2 e_i$$

$$A^3 e_i = \lambda_i^3 e_i$$

$$\left. \begin{aligned} A^k e_i &= \lambda_i^k e_i \end{aligned} \right\}$$

$$\lambda_i^l e_i + c_1 \lambda_i^{l-1} e_i + \dots + c_l e_i = 0_{n \times 1}$$

$$(\lambda_i^l + c_1 \lambda_i^{l-1} + \dots + c_l) e_i = 0_{n \times 1}$$

↑  
≠ 0<sub>n × 1</sub>  
by  
definition

$$\Rightarrow \lambda_i^l + c_1 \lambda_i^{l-1} + \dots + c_l = 0$$

$$\Rightarrow m(\lambda_i) = 0$$

$\lambda_i$  is a root of  $m(s)$

EXAMPLE:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

$$d(s) = (s-1)(s-2)(s-3)$$

$$m(s) = (s-1)^{r_1} (s-2)^{r_2} (s-3)^{r_3}$$

When A has distinct eigenvalues we have

$$d(s) = m(s) = (s-\lambda_1)(s-\lambda_2)\dots(s-\lambda_n)$$

$$\mathbb{R}^3 = N(A - \lambda_1 I) \oplus N(A - \lambda_2 I) \oplus N(A - \lambda_3 I)$$

$$d(s) = (s-\lambda_1)^{r_1} (s-\lambda_2)^{r_2} \dots (s-\lambda_n)^{r_n}$$

$$m(s) = (s-\lambda_1)^{m_1} (s-\lambda_2)^{m_2} \dots (s-\lambda_n)^{m_n}$$

$$1 \leq m_i \leq r_i$$

$$r_1 + r_2 + \dots + r_n = n$$

$$A - I = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \quad N(A - I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}}_{e_1} \right\}$$

$$A - 2I = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad N(A - 2I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_{e_2} \right\}$$

$$A - 3I = \begin{bmatrix} -2 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad N(A - 3I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}_{e_3} \right\}$$

### 3.1.1 eigen vectors

What happens when there is repeated eigen values?

$$A_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\therefore d_1(s) = (s-1)(s-2)^2$$

$$d_2(s) = (s-1)(s-2)^2$$

$$m_1(s) = (s-1)(s-2) \checkmark$$

$$m_2(s) = (s-1)(s-2) \times \rightarrow \text{not satisfy}$$

satisfy eqn.

$$\text{but it has } (A_1 - I)(A_1 - 2I)$$

not lower power

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

$$(A_2 - I)(A_2 - 2I)$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 2 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \neq 0_{3 \times 3}$$

$$A_1 - I = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad N(A_1 - I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}}_{e_1} \right\}$$

$$A_2 - I = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad N(A_2 - I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}}_{e_1} \right\}$$

$$A_1 - 2I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad N(A_1 - 2I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_{e_2}, \underbrace{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}_{e_3} \right\}$$

$$A_2 - 2I = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad N(A_2 - 2I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_{e_2} \right\}$$

$$\mathbb{R}^3 = \underbrace{N(A_1 - I)}_{\text{dim=1}} \oplus \underbrace{N(A_1 - 2I)}_{\text{dim=2}}$$

$$\mathbb{R}^3 = \underbrace{N(A_2 - I)}_{\text{dim=1}} \oplus \underbrace{N(A_2 - 2I)}_{\text{dim=2}}$$

$$\mathbb{R}^3 = N(A - \lambda_1 I) \oplus N(A - \lambda_2 I) \oplus N(A - \lambda_3 I)$$

$$(A_2 - 2I)^2 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$N((A_2 - 2I)^2) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_{\in \mathcal{E}_2}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

$$\mathbb{R}^3 = \underbrace{N(A_2 - I)}_{\dim=1} \oplus \underbrace{N((A_2 - 2I)^2)}_{\dim=2}$$

$$C^0 = \underbrace{N((A - \lambda_1 I)^{m_1})}_{\dim \mathcal{E}_1} \oplus \underbrace{N((A - \lambda_2 I)^{m_2})}_{\dim \mathcal{E}_2} \oplus \dots \oplus \underbrace{N((A - \lambda_n I)^{m_n})}_{\dim \mathcal{E}_n}$$

18.12.2015  
Friday

$$A \in \mathbb{C}^{n \times n}$$

$$\lambda_1, \lambda_2, \dots, \lambda_n \quad \lambda_i + \lambda_j \text{ when } i \neq j$$

$$d(s) = (s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n)$$

$$m(s) = (s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n)$$

$$C^0 = \underbrace{N(A - \lambda_1 I)}_{\text{span } \{\lambda_1\}} \oplus \underbrace{N(A - \lambda_2 I)}_{\text{span } \{\lambda_2\}} \oplus \dots \oplus \underbrace{N(A - \lambda_n I)}_{\text{span } \{\lambda_n\}}$$

$$\tilde{A} = E' A E$$

$$E = [e_1 \ e_2 \ \dots \ e_n]$$

$$\tilde{A} = \begin{bmatrix} \lambda_1 & & & \\ & \ddots & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix}$$

$$A_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$d_1(s) = (s-1)(s-2)^2$$

$$m_1(s) = (s-1)(s-2)$$

$$N(A_1 - I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}}_{\tilde{e}_1} \right\}$$

$$N(A_1 - 2I) = \text{span} \left\{ \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_{\tilde{e}_2}, \underbrace{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}_{\tilde{e}_3} \right\}$$

$$A_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

$$d_2(s) = (s-1)(s-2)^2$$

$$m_2(s) = (s-1)(s-2)^2$$

$$N(A_2 - I) = \text{span} \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \right\}$$

$$N(A_2 - 2I) = N \left( \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \right) = \text{span} \left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$\mathbb{R}^3 = N(A_2 - I) \oplus N(A_2 - 2I)$$

$$\mathbb{R}^3 = N(A_1 - I) \oplus N(A_1 - 2I)$$

$$N((A_2 - 2I)^2) = \left( \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \right) = \text{span} \left\{ \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}$$

$$\mathbb{R}^3 = N(A_2 - I) \oplus N((A_2 - 2I)^2)$$

because it's inside  $N(A_2 - 2I)$

but it is called generalized eigenvector

\* There is some relationship between decomposition form &  $m(s)$

in terms of power.

$$m_2(s) = (s-1)^1(s-2)^2$$

$$\mathbb{R}^3 = N((A_2 - I)^1) \oplus N((A_2 - 2I)^2)$$

**THEOREM:**  $(A - \lambda_1 I)^{m_1} \oplus N((A - \lambda_2 I)^{m_2}) \oplus \dots \oplus N((A - \lambda_{10} I)^{m_{10}})$

$$d(s) = (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \cdots (s - \lambda_5)^{r_5}$$

$$r_1 + r_2 + \dots + r_k = n$$

$$m(s) = (s - \lambda_1)^{m_1} (s - \lambda_2)^{m_2} \dots (s - \lambda_r)^{m_r}$$

$$1 \leq m_i \leq r_i$$

$$\bar{A} = \begin{bmatrix} \bar{A}_1 & & & \\ & \bar{A}_2 & & 0 \\ & & \ddots & \\ 0 & & & \bar{A}_0 \end{bmatrix}$$

$\hat{A} = B^{-1}AB$  where  $B$  is composed of

basis vectors for  $N(A - \lambda_i I)$

$$B = [B_1 \ B_2 \ \dots \ B_D]$$

$B_i$  is composed of basis vectors for  $N(A - \lambda_i I)$

$$\text{Size of } \bar{A}_i = \dim N((A - \lambda_i I)^{m_i})$$

We now concentrate on the structure of  $N((A - \lambda_i I)^{m_i})$

$$\sum_i \triangleq A - \lambda_i I$$

### Theorem:

$$N(\sum_i \xi^i) \subset N(\sum_i \xi^{2i}) \subset N(\sum_i \xi^{3i}) \subset \dots$$

$$N(A-\lambda I)$$

 proper Subset

$$A \nsubseteq B \Rightarrow A \subset B$$

$A \neq B$

Proof: We first show that  $N(\Sigma_i^1) \subset N(\Sigma_i^{1+1})$

let  $x$  be arbitrary and

$$x \in N(\Sigma_i^1)$$

$$\Rightarrow \sum_i^1 x = 0$$

$$\Sigma_i \Sigma_i^1 x = \Sigma_i 0 = 0$$

$$\Sigma_i^{1+1} x = 0$$

$$\Rightarrow x \in N(\Sigma_i^{1+1})$$

We show that when

$$N(\Sigma_i^1) = N(\Sigma_i^{1+1})$$

then

$$N(\Sigma_i^{1+1}) = N(\Sigma_i^{1+2})$$

$$- N(\Sigma_i^{1+1}) \subset N(\Sigma_i^{1+2}) \rightarrow \text{this is already proven.}$$

$$- N(\Sigma_i^{1+2}) \subset N(\Sigma_i^{1+1})$$

$$\hookrightarrow x \in N(\Sigma_i^{1+2})$$

$$\Sigma_i^{1+2} x = 0$$

$$\Sigma_i^{1+1} \Sigma_i x = 0$$

~~~~~

$$\Sigma_i x \in N(\Sigma_i^{1+1})$$

$$\Sigma_i x \in N(\Sigma_i^1)$$

$$\sum_i^1 \Sigma_i x = 0 \Rightarrow \sum_i^{l+1} x = 0 \Rightarrow x \in N(\Sigma_i^{l+1})$$

Suppose we call the smallest power  $\ell$  where  $N(\Sigma_i^\ell) = N(\Sigma_i^{l+1})$   
to be  $k_1$ ,

$$N(\Sigma_i) \subset N(\Sigma_i^2) \subset N(\Sigma_i^3) \subset \dots \subset N(\Sigma_i^{k_1}) = N(\Sigma_i^{k_1+1}) = N(\Sigma_i^{k_1+2}) = \dots$$

EXAMPLE:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix} \quad d(s) = (s-1)^3(s-2)$$

$$m(s) = ? = (s-1)^2(s-2)$$

$$(A - I) = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\Sigma_1} \quad \dim N(A - I) = 2$$

$$\downarrow$$

$$\Sigma_1^2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \rightarrow \dim N(\Sigma_1^2) = 3$$

$$\downarrow$$

$$\Sigma_1^3 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \rightarrow \dim N(\Sigma_1^3) = 3 = r_1$$

$$\dim N(\Sigma_1^4) = 3$$

$$\Sigma_2 = A - \lambda_2 I = A - 2I = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \dim N(\Sigma_2^1) = 1 = r_2$$

$$\downarrow$$

$$\Sigma_2^2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -2 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \dim N(\Sigma_2^2) = 1$$

$$m(s) = (s-1)(s-2)$$

$$(A - I)(A - 2I) = 0$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \neq 0$$

$$m(s) = (s-1)^2(s-2)$$

$$\Sigma_1^2 \Sigma_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Theorem:  $d(s) = (s-\lambda_1)^{r_1} (s-\lambda_2)^{r_2} \dots (s-\lambda_\sigma)^{r_\sigma}$

$$m(s) = (s-\lambda_1)^{m_1} (s-\lambda_2)^{m_2} \dots (s-\lambda_\sigma)^{m_\sigma}$$

$$1 \leq m_i \leq r_i$$

$$- k_i = m_i$$

$$- \dim((A - \lambda_i I)^{m_i}) = r_i$$

$$\dim N\left(\sum_i^{m_i=1}\right) < r_i$$

$$N(\Sigma_i) \subset N(\Sigma_i^2) \subset \dots \subset \underbrace{N(\Sigma_i^{m_i})}_{\dim=r_i} = \underbrace{N(\Sigma_i^{m_i+1})}_{\dim=r_i} = \dots$$

EXAMPLE:

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}$$

$$d(s) = (s-1)^3(s-2)$$

$$m(s) = (s-1)^3(s-2)$$

$$\Sigma_1 \triangleq A - I = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\Rightarrow \dim N(\Sigma_1) = 1 \rightarrow \text{not } 3$$

continue to take power of  $\Sigma_1$

$$\Sigma_1^2 = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \dim(N(\Sigma_1^2)) = 2$$

$$\Sigma_1^3 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \dim(N(\Sigma_1^3)) = 3 = r_1 \Rightarrow m_1 = 3$$

$$\Rightarrow M(s) = (s-1)^3(s-2)$$

EXAMPLE:

$$A = \left[ \begin{array}{ccc|cc|cc|c} 2 & 1 & 0 & & & & & & \\ 0 & 2 & 1 & & & & & & \\ 0 & 0 & 2 & & & & & & \\ \hline & & & 2 & 1 & & & & \\ & & & 0 & 2 & & & & \\ & & & & & 2 & & & \\ & & & & & 0 & 3 & & \\ & & & & & & & 3 & \\ \hline & & & & & & & & \end{array} \right]$$

A matrix in Jordan Canonical form

Consider a single Jordan block:

$$A_1 = \begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} \quad d_1(s) = (s-2)^3$$

$$A_1 - 2I = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad \dim N(A_1 - 2I) = 1$$

$$(A_1 - 2I)^2 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \dim N((A_1 - 2I)^2) = 2$$

$$(A_1 - 2I)^3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \dim N((A_1 - 2I)^3) = 3$$

$$\dim(N(A_1 - 2I)^l) = 3$$

$$l \geq 3$$

Now, let's go back to  $10 \times 10$  matrix,

$$d(s) = (s-2)^7 (s-3)^3$$

$$m(s) = (s-2)^? (s-3)^?$$

$$\Sigma_1 = A - 2I \rightarrow \dim N(\Sigma_1) = 6$$

$$\dim N(\Sigma_1^2) = 6$$

$$\dim N(\Sigma_1^3) = 7$$

$$\dim N(\Sigma_1^4) = 7$$

$$\Sigma_2 = A - 3I \rightarrow \dim N(\Sigma_2) = 2$$

$$\dim N(\Sigma_2^2) = 3$$

$$\dim N(\Sigma_2^3) = 3$$

$$\Rightarrow m(s) = (s-2)^3 (s-3)^2$$

$\dim N(\Sigma_i)$ : # of Jordan blocks corresponding to eigenvalue  $\lambda_i$ .

= # of Jordan blocks with size  $\geq 1$

$\dim N(\Sigma_i^2) - \dim N(\Sigma_i)$ : # of Jordan blocks with size  $\geq 2$  corresponding to  $\lambda_i$ .

$\dim N(\Sigma_i^3) - \dim N(\Sigma_i^2)$ : # of Jordan blocks with size  $\geq 3$  corresponding to  $\lambda_i$

$\dim N(\Sigma_i^k) - \dim N(\Sigma_i^{k-1})$ : # of " " " " site  $\geq k$  " "

$m_i$ : size of the largest Jordan block corresponding to  $\lambda_i$ .

$$m(S) = (s-2)^3 (s-3)^2$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} \quad \begin{bmatrix} 3 & 1 \\ 0 & 3 \end{bmatrix}$$

$3 \times 3$        $2 \times 2$

$\tilde{A} = B^{-1} A B$   
 ↳ in Jordan canonical form       $\Rightarrow B = ?$   
 What should be chosen our basis set such that  
 the simple representation  $\tilde{A}$  is in J.C.F.

22.12.2015  
 Tuesday

$A \in \mathbb{C}^{n \times n}$

$$\mathbb{C}^n = N\left(\underbrace{(A - \lambda_1 I)}_{\dim r_1}^{m_1}\right) \oplus \dots \oplus N\left(\underbrace{(A - \lambda_\sigma I)}_{\dim r_\sigma}^{m_\sigma}\right)$$

$$d(S) = (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \dots (s - \lambda_\sigma)^{r_\sigma}$$

$$m(S) = (s - \lambda_1)^{m_1} (s - \lambda_2)^{m_2} \dots (s - \lambda_\sigma)^{m_\sigma}$$

$$r_1 + r_2 + \dots + r_\sigma = n$$

$$1 \leq m_i \leq r_i$$

$$\Sigma_i = A - \lambda_i I$$

$$N(\Sigma_i) \subset N(\Sigma_i^2) \subset \dots \subset N(\Sigma_i^{m_i}) = N(\Sigma_i^{m_i})$$

$$\dim r_i$$

$$N(\Sigma_i^{m_i}) = N(\Sigma_i^{m_i})$$

A matrix in JCF

$\dim N(A - \lambda_i I)$ : # of Jordan block for  $\lambda_i$  with size  $\geq 1$

$\dim N((A - \lambda_i I)^2) - \dim N(A - \lambda_i I)$ : # of Jordan blocks for  $\lambda_i$  with size  $\geq 2$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \xrightarrow{(1)}^3 \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$\downarrow (1)^2$

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

$\dim N((A - \lambda_i I)^k) - \dim N((A - \lambda_i I)^{k-1})$ : # of Jordan blocks for  $\lambda_i$  with size  $\geq k$

$m_i$ : size of the largest Jordan block for  $\lambda_i$ .

Finding JCF for a matrix  $A$  from Subspace Dimensions

$$\bar{A} = B^{-1} A B$$

$\text{rank } A = \text{rank } BA$  where  $B$  is an invertible matrix

$\text{rank } A = \text{rank } AB$  where " " "

$$(\bar{A} - \lambda_i I) B^{-1} (A - \lambda_i I) B = B^{-1} A B - \lambda_i B^{-1} B = \bar{A} - \lambda_i I$$

$$\dim N(A - \lambda_i I) = \dim N(\bar{A} - \lambda_i I)$$

$\downarrow$   
 $A$  is not in JCF  
but we will still  
find  $\dim$  of null  
space of  $\bar{A}$  with this.

EXAMPLE: Suppose a matrix  $A \in \mathbb{R}^{8 \times 8}$  has the following subspace dimensions.

$$\dim N(A - 3I) = 5 \rightarrow \begin{matrix} 2 \\ 2 \\ 2 \end{matrix} \rightarrow 2$$

$$\dim N((A - 3I)^2) = 7 \rightarrow$$

$$\dim N((A - 3I)^3) = 8 \quad \mathbb{R}^8 = ((A - 3I)^3)$$

a) Find  $\text{d}(S)$

$$\text{d}(S) = (s-3)^8$$

b) Find  $m(S)$

$$m(S) = (s-3)^3$$

c) What is JCF for  $A$ ? ( $\bar{A} = ?$ )

$\dim N(A - 3I) = \# \text{ of Jordan blocks for } \lambda = 3 \text{ with size } \geq 1$

$\Rightarrow \# \text{ of Jordan blocks} = 5$

$\dim N((A - 3I)^2) - \dim N(A - 3I) = 2 = \# \text{ of Jordan blocks with size } \geq 2$

$\dim N((A - 3I)^3) - \dim N((A - 3I)^2) = 1 = \# \text{ of Jordan blocks with size } \geq 3$

Further substractions will give us zero.  $\Rightarrow \# \text{ of JB with size } \geq 4 = 0$

# of Jordan blocks with size = 3  $\geq 1 \rightarrow 5$

$\geq 2 \rightarrow 2$

# of Jordan blocks with size = 2  $\geq 3 \rightarrow 1$

# of Jordan blocks with size = 1 = 3

$$\bar{A} = \left[ \begin{array}{ccccc|cc} 3 & 1 & & & & 0 & 7 \\ 3 & 3 & 1 & & & & \\ 3 & 3 & 3 & & & & \\ & & & 3 & 1 & & \\ & & & & 3 & & \\ & & & & & 3 & \\ 0 & & & & & 3 & \\ & & & & & 3 & \end{array} \right]$$

EXAMPLE: Let  $A \in \mathbb{R}^{4 \times 4}$

Simple eigen value  $\lambda_1 = ?$

$$m_1 = 2$$

Find all possible JCFs.

$$d(s) = (s-7)^4$$

$$m(s) = (s-7)^2$$

$$N(A-7I) \subset N((A-7I)^2)$$

$$\dim = 3$$

$$= 2$$

$$= 1$$

$$\dim N((A-7I)^2) = 4$$

$$\dim N(A-7I) = 3$$

$$\# \text{ of blocks} = 3$$

$$\begin{array}{l} \# \text{ of blocks} \\ \text{size} \geq 2 \end{array} = 1$$

$$\begin{array}{l} \# \text{ of blocks} \\ \text{size} \geq 3 \end{array} = 0$$

$$\# \text{ of blocks with size} = 1 = 2$$

$$\# \text{ of blocks with size} = 2 = 1$$

$$\bar{A} = \left[ \begin{array}{c|c} 7 & 0 \\ \hline 7 & 0 \\ 0 & 7 \\ 0 & 7 \end{array} \right]$$

$$\dim N(A-7I) = 2$$

$$\# \text{ of blocks} = 2$$

$$\begin{array}{l} \# \text{ of blocks} \\ \text{size} \geq 2 \end{array} = 2$$

$$\bar{A} = \left[ \begin{array}{c|c} 7 & 0 \\ \hline 0 & 7 \\ 0 & 7 \\ 0 & 7 \end{array} \right]$$

$$\dim N(A-7I) = 1$$

$$\# \text{ of blocks} = 1$$

$$\begin{array}{l} \# \text{ of blocks} \\ \text{size} \geq 2 \end{array} = 3$$

There cannot be such an A matrix.  
This case is not possible!

2. Midterm Up to /

How to Find a Basis set to Convert a Matrix  $A$  into JCF

$$A \in \mathbb{C}^{n \times n}$$

$$J = B^{-1}AB$$

$$B = ?$$

$$C^1 = N\left(\underbrace{(A - \lambda_1 I)^{m_1}}_{F_1}\right) \oplus \dots \oplus N\left(\underbrace{(A - \lambda_d I)^{m_d}}_{F_d}\right)$$

$$B = [B_1 | B_2 | \dots | B_d]$$

$$B_i = \underbrace{\left[ b_i^{(1)} | b_i^{(2)} | \dots | b_i^{(r)} \right]}_{A \text{ basis set for } N((A - \lambda_i I)^{m_i})}$$

$$b_i^{(j)} = ?$$

$$J = \begin{bmatrix} \bar{A}_1 & & & \\ & \bar{A}_2 & & \\ & & \ddots & \\ & & & \bar{A}_d \end{bmatrix}$$

Since  $\bar{A}_i$  are going to be  $r_i \times r_i$

$$\bar{A}_i = \begin{bmatrix} x_i * & & & \\ & x_i * & 0 & \\ & & \ddots & \\ 0 & & & x_i * \end{bmatrix}_{r_i \times r_i} \quad \text{it can be } 1 \text{ or } 0.$$

$$\left[ \begin{array}{cc|cc} 7 & 1 & 0 & 0 \\ 0 & 7 & 0 & 0 \\ 0 & 0 & 7 & 1 \\ 0 & 0 & 0 & 7 \end{array} \right] \rightarrow \text{With } 180^\circ, \text{ we can determine size of JB.}$$

$A \in \mathbb{C}^{n \times n}$ 24.12.2015  
Thursday

$$\bar{A} = J = B^{-1}AB$$

$$J^n = N((A - \lambda_1 I)^{m_1}) \oplus \dots \oplus N((A - \lambda_d I)^{m_d})$$

we look for basis vectors for  $N((A - \lambda_i I)^{m_i})$

$$B = [B_1 \mid B_2 \mid \dots \mid B_d]$$

$B_i = [b_i^1 \mid b_i^2 \mid \dots \mid b_i^{r_i}]$   $b_i^1, \dots, b_i^{r_i}$  have to be basis vectors for  $N((A - \lambda_i I)^{m_i})$

$$\bar{A} = \begin{bmatrix} \bar{A}_1 & & & \\ & \bar{A}_2 & & \\ & & \ddots & \\ & & & \bar{A}_d \end{bmatrix}$$

$$\bar{A}_i \in \mathbb{C}^{n \times n}$$

$$\& \bar{A}_i = \begin{bmatrix} \lambda_i^{m_i} & & & & 0 \\ & \lambda_i^{m_i} & & & \\ & & \ddots & & \\ & & & \ddots & \\ 0 & & & & \lambda_i^{m_i} \end{bmatrix}$$
  
 $\neq \in \{0, 1\}$

$$\Sigma_i \stackrel{\Delta}{=} A - \lambda_i I$$

$$N(\Sigma_i) \subset N(\Sigma_i^{2}) \subset \dots \subset N(\Sigma_i^{m_i-1}) \subset N(\Sigma_i^{m_i}) = \dots$$
  
$$x \notin N(\Sigma_i^{m_i-1}) \quad x \in N(\Sigma_i^{m_i})$$

We can always find a vector  $x$  st  $x \in N(\Sigma_i^{m_i}) \& x \notin N(\Sigma_i^{m_i-1})$

Consider the chain of vectors:  $\{ \Sigma_i^{m_i-1} x, \Sigma_i^{m_i-2} x, \dots, \Sigma_i x, x \}$

Claim: The set  $\left\{ \sum_i^{m_i-1} x, \dots, x \right\}$  is li.

Proof:

$$\sum_i^{m_i-1} x + \alpha_1 \sum_i^{m_i-1} x + \alpha_2 \sum_i^{m_i-2} x + \dots + \alpha_{m_i-1} \sum_i^1 x + \alpha_{m_i} x = 0$$

$$\alpha_1 \sum_i^{2m_i-2} x + \alpha_2 \sum_i^{2m_i-3} x + \dots + \alpha_{m_i-1} \sum_i^m x + \alpha_{m_i} \sum_i^{m_i-1} x = 0$$

$$\alpha_{m_i} \underbrace{\sum_i^{m_i-1} x}_{\text{cannot be zero}} = 0 \Rightarrow \alpha_{m_i} = 0$$

$$\sum_i^{m_i-2} x + \alpha_1 \sum_i^{m_i-1} x + \alpha_2 \sum_i^{m_i-2} x + \dots + \alpha_{m_i-1} \sum_i^1 x = 0$$

$$\alpha_1 \sum_i^{2m_i-3} x + \alpha_2 \sum_i^{2m_i-4} x + \dots + \alpha_{m_i-1} \sum_i^{m_i-1} x = 0$$

$$\Rightarrow \alpha_{m_i-1} = 0$$

We can continue in this manner to show that  $\alpha_1, \dots, \alpha_{m_i}$  are all equal to zero

$\Rightarrow \left\{ \sum_i^{m_i-1} x, \dots, \sum_i^1 x \right\}$  is a li. set

$$(\sum_i^{m_i-1} x)$$

$$x \in N(\sum_i^{m_i}) \quad x \notin N(\sum_i^{m_i-1})$$

$$\sum_i (\sum_i^{m_i-1} x) = \sum_i^{m_i} x = 0$$

$$\sum_i^{m_i-1} x \in N(\sum_i) \subset N(\sum_i^2) \subset \dots$$

$$N(A - \lambda_i I)$$

$\sum_i^{m_i-1} x$  is an eigenvector corresponding to  $\lambda_i$ .

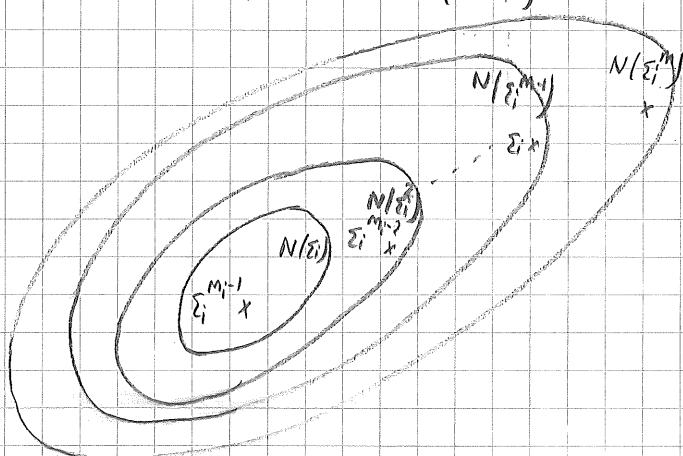
$$\sum_i \sum_i^{m_i-2} x = \sum_i^{m_i-1} x \neq 0$$

$$x \notin N(\Sigma_i)$$

$$\sum_i^2 \sum_i^{m_i-2} x = \sum_i^{m_i} x = 0$$

$$\Rightarrow \sum_i^{m_i-2} x \in N(\Sigma_i^2)$$

$$\sum_i^{m_i-k} x \in N(\Sigma_i^k)$$



If  $n=m$ , set is sufficient

but if it is NOT, we have

to add new vectors to set  
to make  $n=m$ .

### EXAMPLE:

$$A = \begin{bmatrix} 1 & 1 & -1 \\ -1 & 3 & 2 \\ 0 & 0 & 1 \end{bmatrix} \quad m(s) \\ A = ? = J \\ B = ? \text{ st } B^T A B = J$$

$$(sI - A) = \begin{bmatrix} s-1 & -1 & 1 \\ 1 & s-3 & -2 \\ 0 & 0 & s-1 \end{bmatrix}$$

$$d(s) = \det(sI - A) = (s-2)^2(s-1)$$

$\downarrow \lambda_1 \quad \downarrow \lambda_2$

$$\Sigma_1 = A - 2I = \begin{bmatrix} -1 & 1 & 1 \\ -1 & 1 & 2 \\ 0 & 0 & -1 \end{bmatrix} \quad \dim N(A - 2I) = 1$$

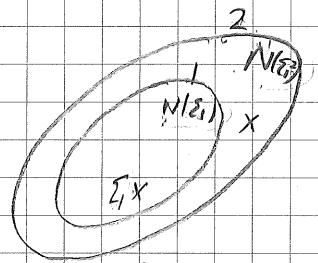
$m(s) = \cancel{(s-2)}(s-1)$

$$\Sigma_1^2 = \begin{bmatrix} 0 & 0 & 4 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad \dim N((A - 2I)^2) = 2$$

$\Rightarrow m(s) = (s-2)^2(s-1) = d(s)$

$$J = \left[ \begin{array}{cc|c} 2 & 1 & 0 \\ 0 & 2 & 0 \\ \hline 0 & 0 & 1 \end{array} \right]$$

$$\Sigma_2 = A - I = \begin{bmatrix} 0 & 1 & -1 \\ -1 & 2 & 2 \\ 0 & 0 & 0 \end{bmatrix} \quad \dim (A - I) = 1$$



$$x = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \Sigma_1 x = \begin{bmatrix} -1 \\ 0 \\ 0 \end{bmatrix}$$

↓ eigenvector

~~$x = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$~~  if it is inside  
of  $N(\Sigma_1)$  also  
so we cannot  
choose  $x$  like  
that

Chain for  $\lambda_1 = \{\Sigma_1 x, x\}$



$$y = \begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix}$$

↓  
eigenvectors

Chain for  $\lambda_2 = \{y\}$

$$B = \begin{bmatrix} 1 & x & y \\ x & 1 & y \\ y & y & 1 \end{bmatrix}$$

$$J = B^T A B \Rightarrow B J = A B$$

$$\underbrace{\begin{bmatrix} -1 & 1 & 4 \\ -1 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}}_B \underbrace{\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_J = \underbrace{\begin{bmatrix} 1 & 1 & -1 \\ -1 & 3 & 2 \\ 0 & 0 & 1 \end{bmatrix}}_{\text{Matrix}} \underbrace{\begin{bmatrix} -1 & 1 & 4 \\ -1 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}}_{\begin{bmatrix} 2 & 1 & 4 \\ -2 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}}$$

$$\underbrace{\begin{bmatrix} 1 & -1 & 4 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}}_{B_1} \underbrace{\begin{bmatrix} 2 & 0 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_J = \underbrace{\begin{bmatrix} 1 & 1 & -1 \\ -1 & 3 & 2 \\ 0 & 0 & 1 \end{bmatrix}}_{\text{Matrix}} \underbrace{\begin{bmatrix} 1 & 1 & 4 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}}_{\begin{bmatrix} 1 & -2 & 4 \\ 0 & -2 & 1 \\ 0 & 0 & 1 \end{bmatrix}}$$

$$B_2 = \begin{bmatrix} 4 & -1 & 1 \\ 1 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \rightarrow J_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} \checkmark$$

### Special Cases

Case - I: Let  $A$  have a single eigenvalue  $\lambda_i$  and we have  $m_i = r_i$ .

$$A \in \mathbb{C}^{r_i \times r_i}$$

$$d(s) = (s - \lambda_i)^{r_i} \quad \text{and} \quad (s - \lambda_i)^{m_i - r_i}$$

$$N(\Sigma_i) \subset N(\Sigma_i^2) \subset \dots \subset N(\Sigma_i^{m_i}) \subset \underbrace{N(\Sigma_i^{m_i+1})}_{r_i = m_i}$$

$$1 < 2 < \dots < m_i-1 < m_i$$

We have a single chain

$$\left\{ \sum_i^{m_i-1} x, \sum_i^{m_i-2} x, \dots, \sum_i^1 x, x \right\} \text{ A basis for } N(\sum_i^{m_i} x)$$

$m_i = r_i$

$$B = \left[ \begin{array}{c|c|c|c} \sum_i^{m_i-1} x & \sum_i^{m_i-2} x & \dots & \sum_i^1 x & x \end{array} \right]$$

$$B \left[ \begin{array}{ccccc} x_1 & 1 & 0 & & \\ 0 & x_1 & 1 & & \\ 0 & 0 & x_1 & 1 & \\ \vdots & \vdots & \vdots & \ddots & \\ 0 & 0 & 0 & \dots & 0 x_i \end{array} \right] = AB$$

↓  
for  $\sum_i^{m_i-1} x$

$$\text{For } \sum_i^{m_i-2} x \rightarrow \sum_i^{m_i-2} \sum_i^{m_i-1} x = \sum_i^{m_i-1} x$$

$$(A - \lambda_i I) \sum_i^{m_i-1} x = \sum_i^{m_i-1} x$$

$$A \sum_i^{m_i-2} x - \lambda_i \sum_i^{m_i-1} x = \sum_i^{m_i-1} x$$

$$A \sum_i^{m_i-2} x = \sum_i^{m_i-1} x + \lambda_i \sum_i^{m_i-2} x \Rightarrow \begin{bmatrix} 1 \\ \lambda_i \\ \vdots \end{bmatrix}$$

$$\text{For } \sum_i^{m_i-3} x \rightarrow \sum_i^{m_i-3} \sum_i^{m_i-2} x = \sum_i^{m_i-2} x$$

$$(A - \lambda_i I)$$

$$\Rightarrow A \sum_i^{m_i-3} x = \sum_i^{m_i-2} x + \lambda_i \sum_i^{m_i-3} x \Rightarrow \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$\Rightarrow J = \begin{bmatrix} \lambda_i & 1 & & & \\ 0 & \lambda_i & 1 & & \\ 0 & 0 & \lambda_i & 1 & \\ \vdots & \vdots & \vdots & \ddots & \\ 0 & 0 & 0 & \dots & \lambda_i \end{bmatrix}$$

We have a single block with size  $r_i = m_i$

$\sum_i^{m_i-1} x$  is the only eigenvector

The other vectors in the chain

are called "generalized eigen vectors."

Case II: A has a single eigenvalue  $\lambda_i$

$$m_i = 1$$

$$d(s) = (s - \lambda_i)^{r_i}$$

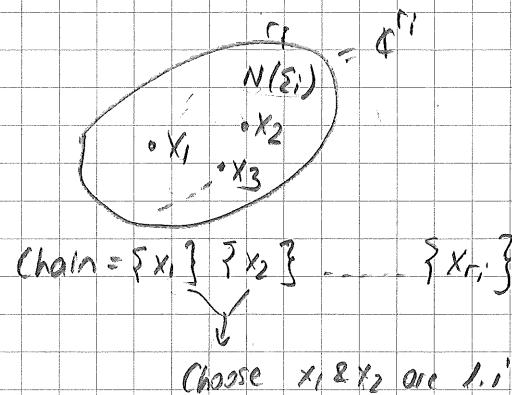
$$m(s) = (s - \lambda_i)$$

$$\underline{N(\Sigma_i)} = \underline{N(\Sigma^2)}$$

$$\dim r_i$$

$$\underbrace{\mathbb{C}^{r_i}}$$

$$r_i$$



Vectors  $x_1, \dots, x_i$  should be l.i.

We have  $r_i$  chains with size 1.

$r_i$  l.i. eigenvectors corresponding to  $\lambda_i$ .

$$B = [x_1 \mid x_2 \mid \dots \mid x_{r_i}]$$

$$B \begin{bmatrix} \lambda_i & 0 & 0 & 0 \\ 0 & \lambda_i & 0 & 0 \\ 0 & 0 & \lambda_i & 0 \\ \vdots & \vdots & \vdots & \lambda_i \end{bmatrix} = AB$$

We have diagonal J.C.F

It is not surprise  $m(s) = (s - \lambda_i) \Rightarrow A - \lambda_i I = 0 \Rightarrow A = \lambda_i I$

EXAMPLE:  $A$  is a  $6 \times 6$  matrix,  $\lambda_i$  is the only eigenvalue.

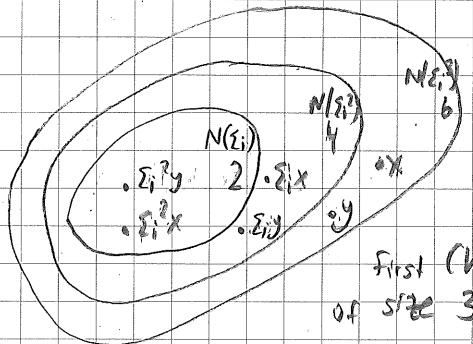
$$d(s) = (s - \lambda_i)^6 \quad \dim N(\Sigma_i) = 2$$

$$m(s) = (s - \lambda_i)^3 \quad \dim N(\Sigma_i^2) = 4$$

$B = ?$

$$N(\Sigma_i) \subset N(\Sigma_i^2) \subset N(\Sigma_i^3) = N(\Sigma_i^4) = \dots$$

2                  4                  6



Find  $x \in N(\Sigma_i^3)$

$x \notin N(\Sigma_i^2)$

first chain =  $\{\Sigma_i^2 x, \Sigma_i x, x\}$   
of size 3

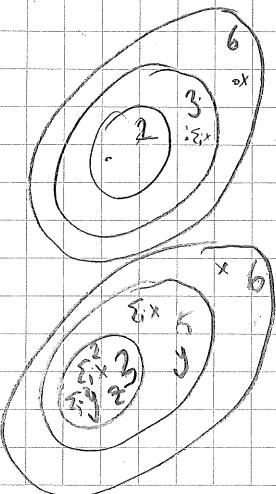
We can find  $y$  which is  $\perp$  with  $x$  because  
dimension is increase from 4 to 6.

Find  $y \in N(\Sigma_i^3)$

$y \notin N(\Sigma_i^2)$

$\Sigma_i^2 x$  &  $\Sigma_i^2 y$  should be  $\perp$ . i.e. (if we guarantee this condition, we already have  $\perp$  i.e.  $\Sigma_i^2 x, \Sigma_i x, x$  &  $\Sigma_i^2 y, \Sigma_i y, y$ )

The vectors in the inner most space have to be  $\perp$ ;  $\{\Sigma_i^2 y, \Sigma_i y, y\}$   
second chain with size 3.



then  
size  $\geq 1 = 3$   
size  $\geq 2 = 1$   
size  $\geq 3 = 3$

Not possible  
must be  
decrease

$\{\Sigma_i^2 x, \Sigma_i x, x, \Sigma_i y, y, z\}$

size  $\geq 1 = 3$

size  $\geq 2 = 2$

size  $\geq 3 = 1$

$$\begin{bmatrix} x_1 & 0 \\ x_2 & 0 \\ x_3 & 0 \\ x_4 & 0 \\ x_5 & 0 \\ x_6 & 0 \end{bmatrix} \cdot \begin{bmatrix} \Sigma_i^2 x \\ \Sigma_i x \\ x \\ \Sigma_i y \\ y \\ z \end{bmatrix} = 0$$

$$B = [\Sigma_i^2 x, \Sigma_i x, x, \Sigma_i^2 y, \Sigma_i y, y]$$

$$J = \begin{bmatrix} \lambda_i & 0 & & & & \\ 0 & \lambda_i & & & & \\ & 0 & \lambda_i & & & \\ & & 0 & \lambda_i & 0 & \\ & & & 0 & \lambda_i & \\ & & & & 0 & \lambda_i \end{bmatrix}$$

! # of Jordan blocks will be equal to # of chains.

! Sizes of the Jordan blocks will be equal to the sizes of the chains.

EXAMPLE:  $4 \times 4$  matrix

Single eigen value  $\lambda_1$ :  $M_1 = 2$

Find all possible chains and JCFs.

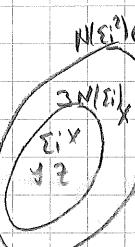
$$d(s) = (s - \lambda_1)^4$$

$$m(s) = (s - \lambda_1)^2$$

$$\begin{aligned} N(\Sigma_1) &\subset N(\Sigma_1^2) \\ 3, 2, 1 & \quad 4 \end{aligned}$$

Case I:  $N(\Sigma_1) \subset N(\Sigma_1^2)$

$$\begin{bmatrix} \lambda_1 & 1 & & \\ 0 & \lambda_1 & & \\ & 0 & \lambda_1 & \\ & & 0 & \lambda_1 \end{bmatrix}$$



(choose  $x \in N(\Sigma_1^2)$ )  
 $x \notin N(\Sigma_1)$

$\Sigma_1 x$  &  $\Sigma_1^2 x$  should be linearly independent

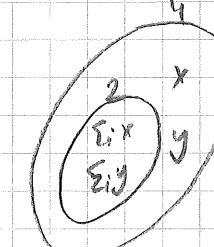
$$\{\Sigma_1 x, \Sigma_1^2 x\} \neq \emptyset$$

$$B = [\Sigma_1 x, x, y, z]$$

3 eigenvectors:  $\Sigma_1 x, y, z$

Case II:  $N(\Sigma_1) \not\subset N(\Sigma_1^2)$

$$\begin{bmatrix} \lambda_1 & 1 & & \\ 0 & \lambda_1 & & \\ & 0 & \lambda_1 & 1 \\ & & 0 & \lambda_1 \end{bmatrix}$$



(choose  $x \in N(\Sigma_1^2)$ )  
 $x \notin N(\Sigma_1)$  (choose  $y \in N(\Sigma_1^2)$ )  
 $y \notin N(\Sigma_1)$

$\Sigma_1 x$  &  $\Sigma_1 y$  should be linearly independent

$$\{\Sigma_1 x, x\} \cap \{\Sigma_1 y, y\} = \emptyset$$

2 eigenvectors:  $\Sigma_1 x, \Sigma_1 y$

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$$J = B^T A B \quad B = ?$$

Ex

$4 \times 4$  Matrix

Single eigenvalue  $\lambda_i$ :

$$m_i = 2$$

Find all JCF's  $J \otimes B$

$$d(s) = (s - \lambda_i)^4$$

$$m(s) = (s - \lambda_i)^2$$

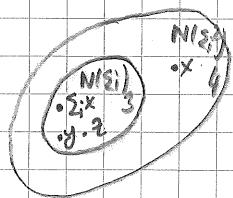
$$\Sigma_i = A - \lambda_i I$$

$$N(\Sigma_i) \subset N(\Sigma_i^2)$$

$$\begin{matrix} 3 & & 4 \\ 2 & & \\ 1 & & \end{matrix}$$

Case 2:

$$N(\Sigma_i) \not\subset N(\Sigma_i^2)$$



$$J = \left[ \begin{array}{c|c} \lambda_i & 1 \\ 0 & \lambda_i \\ \hline 0 & \lambda_i \\ \hline 0 & \lambda_i \end{array} \right]$$

$$x \in N(\Sigma_i^2) \quad x \notin N(\Sigma_i)$$

$\{\Sigma_j x, x\}$   
↓  
eigenvectors      generalized  
eigenvector

$\{y\} \quad y \in N(\Sigma_i) \quad y \text{ is } l_i \text{ with } \Sigma_i x$

$\{z\} \quad z \in N(\Sigma_i) \quad z \text{ is } l_i \text{ with } \Sigma_i x$

$$B = \begin{bmatrix} \Sigma_i x & | & x & | & y & | & z \end{bmatrix}$$

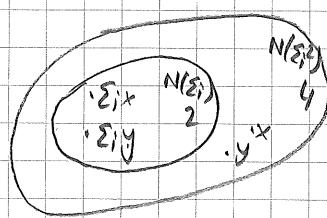
$$J = B^{-1} A B$$

Case II

$$N(\Sigma_i) \subset N(\Sigma_i^2)$$

2

4



$$J = \left[ \begin{array}{cc|c} x_1 & 1 & 0 \\ 0 & x_1 & 0 \\ \hline 0 & 0 & x_1 \end{array} \right]$$

$$x \in N(\Sigma_i^2) \quad x \notin N(\Sigma_i)$$

$$\{ \Sigma_i x, x \}$$

eigen vector  
y  $\in N(\Sigma_i^2)$   $y \notin N(\Sigma_i)$  &  $\Sigma_i y$  &  $\Sigma_i x$  have  
to be li.

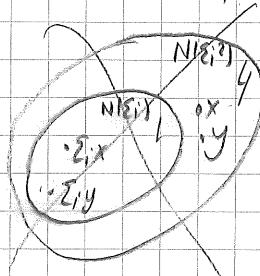
$$B = \begin{bmatrix} \Sigma_i x & | & x & | & \Sigma_i y & | & y \end{bmatrix}$$

Case III

$$N(\Sigma_i) \not\subset N(\Sigma_i^2)$$

1

4



$$J = \boxed{\quad}$$

$$A = \boxed{\quad}$$

$\rightarrow$  cannot be possible

$\Sigma_i x$  &  $\Sigma_i y$  cannot be li. So it's impossible.

This case is not possible

There cannot be a matrix A

with these null space dimensions.

EXAMPLE:

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -1 & 1 & 0 & 2 \end{bmatrix} \quad \det(sI - A) = (s-1)^3(s-2)$$

$J = ?$

$$B = ? \quad sI + J = B^{-1}AB$$

$$\Sigma_1 = A - \lambda_1 I = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -1 & 1 & 0 & 1 \end{bmatrix} \quad \dim N(\Sigma_1) = 2$$

$$\Sigma_1^2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix} \quad \dim N(\Sigma_1^2) = 3 \quad \Rightarrow \quad m(s) = (s-1)^2(s-2)$$

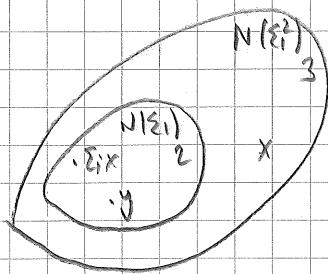
$$\Sigma_2 = A - 2I = \begin{bmatrix} -1 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ -1 & 1 & 0 & 0 \end{bmatrix} \quad \dim N(\Sigma_2) = 1$$

$$N(\Sigma_1) \subset N(\Sigma_1^2)$$

2

3

$$J = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix}$$



$$x = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad \cancel{x = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}} \quad x = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

choose this one

$$\Sigma_1 x = \begin{bmatrix} 1 \\ 3 \\ 3 \\ 1 \end{bmatrix}$$

eigen vector

$$A \Sigma_1 x = 1 \Sigma_1 x$$

$$y \in N(\Sigma_1) \text{ & } y \text{ is li with } \Sigma_{11} \quad y = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

Find  $z$  s.t  $z \in N(\Sigma_2)$

$$(A - \lambda_2 I)z = 0$$

$$\text{N}(\Sigma_2) \cdot z \quad z = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \Rightarrow B = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \end{bmatrix} = [\Sigma_1 | x | y | z]$$

## HERMITIAN MATRICES

**Definition:** An  $n \times n$  complex matrix  $A$  is called Hermitian if

$$\bar{A}^T = A,$$

i.e., its complex conjugate transpose equals itself.

$$\bar{A}^T = A^H$$

For Hermitian matrix, we have  $A^H = A$

When  $A^H = A$  for real matrix, we have  $A^T = A$  which means

$A$  is symmetric matrix.

$$\begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad d(s) = (s-2)^2 - 1 = s^2 - 4s + 3 = (s-3)(s-1) \quad \lambda_1 = 3 \quad \lambda_2 = 1$$

For Hermitian matrices, eigen values are always real.

$$e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad e_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Eigenvectors are going to be orthogonal to each other, for different eigenvalues.

Theorem: Let  $A$  be Hermitian. Then,  $\langle x, Ax \rangle$  is real for all  $x \in \mathbb{C}^n$

Proof:  $\langle x, y \rangle = y^H x$

$$\langle x, Ax \rangle = (Ax)^H x = x^H A^H x = x^H Ax = 1 \times 1 \text{ matrix, scalar}$$

$$\langle x, Ax \rangle = x^H Ax : \text{scalar (transpose of scalar is itself)}$$

$$\overline{\langle x, Ax \rangle} = \overline{x^T A \bar{x}} = \overline{x^T \bar{A}^T} \bar{x} = x^H A^H x = \langle x, Ax \rangle$$

$\downarrow$   
take  
transpose

$\Rightarrow \langle x, Ax \rangle$  is real

Property:

$$\langle x, Bx \rangle = x^H B^H x = (Bx)^H x = x^H (B^H x) = \langle B^H x, x \rangle$$

$$\Rightarrow \langle x, Bx \rangle = \langle B^H x, x \rangle$$

where  $B$  is arbitrary square matrix

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$$\begin{aligned}\langle x, y \rangle &\stackrel{A}{=} y^H x \\ \langle x, By \rangle &= (By)^H x \\ &= y^H B^H x \\ \langle B^H x, y \rangle &= y^H B^H x\end{aligned}\quad \left.\right\} \boxed{\langle x, By \rangle = \langle B^H x, y \rangle}$$

Theorem: Let  $A$  be Hermitian. Then,  $\langle x, Ax \rangle$  is real.

$$\bar{A}^T = A^H = A$$

$$\overline{\langle x, Ax \rangle} = \langle Ax, x \rangle = \langle x, A^H x \rangle = \langle x, Ax \rangle$$

$\Rightarrow \langle x, Ax \rangle$  is real  $\forall x$

Theorem: If  $A$  is Hermitian, its eigenvalues are real.

Proof: Let  $\lambda_i$  be an eigenvalue of  $A$ .

Let  $e_i$  be an eigenvector corresponding to  $\lambda_i$ .

$$\langle e_i, Ae_i \rangle = \langle e_i, \lambda_i e_i \rangle = \bar{\lambda}_i \langle e_i, e_i \rangle = \bar{\lambda}_i \|e_i\|^2$$

$$\langle e_i, Ae_i \rangle = \langle A^H e_i, e_i \rangle = \langle Ae_i, e_i \rangle = \langle \lambda_i e_i, e_i \rangle = \lambda_i \|e_i\|^2$$

$$\Rightarrow \bar{\lambda}_i \|e_i\|^2 = \lambda_i \|e_i\|^2 \Rightarrow \bar{\lambda}_i = \lambda_i$$

$\Rightarrow \lambda_i$  is always real!

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

$$\lambda_1 = 3 \quad e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 1 \quad e_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$e_1^T e_2 = \langle e_1, e_2 \rangle = 0$$

Theorem: Let  $A$  be Hermitian and  $\lambda_i, \lambda_j$  be two distinct eigenvalues with eigenvectors  $e_i, e_j$  ( $\lambda_i \neq \lambda_j$ ). Then eigenvectors  $e_i$  &  $e_j$  are orthogonal.

$$\langle e_i, A e_j \rangle = \langle e_i, \lambda_j e_j \rangle = \lambda_j \langle e_i, e_j \rangle$$

$$\begin{aligned} \langle e_i, A e_j \rangle &= \langle A^H e_i, e_j \rangle = \langle A e_i, e_j \rangle = \langle \lambda_i e_i, e_j \rangle \\ &= \lambda_i \langle e_i, e_j \rangle \end{aligned}$$

$$\Rightarrow \lambda_j \langle e_i, e_j \rangle = \lambda_i \langle e_i, e_j \rangle$$

↓                          ↓  
3                          2

$$(\underbrace{\lambda_j - \lambda_i}_{\neq 0}) \underbrace{\langle e_i, e_j \rangle}_{\neq 0} = 0 \Rightarrow \langle e_i, e_j \rangle = 0$$

Theorem: Let  $A$  be Hermitian. Then its minimal polynomial is

$$m(s) = (s - \lambda_1) (s - \lambda_2) \dots (s - \lambda_5)$$

i.e.,  $m_i = 1$  for  $i = 1, 2, \dots, 5$

$$d(s) = (s - \lambda_1)^{r_1} (s - \lambda_2)^{r_2} \dots (s - \lambda_5)^{r_5} \quad \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{If } A \text{ is Hermitian}$$

$$m(s) = (s - \lambda_1)^{m_1} (s - \lambda_2)^{m_2} \dots (s - \lambda_5)^{m_5} \quad \left. \begin{array}{l} \\ \\ \end{array} \right\} m_1 = m_2 = \dots = m_5 = 1$$

Proof:

$$N((A - \lambda_i I)) = N((A - \lambda_i I)^2)$$

We need to prove that

$$N((A - \lambda_i I)) \subset N((A - \lambda_i I)^2) \quad \text{This was already proven in previous lectures.}$$

So, we have to prove that

$$N((A - \lambda_i I)^2) \subset N((A - \lambda_i I))$$

Let  $x$  be arbitrary in  $N((A - \lambda_i I)^2)$

$$x \in N((A - \lambda_i I)^2)$$

$$(A - \lambda_i I)^2 x = 0$$

$$\langle x, (A - \lambda_i I)^2 x \rangle = 0$$

$$\langle x, (A - \lambda_i I)(A - \lambda_i I)x \rangle = \underbrace{\langle (A - \lambda_i I)^H x, (A - \lambda_i I)x \rangle}_{\substack{A^H - \lambda_i I \\ A - \lambda_i I}} = \langle (A - \lambda_i I)x, (A - \lambda_i I)x \rangle \geq 0$$

$$\Rightarrow (A - \lambda_i I)x = 0 \Rightarrow x \in N(A - \lambda_i I)$$

$$\Rightarrow \underbrace{N(A - \lambda_i I)}_{\cap} = N((A - \lambda_i I)^2)$$

$$\Rightarrow m_i = 1 \text{ for } i = 1, 2, \dots, 5$$

General Case:

$$\mathbb{C}^n = \underbrace{N((A - \lambda_1 I)^{m_1})}_{\dim r_1} \oplus \underbrace{N((A - \lambda_2 I)^{m_2})}_{\dim r_2} \oplus \dots \oplus \underbrace{N((A - \lambda_d I)^{m_d})}_{\dim r_d}$$

Hermitian Case

$$\mathbb{C}^n = \underbrace{N((A - \lambda_1 I))}_{\dim r_1} \oplus \underbrace{N((A - \lambda_2 I))}_{\dim r_2} \oplus \dots \oplus \underbrace{N((A - \lambda_d I))}_{\dim r_d}$$

$$\underbrace{N((A-\lambda_i I))}_{r_i} = \underbrace{N((A-\lambda_i I)^2)}_{r_i}$$

# of blocks corresponding to  $\lambda_i$  (with size  $\geq 1$ ) is  $r_i$

# " " " " " (with size  $\geq 2$ ) is 0

$$J = \begin{bmatrix} \bar{A}_1 & & \\ & \ddots & \\ & & \bar{A}_{r_i} \end{bmatrix}$$

$\bar{A}_i$  is of size  $r_i \times r_i$

$$\bar{A}_i = \lambda_i I = \begin{bmatrix} \lambda_i & & \\ & \ddots & \\ & & \lambda_i \end{bmatrix} \xrightarrow[r_i \times r_i]{\text{size } 1.}$$

Jordan canonical form for a Hermitian Matrix is DIAGONAL.

$$J = \begin{bmatrix} \lambda_1 I_{r_1 \times r_1} & & & \\ & \lambda_2 I_{r_2 \times r_2} & & \\ & & \ddots & \\ & & & \lambda_r I_{r_r \times r_r} \end{bmatrix}$$

Theorem: Let  $A$  be an  $n \times n$  Hermitian Matrix with

$$d(s) = \prod_{i=1}^r (s - \lambda_i)^{\alpha_i} \text{. Then there exist a unitary matrix}$$

$P$ . (i.e  $P^{-1} = P^H$ ) such that

$$J = P^H A P$$

~~Proof:~~ We know that  $\exists P$  such that

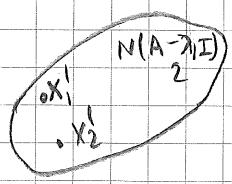
$$J = \underset{= P^H}{P^H} A P$$

let us have  $A \in \mathbb{C}^{5 \times 5}$   $A^H = A$

Suppose that

$$d(s) = (s - \lambda_1)^2 (s - \lambda_2)^3$$

$$m(s) = (s - \lambda_1)^1 (s - \lambda_2)$$



$$\{x_1^1\} \{x_2^1\} \quad \{x_1^2\} \{x_2^2\} \{x_3^2\}$$

Apply Gram Schmidt  
Orthonormalization  
to each set of vectors

$$\{e_1^1, e_2^1\} \quad \{e_1^2, e_2^2, e_3^2\}$$

$$P = [e_1^1 \ e_2^1 \ e_1^2 \ e_2^2 \ e_3^2]$$

$$P^H P = \begin{bmatrix} (e_1^1)^H \\ (e_2^1)^H \\ (e_1^2)^H \\ (e_2^2)^H \\ (e_3^2)^H \end{bmatrix} \begin{bmatrix} e_1^1 & e_2^1 & e_1^2 & e_2^2 & e_3^2 \end{bmatrix} = I$$

(2 soat EK Ders)

$$A^H = A$$

$$\langle x, B y \rangle = \langle B^H x, y \rangle$$

arbitrary

\*  $\langle x, Ax \rangle$  is real

\*  $\lambda_i$  is real

as  $\lambda_i \neq \lambda_j$   $e_i$  &  $e_j$  are orthogonal

$$\langle e_i, e_j \rangle = 0$$

$$d(s) = (s - \lambda_1)^{\gamma_1} (s - \lambda_2)^{\gamma_2} \cdots (s - \lambda_r)^{\gamma_r}$$

$$m(s) = (s - \lambda_1) (s - \lambda_2) \cdots (s - \lambda_r)$$

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$$N(A - \lambda_i I) = N((A - \lambda_i I)^2)$$

$\cap$

$$\mathbb{C}^n = N((A - \lambda_1 I)^{m_1}) \oplus N((A - \lambda_2 I)^{m_2}) \oplus \dots \oplus N((A - \lambda_k I)^{m_k}) \leftarrow \text{general case}$$

$$\mathbb{C}^n = N(A - \lambda_1 I) \oplus N(A - \lambda_2 I) \oplus \dots \oplus N(A - \lambda_k I) \leftarrow \text{Hermitian Case}$$

$$J = \begin{bmatrix} \bar{A}_1 & & & \\ & \bar{A}_2 & & \\ & & \ddots & \\ & & & \bar{A}_k \end{bmatrix} \quad \bar{A}_i = \lambda_i I_{r_i \times r_i}$$

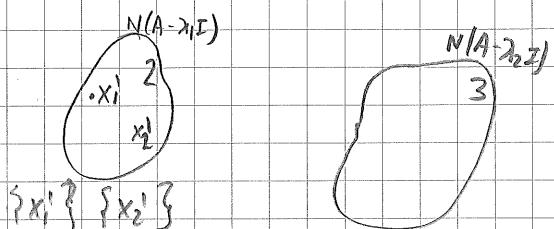
$$J = P^{-1}AP$$

$$\exists P \text{ which satisfies } \underbrace{P^{-1} = P^H}_{\text{unitary matrix}} \quad J = P^HAP$$

Idea of the Proof:  $A \in \mathbb{C}^{n \times n}$

$$\Delta(s) = (s - \lambda_1)^2 (s - \lambda_2)^3$$

$$M(s) = (s - \lambda_1)(s - \lambda_2)$$



$$\{x_1'\}, \{x_2'\}, \{x_3'\}$$

$x_1'$  &  $x_2'$  are li but they don't have to be orthogonal. However,  $x_1'$  &  $x_2', x_3'$  must be both li & orthogonal.

$$\{e_1', e_2'\}$$

$\underbrace{\text{both li}}_{\text{& orthonormal}}$

$\underbrace{\text{both li}}_{\text{& orthonormal}}$

$$P = [e_1' \ e_2' \ e_1^2 \ e_2^2 \ e_3^2]$$

$$P^H P$$

$$\begin{bmatrix} (e_1)^H \\ (e_2)^H \\ (e_1^2)^H \\ (e_2^2)^H \\ (e_3^2)^H \end{bmatrix} \begin{bmatrix} e_1 & e_2^1 & e_1^2 & e_2^2 & e_3^2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} = I$$

Theorem: let  $A$  be an  $n \times n$  Hermitian matrix with eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ .

$$\lambda_{\min} \triangleq \min_i \lambda_i \quad \lambda_{\max} \triangleq \max_i \lambda_i$$

Then we have

$$\lambda_{\min} \langle x, x \rangle \leq \langle x, Ax \rangle \leq \lambda_{\max} \langle x, x \rangle \quad \forall x \in \mathbb{C}^n$$

Proof:  $\mathbb{C}^n = N(A - \lambda_1 I) \oplus \mathbb{C}^n / N(A - \lambda_1 I)$

We can decompose an arbitrary  $x \in \mathbb{C}^n$  as

$$x = x_1 + x_2 + \dots + x_n \quad x_i \in N(A - \lambda_i I)$$

$$\langle x_i, x_j \rangle = 0 \text{ when } i \neq j$$

$$x = \sum_{i=1}^n x_i$$

$$\langle x, x \rangle = \left\langle \sum_{i=1}^n x_i, \sum_{j=1}^n x_j \right\rangle = \sum_{i=1}^n \sum_{j=1}^n \langle x_i, x_j \rangle = \sum_{i=1}^n \langle x_i, x_i \rangle$$

$$\Rightarrow \boxed{\langle x, x \rangle = \sum_{i=1}^n \langle x_i, x_i \rangle}$$

$$\langle x, Ax \rangle = \left\langle \sum_{i=1}^n x_i, A \sum_{j=1}^n x_j \right\rangle = \left\langle \sum_{i=1}^n x_i, \sum_{j=1}^n \underbrace{A x_j}_{\lambda_j x_j} \right\rangle = \left\langle \sum_{i=1}^n x_i, \sum_{j=1}^n \lambda_j x_j \right\rangle$$

$$= \sum_{i=1}^n \sum_{j=1}^n \lambda_j \langle x_i, x_j \rangle = \sum_{i=1}^n \lambda_i \langle x_i, x_i \rangle$$

$$\Rightarrow \boxed{\langle x, Ax \rangle = \sum_{i=1}^n \lambda_i \langle x_i, x_i \rangle}$$

$$\langle x, Ax \rangle = \sum_{i=1}^n \lambda_i \langle x_i, x_i \rangle \leq \sum_{i=1}^n \lambda_{\max} \langle x_i, x_i \rangle = \lambda_{\max} \sum_{i=1}^n \langle x_i, x_i \rangle = \lambda_{\max} \langle x, x \rangle$$

$$\langle x, Ax \rangle = \sum_{i=1}^n \lambda_i \langle x_i, x_i \rangle \geq \sum_{i=1}^n \lambda_{\min} \langle x_i, x_i \rangle = \lambda_{\min} \sum_{i=1}^n \langle x_i, x_i \rangle = \lambda_{\min} \langle x, x \rangle$$

$$\Rightarrow \boxed{\lambda_{\min} \langle x, x \rangle \leq \langle x, Ax \rangle \leq \lambda_{\max} \langle x, x \rangle}$$

If  $x \neq 0$

$$\lambda_{\min}(A) \leq \frac{\langle x, Ax \rangle}{\langle x, x \rangle} \leq \lambda_{\max}(A)$$

If  $A$  is not hermitian, this type quantity is not applicable because all  $\lambda_{\max}, \lambda_{\min}, \langle y, Ax \rangle$  can be complex & we cannot 'order' them like that.

Application: Remember the definition of an induced matrix norm

$$\|A\| \triangleq \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$$

Let  $\|\cdot\|$  be the induced norm for the inner product  $\langle x, y \rangle$ .

$$\frac{\|Ax\|^2}{\|x\|^2} \triangleq \frac{\langle Ax, Ax \rangle}{\langle x, x \rangle} = \frac{\langle x, A^H A x \rangle}{\langle x, x \rangle} \leq \lambda_{\max}(A^H A)$$

$$(A^H A)^H = A^H A$$

$$\Rightarrow \|A\|^2 = \lambda_{\max}(A^H A)$$

$$(A^H A)^H = A^H A$$

$$\Rightarrow \|A\| = \sqrt{\lambda_{\max}(A^H A)}$$

DEFINITION: A Hermitian matrix  $A$  is said to be positive definite if

$$\langle x, Ax \rangle > 0 \quad \forall x \neq 0$$

(positive semi-definite when  $\langle x, Ax \rangle \geq 0$ )

$$\langle x, A^H Ax \rangle = \langle Ax, Ax \rangle \geq 0$$

$A^H A$  is at least positive semi-definite.

Theorem: If  $A$  is positive definite, then all eigenvalues of  $A$  are positive.

$\lambda_1, e_1$  is an arbitrary eigenvalue-eigenvector pair for  $A$ .

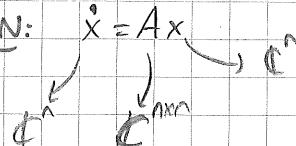
$$\langle e_1, Ae_1 \rangle > 0$$

$$\langle e_1, \lambda_1 e_1 \rangle = \lambda_1 \langle e_1, e_1 \rangle > 0$$

$$\Rightarrow \lambda_1 > 0$$

## FUNCTIONS OF A MATRIX

MOTIVATION:  $\dot{x} = Ax$



$$x(0) = X_0 \in \mathbb{C}^n$$

$$x(t) = \sum_{i=0}^{\infty} \alpha_i t^i$$

$$\alpha_1 \in \mathbb{C}^n$$

$$x(t) = d_0 + d_1 t + d_2 t^2 + \dots$$

$$x_0 = d_0 \Rightarrow d_0 = x_0$$

$$\dot{x} = Ax(t) = d_1 + 2d_2 t + 3d_3 t^2 + \dots$$

$$Ax_0 = d_1 \Rightarrow d_1 = Ax_0$$

$$\ddot{x} = Ax \dot{x} = A^2 x(t) = 2\alpha_2 + 6\alpha_3 t + \dots$$

$$A^2 x_0 = 2\alpha_2 \Rightarrow \alpha_2 = \frac{A^2 x_0}{2}$$

$$\alpha_3 = \frac{A^3 x_0}{6}$$

$$\alpha_i = \frac{A^i x_0}{i!}$$

$$\Rightarrow x(t) = \sum_{i=0}^{\infty} \frac{A^i}{i!} x_0 t^i$$

$$= \sum_{i=0}^{\infty} \frac{(At)^i}{i!} x_0 = \left( \sum_{i=0}^{\infty} \frac{(At)^i}{i!} \right) x_0$$

$$(e^A = \sum_{i=0}^{\infty} \frac{t^i}{i!})$$

$$\Rightarrow \boxed{x(t) = e^{At} x_0}$$

$$e^A \stackrel{def}{=} \sum_{i=0}^{\infty} \frac{A^i}{i!} = c_0 I + c_1 A + c_2 A^2 + \dots + c_{n-1} A^{n-1}$$

$$e^A = c_0 I + c_1 A + c_2 A^2 + \dots + c_{n-1} A^{n-1}$$

$$p(s) = c_0 + c_1 s + c_2 s^2 + \dots + c_{n-1} s^{n-1}$$

$$e^A = p(A)$$

How can we calculate  $e^A = ?$

## SPECIAL CASE

Case that eigenvalues of  $A$  are distinct.

$$d(s) = (s-\lambda_1)(s-\lambda_2) \dots (s-\lambda_n)$$

$$m(s) = (s-\lambda_1)(s-\lambda_2) \dots (s-\lambda_n)$$

$$J = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & 0 \\ & & \ddots & \\ & & 0 & \lambda_n \end{bmatrix}$$

Solution-1: Consider eigenvalue  $\lambda_j$   $j=1, \dots, n$

eigenvector  $e_j$

$$e^A = p(A)$$

$$Ae_j = \lambda_j e_j$$

$$A^2 e_j = \lambda_j^2 e_j$$

$$\boxed{A^i e_j = \lambda_j^i e_j}$$

$$e^A = \sum_{i=0}^{\infty} \frac{A^i}{i!}$$

$$e^A e_j = \sum_{i=0}^{\infty} \frac{A^i}{i!} e_j = \sum_{i=0}^{\infty} \frac{\lambda_j^i}{i!} e_j = \left( \sum_{i=0}^{\infty} \frac{\lambda_j^i}{i!} \right) e_j = e^{\lambda_j} e_j$$

$$\boxed{e^A e_j = e^{\lambda_j} e_j}$$

$$p(s) = c_0 + c_1 s + c_2 s^2 + \dots + c_{n-1} s^{n-1}$$

$$p(A) = c_0 I + c_1 A + c_2 A^2 + \dots + c_{n-1} A^{n-1}$$

$$\begin{aligned} p(A) e_j &= c_0 e_j + c_1 \lambda_j e_j + c_2 \lambda_j^2 e_j + \dots + c_{n-1} \lambda_j^{n-1} e_j \\ &= \underbrace{(c_0 + c_1 \lambda_j + c_2 \lambda_j^2 + \dots + c_{n-1} \lambda_j^{n-1})}_{p(\lambda_j)} e_j \end{aligned}$$

$$= p(\lambda_j) e_j$$

$$\boxed{p(A) e_j = p(\lambda_j) e_j}$$

①

$$e^{\lambda_j} e_j = p(\lambda_j) e_j$$

$$p(\lambda_j) = e^{\lambda_j}$$

$$p(\lambda_1) = e^{\lambda_1}$$

$$p(\lambda_2) = e^{\lambda_2}$$

$$\begin{matrix} | \\ p(\lambda_n) = e^{\lambda_n} \end{matrix}$$

$j=1, \dots, n$

$$c_0 + c_1 \lambda_1 + c_2 \lambda_1^2 + \dots = e^{\lambda_1}$$

$$c_0 + c_1 \lambda_2 + c_2 \lambda_2^2 + \dots = e^{\lambda_2}$$

⋮

$$c_0 + c_1 \lambda_n + c_2 \lambda_n^2 + \dots = e^{\lambda_n}$$

$$\underbrace{\begin{bmatrix} 1 & \lambda_1 & \lambda_1^2 & \dots & \lambda_1^{n-1} \\ 1 & \lambda_2 & \lambda_2^2 & \dots & \lambda_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \lambda_n & \lambda_n^2 & \dots & \lambda_n^{n-1} \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_n \end{bmatrix}}_C = \underbrace{\begin{bmatrix} e^{\lambda_1} \\ e^{\lambda_2} \\ \vdots \\ e^{\lambda_n} \end{bmatrix}}_E \quad \begin{matrix} \rightarrow \sin \lambda_1 & \log \lambda_1 \\ \rightarrow \sin \lambda_2 & \log \lambda_2 \\ \vdots & \vdots \\ \rightarrow \sin \lambda_n & \log \lambda_n \end{matrix}$$

$$C = C^{-1} E$$

In the general case when we try to find  $f(A)$ , we will use the equations

$$p(\lambda_j) = f(\lambda_j) \quad j=1, 2, \dots, n$$

EXAMPLE:

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad \lambda_1 = 3 \quad e_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 1 \quad e_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & \lambda_1 \\ 1 & \lambda_2 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} e^{\lambda_1} \\ e^{\lambda_2} \end{bmatrix}$$

$$+ e^A = p(A) = c_0 I + c_1 A$$

$$\Rightarrow \begin{bmatrix} 1 & 3 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} e^3 \\ e \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} 1 & 3 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} e^3 \\ e \end{bmatrix} = -\frac{1}{2} \begin{bmatrix} e^3 - 3e \\ -e^3 + e \end{bmatrix}$$

$$\Rightarrow e^A = -\frac{1}{2} (e^3 - 3e) \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \frac{e^3 - e}{2} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

→ calculate  $\log(A)$

$$\begin{bmatrix} 1 & 3 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} \log 3 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} 1 & 3 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \log 3 \\ 0 \end{bmatrix} = -\frac{1}{2} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \log 3$$

$$\Rightarrow \log A = p(A) = c_0 I + c_1 A = -\frac{\log 3}{2} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \frac{1}{2} \log 3 \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

# FIRST SOLUTION

$A \in \mathbb{C}^{n \times n}$

$$f(A) = P(A)$$

$$= c_0 I + c_1 A + \dots + c_{n-1} A^{n-1} \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{Case of distinct eigenvalues}$$

↳ If eigenvalues are NOT distinct, power of  $m(s)$  can change, then power of  $P(A)$  can also change.

## Distinct Eigenvalue Case

$$d(s) = (s - \lambda_1)(s - \lambda_2) \dots (s - \lambda_n)$$

$$m(s) = (s - \lambda_1) \dots (s - \lambda_n)$$

$$p(\lambda_i) = f(\lambda_i) \quad i=1, \dots, n$$

$$p(s) = c_0 + c_1 s + \dots + c_{n-1} s^{n-1}$$

$f(\cdot)$  has to be defined at  $\lambda_i$

[for example  $f(s) = \frac{1}{s}$ , if you have eigenvalue  $\lambda_1=0$ ,  $f(s)$  is not defined.]

$$\underbrace{\begin{bmatrix} 1 & \lambda_1 & \dots & \lambda_1^{n-1} \\ 1 & \lambda_2 & \dots & \lambda_2^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \lambda_n & \dots & \lambda_n^{n-1} \end{bmatrix}}_{\text{Vander Monde Matrix}} \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_{n-1} \end{bmatrix} = \begin{bmatrix} f(\lambda_1) \\ f(\lambda_2) \\ \vdots \\ f(\lambda_n) \end{bmatrix}$$

Vander Monde  
Matrix

# SECOND SOLUTION

(This solution is valid not only when  $A$  has distinct eigenvalues but also when  $A$  is diagonalizable. ( $J$  is diagonal))

$$J = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix}$$

$$J = P^{-1} A P$$

↳ we know how to find  $P$

$$A = P J P^{-1}$$

$$e^A = \sum_{i=0}^{\infty} \frac{A^i}{i!}$$

$$A^2 = P J P^{-1} P J P^{-1} = P J^2 P^{-1}$$

$$A^3 = P J^3 P^{-1}$$

$$A^i = P J^i P^{-1}$$

$$e^A = \sum_{i=0}^{\infty} \frac{P J^i P^{-1}}{i!} = P \left[ \sum_{i=0}^{\infty} \frac{J^i}{i!} \right] P^{-1}$$

$$= P e^J P^{-1}$$

In general,

$$f(A) = P f(J) P^{-1}$$

②

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$$J^i = \begin{bmatrix} \lambda_1^i & & 0 \\ & \ddots & \\ 0 & & \lambda_n^i \end{bmatrix}$$

$$\Rightarrow e^A = P \sum_{i=0}^{\infty} \frac{1}{i!} \begin{bmatrix} \lambda_1^i & & 0 \\ & \ddots & \\ 0 & & \lambda_n^i \end{bmatrix} P^{-1}$$

$$= P \begin{bmatrix} \sum_{i=0}^{\infty} \frac{\lambda_1^i}{i!} & & 0 \\ & \sum_{i=0}^{\infty} \frac{\lambda_2^i}{i!} & \\ 0 & & \ddots & & 0 \\ & & & \sum_{i=0}^{\infty} \frac{\lambda_n^i}{i!} & \end{bmatrix} P^{-1}$$

$$= P \begin{bmatrix} e^{\lambda_1} & & 0 \\ & e^{\lambda_2} & \\ 0 & & \ddots & & e^{\lambda_n} \end{bmatrix} P^{-1}$$

General Case

$$f(A) = P \begin{bmatrix} f(\lambda_1) & & 0 \\ & f(\lambda_2) & \\ 0 & & \ddots & & f(\lambda_n) \end{bmatrix} P^{-1}$$

\* eigenvalues of  $f(A)$   
are  $f(\lambda_i)$   $i=1, \dots, n$

EXAMPLE:

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

$$\begin{aligned} \lambda_1 &= 3 & e_1 &= \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ \lambda_2 &= 1 & e_2 &= \begin{bmatrix} 1 \\ -1 \end{bmatrix} \end{aligned}$$

$$P = [e_1 \ e_2]$$

$$J = \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}$$

$$A = P \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix} P^{-1}$$

$$e^A = P \begin{bmatrix} e^3 & 0 \\ 0 & e^1 \end{bmatrix} P^{-1} \rightarrow \text{the result is the same with the result of first solution.}$$

EVEN IF THE ROOTS OF  $J$  IS REPEATED, WE CAN APPLY THIS SOLUTION METHOD

EXAMPLE:  $f(s) = (1-s)^{-1} = \frac{1}{1-s}$

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad \lambda_1 = 0, \quad \lambda_2 = 1$$

$$\cancel{f(A) = P \begin{bmatrix} f(\lambda_1) & 0 \\ 0 & f(\lambda_2) \end{bmatrix} P^{-1}} \rightarrow \lambda_2 = 1 \text{ is problematic case.}$$

$\rightarrow f(A)$  does NOT exist  
 $\therefore f(\cdot)$  is not analytic at  $\lambda = 1$

EXAMPLE:

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

$$\text{Calculate } A^{1/2} \cdot (\sqrt{A})$$

$$\sqrt{A} \cdot \sqrt{A} = A$$

$$\begin{aligned} \sqrt{A} &= P \sqrt{\lambda} P^{-1} = P \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \end{bmatrix} P^{-1} \\ &= P \begin{bmatrix} \sqrt{3} & 0 \\ 0 & \sqrt{1} \end{bmatrix} P^{-1} \quad \text{where } P = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \\ \sqrt{A} &= P \begin{bmatrix} -\sqrt{3} & 0 \\ 0 & \sqrt{1} \end{bmatrix} P^{-1} \quad \text{positive definite sqrt of } A \text{ because its roots are positive} \\ \Rightarrow \sqrt{A} &\text{ is not be unique! } [2^{\text{nd}} \text{ done ver}] \end{aligned}$$

GENERAL CASE

$A$  does not have distinct eigenvalues.

$$f(A) = \sum_{i=0}^{\infty} \beta_i A^i$$

$$d(s) = (s-\lambda_1)^{r_1} (s-\lambda_2)^{r_2} \cdots (s-\lambda_n)^{r_n}$$

$$m(s) = (s-\lambda_1)^{m_1} (s-\lambda_2)^{m_2} \cdots (s-\lambda_n)^{m_n}$$

$$M(A) = 0 \quad M \stackrel{\Delta}{=} \sum_{i=1}^n m_i$$

↓  
order of m(s)

$A^M$  = linear combination of smaller powers of  $A$ .

$$f(A) = c_0 I + c_1 A + \cdots + c_{M-1} A^{M-1}$$

## SOLUTION-1

$$f(A) = p(A)$$

Apply the same analysis

$M$  unknowns

$$\left. \begin{array}{l} p(\lambda_1) = f(\lambda_1) \\ p(\lambda_2) = f(\lambda_2) \\ \vdots \\ p(\lambda_M) = f(\lambda_M) \end{array} \right\} \text{ } \begin{array}{l} \text{or different} \\ \text{equations} \end{array}$$

- If  $\sigma < M$ , we have more unknowns than equations.
- If  $\sigma = M = n$  (distinct eigenvalues)

### EXAMPLE:

$$d(s) = (s-3)^2 (s-4)^5$$

$$m(s) = (s-3)^2 (s-4)^3$$

$$M=5$$

$$p(s) = c_0 + c_1 s + c_2 s^2 + c_3 s^3 + c_4 s^4$$

$$\hookrightarrow \# \text{ of unknowns} = 5$$

$$\lambda_1 = 3$$

$$p(3) = f(3)$$

$$p'(3) = f'(3)$$

$$\lambda_2 = 4$$

$$p(4) = f(4)$$

$$p'(4) = f'(4)$$

$$p''(4) = f''(4)$$

Now, we have  
5 equations!



# of equations 2

DEFINITION: Let  $f$  be an analytic complex valued function defined in an open set containing  $\sigma(A) = \{\lambda_1, \lambda_2, \dots, \lambda_M\}$  (spectrum of  $A$ ) Let  $p$  be any polynomial satisfying

$$p^{(k)}(\lambda_i) = f^{(k)}(\lambda_i) \quad i=1, \dots, M \quad 0 \leq k \leq m_i - 1$$

Then, we define

$$f(A) = p(A)$$

EXAMPLE:

$$A = \begin{bmatrix} 0 & 0 & -2 \\ 0 & 1 & 0 \\ 1 & 1 & 3 \end{bmatrix} \quad d(s) = (s+1)^2(s-2)$$

$$m(s) = (s+1)^2(s-2)$$

$$\mu = 3$$

Find  $\sin(\pi A)$ 

SOLUTION-1

$$f(s) = \sin(\pi s)$$

$$p(s) = c_0 + c_1 s + c_2 s^2$$

$$\begin{aligned} p(1) = f(1) &\Rightarrow c_0 + c_1 + c_2 = 0 \\ p'(1) = f'(1) &\Rightarrow c_1 + 2c_2 = -\pi \\ p(2) = f(2) &\Rightarrow c_0 + 2c_1 + 4c_2 = 0 \end{aligned}$$

$$\begin{aligned} f(A) = p(A) &= c_0 I + c_1 A + c_2 A^2 \\ &= 2\pi \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - 3\pi \begin{bmatrix} 0 & 0 & -2 \\ 0 & 1 & 0 \\ 1 & 1 & 3 \end{bmatrix} + \pi \begin{bmatrix} -2 & -2 & -6 \\ 0 & 1 & 0 \\ 3 & 4 & 7 \end{bmatrix} \end{aligned}$$

SOLUTION-2

$$J = P^{-1}AP$$

we know how to find  $P$

$$A = PJP^{-1}$$

$J$  does not have to be diagonal

$$J = \begin{bmatrix} J_1 & & & 0 \\ & J_2 & & \\ & & \ddots & \\ 0 & & & J_L \end{bmatrix}$$

↓  
Jordan  
blocks

$$J = \begin{bmatrix} 2 & 1 & & 0 \\ & 2 & & \\ & & 2 & \\ 0 & & & 1 \end{bmatrix} \quad J_1 = \begin{bmatrix} 2 & 1 \\ 0 & 2 \end{bmatrix} \quad J_2 = 2 \quad J_3 = 1 \quad J_6 = 1$$

$$f(s) = \sum_{i=0}^{\infty} \beta_i s^i \rightarrow f(A) = \sum_{i=0}^{\infty} \beta_i A^i \quad \& \quad A' = PJP^{-1}$$

$$\Rightarrow f(A) = \sum_{i=0}^{\infty} \beta_i P J^i P^{-1} = P \left[ \sum_{i=0}^{\infty} \beta_i J^i \right] P^{-1} = P f(J) P^{-1}$$

$$J_l^i = \begin{bmatrix} J_1^i & & & \\ & J_2^i & & \\ & & \ddots & \\ & & & J_L^i \end{bmatrix}$$

$$\Rightarrow f(A) = P \left[ \sum_{i=0}^{\infty} \beta_i \begin{bmatrix} J_1^i & & & \\ & J_2^i & & \\ & & \ddots & \\ & & & J_L^i \end{bmatrix} \right] P^{-1}$$

$$= P \begin{bmatrix} \sum_{i=0}^{\infty} \beta_i J_1^i & & & \\ & \sum_{i=0}^{\infty} \beta_i J_2^i & & \\ & & \ddots & \\ & & & \sum_{i=0}^{\infty} \beta_i J_L^i \end{bmatrix} P^{-1}$$

$$= P \begin{bmatrix} f(J_1) & & & \\ & f(J_2) & & \\ & & \ddots & \\ & & & f(J_L) \end{bmatrix} P^{-1}$$

$$f(J_L) = ?$$

$$J_l = \begin{bmatrix} \lambda & & & \\ & \lambda & & \\ & & \ddots & \\ & & & \lambda \end{bmatrix} \quad l=1, \dots, L$$

$$f(s) = \sum_{i=0}^{\infty} \beta_i s^i \rightarrow \text{it is around } 2\pi i \mathbb{C},$$

$$f(s) = \sum_{i=0}^{\infty} \frac{f^{(i)}(\lambda)}{i!} (s-\lambda)^i \rightarrow \text{it is around } \lambda$$

$$= f(\lambda) + f'(\lambda) (s-\lambda) + \frac{f''(\lambda)}{2} (s-\lambda)^2 + \dots$$

$$f(J_L) = \sum_{i=0}^{\infty} \frac{f^{(i)}(\lambda)}{i!} (J_L - \lambda I)^i$$

$$= f(\lambda) I + f'(\lambda) (J_L - \lambda I) + \frac{f''(\lambda)}{2} (J_L - \lambda I)^2 + \dots$$

$$J_L - \lambda I = \begin{bmatrix} 0 & & & & & \\ & 0 & & & & \\ & & \ddots & & & \\ & & & 0 & & \\ & & & & \ddots & \\ & & & & & 0 \end{bmatrix} \rightarrow (J_L - \lambda I)^k = \begin{bmatrix} 0 & 0 & 1 & & & \\ & 0 & 0 & 1 & & \\ & & \ddots & \ddots & & \\ & & & 0 & 0 & 1 \\ & & & & \ddots & \\ & & & & & 0 \end{bmatrix} \rightarrow (J_L - \lambda I)^k = 0$$

$$f(\mathcal{J}_k) = \sum_{i=0}^{k-1} \frac{f^{(i)}(\lambda)}{i!} (\mathcal{J}_k - \lambda I)^i$$

$$f(\mathcal{J}_k) = \begin{bmatrix} f(\lambda) & f'(\lambda) & \frac{f''(\lambda)}{2} & \cdots & \frac{f^{(k-1)}(\lambda)}{k-1} \\ 0 & f(\lambda) & f'(\lambda) & \frac{f''(\lambda)}{2} & \vdots \\ 0 & 0 & f(\lambda) & f'(\lambda) & \vdots \\ & & & f(\lambda) & \end{bmatrix}$$

EXAMPLE

$$A = \begin{bmatrix} 0 & 0 & -2 \\ 0 & 1 & 0 \\ 1 & 1 & 3 \end{bmatrix} \quad f(s) = \sin(\pi s)$$

$$f(A) = ?$$

$$\mathcal{J} = P^{-1}AP$$

$$d(s) = (s-1)^2(s-2)$$

$$m(s) = d(s)$$

$$\mathcal{J} = \left[ \begin{array}{cc|c} 1 & 1 & 0 \\ 0 & 1 & 0 \\ \hline 0 & 0 & 2 \end{array} \right]$$

$$A = PJP^{-1}$$

$$f(A) = Pf(\mathcal{J})P^{-1}$$

$$= P \left[ \begin{array}{c|c} f\left(\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}\right) & 0 \\ \hline 0 & f(2) \end{array} \right] P^{-1} = P \left[ \begin{array}{cc|c} \sin \pi & \cos \pi & 8 \\ 0 & \sin \pi & \hline 0 & 0 & \sin 2\pi \end{array} \right] P^{-1}$$

$$= P \begin{pmatrix} 0 & -1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} P^{-1}$$

