

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

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

Fundamental Law of Matrix Multiplication

$$\begin{bmatrix} * & & & \\ a_{i1} & a_{i2} \dots a_{is} & & \\ * & & & \\ * & & & \end{bmatrix} \begin{bmatrix} * & * & b_{ij} & * & * & * \\ & b_{2j} & & & & \\ & : & & & & \\ & b_{sj} & & & & \end{bmatrix} = \begin{bmatrix} * & * & (AB)_{ij} & * & * & * \\ & * & & & & \\ & * & & & & \end{bmatrix}$$

The second and third ways : Rows and columns

$$\begin{bmatrix} \rightarrow \\ \rightarrow \\ \rightarrow \end{bmatrix} \begin{bmatrix} \text{row } i \text{ of } A \\ \text{row } j \text{ of } B \end{bmatrix} = \begin{bmatrix} \rightarrow \\ \rightarrow \\ \rightarrow \end{bmatrix}$$

$$[\text{row } i \text{ of } A] \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = [\text{row } i \text{ of } AB]$$

Every row of A times matrix B

Every row/column of AB

$$\begin{bmatrix} [] & [] & \dots & [] \end{bmatrix} \begin{bmatrix} [] \\ [] \end{bmatrix} = \begin{bmatrix} [] \\ [] \end{bmatrix}$$

is a combination of the row/column of A/B

Every column of B times Matrix A

Elimination

For $\begin{vmatrix} a_1 & \dots \\ a_2 & \dots \\ \vdots & \ddots \end{vmatrix}$ if we want to eliminate a_2

we need

$$\begin{vmatrix} a_1 & 0 & 0 & \dots \\ -\frac{a_2}{a_1} & 1 & 0 & \dots \\ 0 & 0 & 1 & \dots \\ \vdots & & \ddots & \end{vmatrix} \begin{vmatrix} a_1 & \dots \\ a_2 & \dots \\ \vdots & \ddots \end{vmatrix} = \begin{vmatrix} a_1 & \dots \\ 0 & \dots \\ \vdots & \ddots \end{vmatrix}$$

$$\left[\begin{array}{c|c} A_1 & A_2 \\ \hline A_3 & A_4 \end{array} \right] \cdot \left[\begin{array}{c|c} B_1 & B_2 \\ \hline B_3 & B_4 \end{array} \right] = \left[\begin{array}{c|c} A_1B_1 + A_2B_3 & A_1B_2 + A_2B_4 \\ \hline A_3B_1 + A_4B_3 & A_3B_2 + A_4B_4 \end{array} \right]$$

A

Important special case

Let the blocks of A be its n columns. Let the blocks of B be its n rows. Then block multiplication AB adds up column times rows;

Columns times rows

$$\left[\begin{array}{ccc|c} 1 & & & -b_1 \\ a_1 & \cdots & a_n & \vdots \\ 1 & & & -b_n \end{array} \right] = \left[a_1 b_1 + \cdots + a_n b_n \right]$$

e.g. $\begin{bmatrix} 1 & 4 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} 3 & 2 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 3 & 2 \end{bmatrix} + \begin{bmatrix} 4 \\ 3 \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} = \begin{bmatrix} 3 & 2 \\ 3 & 2 \end{bmatrix} + \begin{bmatrix} 4 & 0 \\ 3 & 0 \end{bmatrix}$

$$= \begin{bmatrix} 7 & 2 \\ 8 & 2 \end{bmatrix}$$

Elimination by blocks

$$\begin{bmatrix} I & 0 \\ -CA^{-1} & I \end{bmatrix} \begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & D - CA^T B \end{bmatrix}$$

Inverse (逆) (square matrix)

$$A^T A = I = AA^{-1}$$

invertible

↑
If this exists

What time doesn't a matrix be . invertible?

e.g. $\begin{bmatrix} 1 & 3 \\ 2 & 6 \end{bmatrix}$ isn't invertible

① because $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ $\begin{bmatrix} 3 \\ 6 \end{bmatrix}$ are parallel, and $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ isn't on the line they make

② $\det \begin{bmatrix} 1 & 3 \\ 2 & 6 \end{bmatrix} = 0$

③ $\begin{bmatrix} 1 & 3 \\ 2 & 6 \end{bmatrix} \cdot \begin{bmatrix} -3 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

if inverse exists

$$A^{-1} \cdot A \cdot \begin{bmatrix} -3 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} A^{-1} \quad \begin{bmatrix} -3 \\ 1 \end{bmatrix} = 0 \quad \text{paradox}$$

$$\text{If } A = \begin{bmatrix} d_1 & & \\ & \ddots & \\ & & d_n \end{bmatrix} \text{ then } A^{-1} = \begin{bmatrix} \frac{1}{d_1} & & \\ & \ddots & \\ & & \frac{1}{d_n} \end{bmatrix}$$

reverse order :

$$(AB)^{-1} = B^{-1} A^{-1}$$

Gauss-Jordan [solve 2 eqns at once]

e.g. $\begin{bmatrix} 1 & 3 \\ 2 & 7 \end{bmatrix} \begin{bmatrix} a & c \\ b & d \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

$$\begin{bmatrix} 1 & 3 \\ 2 & 7 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 \\ 2 & 7 \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 & | & 1 & 0 \\ 2 & 7 & | & 0 & 1 \end{bmatrix} \xrightarrow{\text{R2} - 2\text{R1}} \begin{bmatrix} 1 & 3 & | & 1 & 0 \\ 0 & 1 & | & -2 & 1 \end{bmatrix} \xrightarrow{\text{R2} \times -1} \begin{bmatrix} 1 & 0 & | & 7 & -3 \\ 0 & 1 & | & -2 & 1 \end{bmatrix}$$

I A⁻¹

$$A^{-1} [A \ I] = [I \ A^{-1}]$$

$$(R^T R)^T = R^T \cdot R^{TT} = R^T R$$

Conclusion $R^T R$ is symmetric

rule in transpose (转置)

$(A \cdot B)^T = B^T \cdot A^T \rightarrow$ easy prove by write out the items

Vector space and subspace

Every subspace contains the zero vector

A subspace containing \vec{v} and \vec{w} must contain all linear combinations $c\vec{v} + d\vec{w}$

The system $Ax = b$ is solvable if and only if b is in the column space of A 

e.g.

$$A = \begin{bmatrix} 1 & 1 & 2 \\ 1 & 2 & 3 \\ 1 & 3 & 4 \\ 1 & 4 & 5 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

b is a subspace of \mathbb{R}^4

$$\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \\ 4 \\ 5 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

So we can say ^{only} $\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} 2 \\ 3 \\ 4 \\ 5 \end{bmatrix}$ can constitute

the subspace \downarrow and call them pivot column

Nullspace

e.g.

$$Ax = \begin{bmatrix} 1 & 1 & 2 \\ 2 & 1 & 3 \\ 3 & 1 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Nullspace

Check the solution to $Ax=0$

always give a subspace

Proof:
If $Av=0$ and $Aw=0$ then $A(v+w)=0$
so its a subspace

Attention \downarrow
 $Ax=b$
not a subspace

\downarrow
 $Ax=0$
sub space

In elimination the solution don't change,
so the null space won't change

rank of A ^秩

It equal to the number of pivots

the columns pivot on called pivot column
others called free column

free columns : We can assign any number freely to the

e.g.

$$\left[\begin{array}{cccc} 1 & 2 & 2 & 2 \\ 0 & 0 & 2 & 4 \\ 0 & 0 & 0 & 0 \end{array} \right] \xrightarrow{\text{free}} \left[\begin{array}{c} 1 \\ 0 \\ 0 \end{array} \right] = \left[\begin{array}{c} 0 \\ 3 \\ 3 \end{array} \right]$$

$$\left[\begin{array}{cccc} 1 & 2 & 2 & 2 \\ 0 & 0 & 2 & 4 \\ 0 & 0 & 0 & 0 \end{array} \right] \left[\begin{array}{c} 1 \\ 0 \\ 0 \end{array} \right] = \left[\begin{array}{c} 0 \\ 3 \\ 3 \end{array} \right]$$

we could get $X = \left[\begin{array}{c} -2 \\ 1 \\ 0 \end{array} \right] + d \left[\begin{array}{c} 2 \\ 0 \\ 1 \end{array} \right]$

we call them
special solution

* The null space contains exactly all the combination of the special solutions

(columns(X) is the column in S degree of personal idea: the dimension↑ of null space $\stackrel{I}{=}$ equals to the number(s) of free columns(X), so we need X^{and} set of special solutions to get the null space

We can also say null space = $c \begin{bmatrix} -F \\ I \end{bmatrix}$

e.g.

$$\left[\begin{array}{ccc|c} 1 & 2 & 3 & F \\ 2 & 4 & 6 & \\ 2 & 6 & 8 & \\ 2 & 8 & 10 & \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 2 & 3 & F \\ 0 & 2 & 2 & \\ 0 & 0 & 0 & \\ 0 & 0 & 0 & \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 0 & 0 & F \\ 0 & 1 & 0 & \\ 0 & 0 & 1 & \\ 0 & 0 & 0 & \end{array} \right]$$

R

$$X = c \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix} = c \begin{bmatrix} -F \\ I \end{bmatrix}$$

Identity matrix

$$Ax = b$$

To find a complete solution to $Ax = b$

① $x_{\text{particular}}$: set all free variables to zero

solve $Ax = b$ for pivot variables

+

② $x_{\text{nullspace}}$

$$x = x_p + x_n$$

$$b = \begin{bmatrix} 1 \\ 5 \\ 6 \end{bmatrix}$$

e.g.

$$\left[\begin{array}{cccc|c} 1 & 2 & 2 & 2 & b_1 \\ 2 & 4 & 6 & 8 & b_2 \\ 3 & b & 8 & 10 & b_3 \end{array} \right] \rightarrow \left[\begin{array}{cccc|c} 1 & 2 & 2 & 2 & b_1 \\ 0 & 0 & 24 & b_2 - 2b_1 & \\ 0 & 0 & 0 & b_3 - b_2 - b_1 & \end{array} \right]$$

\downarrow

$$x_p = \begin{bmatrix} -2 \\ 0 \\ \frac{3}{2} \end{bmatrix}$$

proof: $Ax_p = b$

$$Ax_n = 0$$

The geometric mean of X :

$$X = \begin{bmatrix} -2 \\ 0 \\ \frac{3}{2} \\ 0 \end{bmatrix} + C_1 \begin{bmatrix} -2 \\ 1 \\ 0 \\ 1 \end{bmatrix} + C_2 \begin{bmatrix} 2 \\ 0 \\ \frac{3}{2} \\ 1 \end{bmatrix}$$

x_p

a plane in 4 dimension space

X is a plane which across $(-2, 0, \frac{3}{2}, 0)$ in
4 dimension space so X isn't a subspace

m by n matrix A of rank r (know $r \leq m, r \leq n$)

Full column rank means $r=n$ No free variables

$$N(A) = \begin{cases} \text{zero} \\ \text{vector} \end{cases}$$

$$R \left[\begin{array}{cccc|c} 1 & 2 & 3 & 4 & 5 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \right]$$

Solution to $Ax=b$: $x=x_p$ (if solution exists)

e.g. $\left[\begin{array}{cc|c} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{array} \right] \cdot x = \left[\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} \right]$

because $(1,2,3,4) \rightarrow$ combination can't cover all 4 dimension space

Full row rank means $r=m$

every row has a pivot

Can solve $Ax=b$ for every b

$$\left[\begin{array}{cccc|c} 1 & 2 & 3 & 4 & 5 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \right] x = \left[\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} \right]$$

$$R = \left[\begin{array}{cccc|c} 1 & 0 & - & - & \\ 0 & 1 & - & - & \\ \hline I & J & - & - & \end{array} \right]$$

can cover 2 dimension space

Conclusion

$$r=m=n$$

$$r=n < m$$

$$r=m < n$$

$$R = [I]$$

$$R = \left[\begin{smallmatrix} I \\ S \end{smallmatrix} \right]$$

$$R = [I \ F]$$

1 solution

0 or 1 solution

∞ solution

$$r < m, r < n$$

$$R = \left[\begin{smallmatrix} I & F \\ S & S \end{smallmatrix} \right]$$

(0 or ∞ solution)

*: The rank tells you everything about
the number of solutions

Independence

vectors x_1, x_2, \dots, x_n are independent if no combination gives you vector (except the zero comb. all $c_i=0$)

$$c_1 x_1 + c_2 x_2 + \dots + c_n x_n \neq 0$$

rank = n

no free
variables

when v_1, \dots, v_n are columns of A

They are independent if nullspace of A $\{ \begin{matrix} \text{zero} \\ \text{vector} \end{matrix} \}$

they are dependent if $A \cdot c = 0$ for some nonzero c

rank < n

Vectors v_1, \dots, v_p span a space means:

The space consists of all combinations of those vectors

Basis: for a space is a sequence of
基
vectors v_1, v_2, \dots, v_d with 2 properties

1. they are independent

2. they span the space

vectors give basis if $n \times n$ matrix is invertible

For a given space every basis has the same
number of vectors

→ we call it dimension

rank = pivot column = dimension of
column space

$$\dim C(A) = r$$

$$\dim N(A) = \# \text{ free variables} = n - r$$

Q: Given five vectors in \mathbb{R}^7 , how do you find a basis for the space they span?

A: Put the five vectors into the columns of A.
Eliminate to find the pivot columns. Those pivot columns are a basis for the column space.

4 subspace

column space $C(A)$ in R^m

null space $N(A)$ in R^n

row space $C(A^T)$ in R^n

null space of A^T $N(A^T)$ in R^m

$$\dim(C(A)) = \dim(C(A^T)) = r$$

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

$$\dim N(A^T) = m - r$$

E.g. How can we get $N(A^T)$

$$A = \begin{bmatrix} 1 & 2 & 3 & 1 \\ 1 & 1 & 2 & 1 \\ 2 & 3 & 1 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} = R$$

Gauss-Jordan

$$\underset{m \times m}{E} \cdot \begin{bmatrix} A & I \\ m \times n & m \times m \end{bmatrix} \rightarrow \begin{bmatrix} R & E \\ m \times n & m \times m \end{bmatrix}$$

$$E \cdot A = R$$

$$E \cdot \begin{bmatrix} -1 & 2 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \cdot A = R$$

\therefore the last row in R is 0

so the combination of rows in A is the last
row in E

$$\text{So } N(A^T) = \{ [1, 0, 1] \}$$

Exercise : A matrix

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix}$$

1) is it a subspace if $v_1 + v_2 + v_3 + v_4 = 0$?

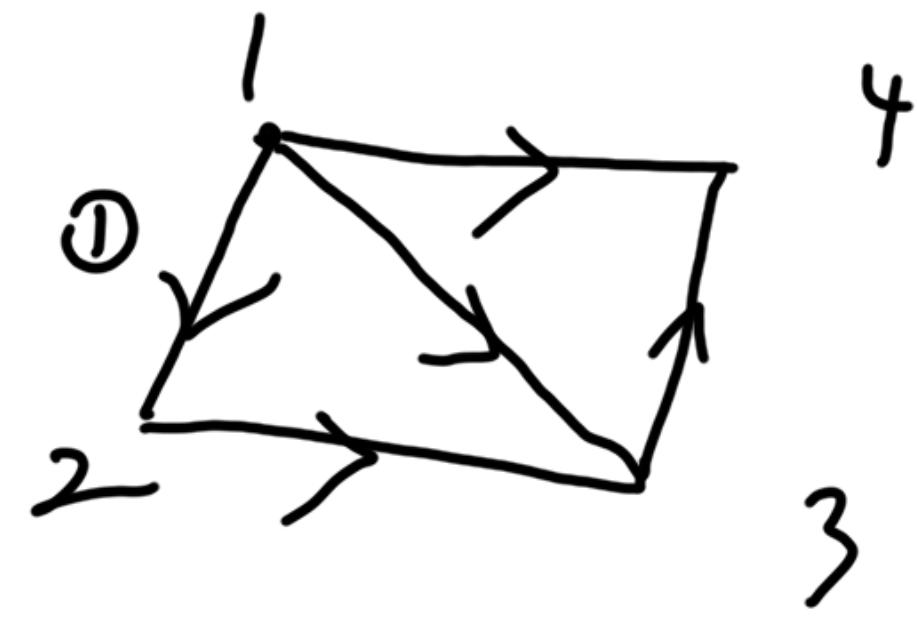
2) what's the dimension of it?

1) easy

2) actually it is the null space of
 $[1, 1, 1, 1]$ the rank = 1

so $\dim(\text{null space}) = 4 - 1 = 3$

An application of matrix



node 1 2 3 4

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

edge 1
 2
 3
 4
 5

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$Ax = 0 = \begin{bmatrix} x_2 - x_1 \\ x_3 - x_2 \\ x_3 - x_1 \\ x_4 - x_1 \\ x_4 - x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\therefore \text{Null space} = C \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$A^T y = 0$$

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

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

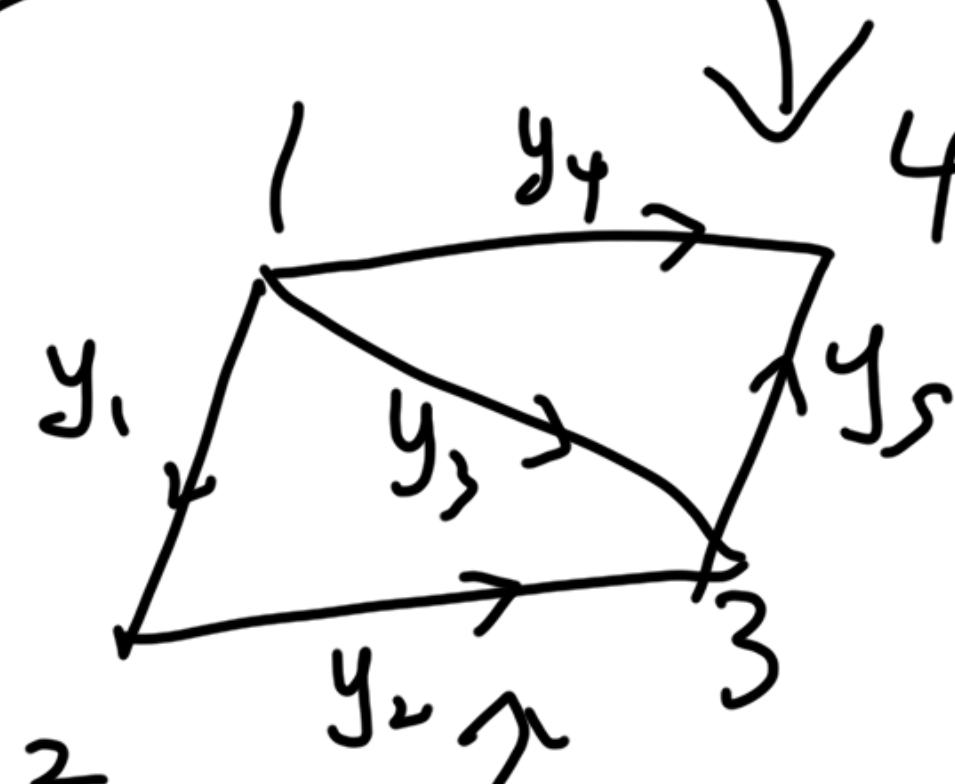
loop(2)

$$-y_1 - y_3 - y_4 = 0$$

$$y_1 - y_2 = 0$$

$$y_2 + y_3 - y_5 = 0$$

$$y_4 + y_5 = 0$$



Basis for $N(A^T)$

$$\begin{bmatrix} 1 \\ -1 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ -1 \end{bmatrix}$$

loop①

so Basis for $N(A^T) = \# \text{loop (independent)}$

*: the pivot columns of A^T y_1, y_2, y_4 , have 4 nodes but 3 edge, so it's not loop, we call it tree

we can convert the formula :

$$\dim N(A^T) = m - r$$

$$\# \text{loops} = \# \text{edge} - (\# \text{nodes} - 1)$$

$$m = \# \text{edge}$$

$$n = \# \text{node}$$

$$\dim N(A) = 1$$

$$\therefore r = n - 1$$

Euler's Formula

$$\# \text{nodes} - \# \text{edges} + \# \text{loops} = 1$$

Exercise: $Ax = \begin{bmatrix} 2 \\ 4 \\ 2 \end{bmatrix}$ $x = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix} + c\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + d\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$

A is a 3×3 matrix

and $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ is the null vector

$$A = \begin{bmatrix} 1 & -1 & 0 \\ 2 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

Orthogonal

Orthogonal space:

def: two vectors and of and inner product space are called orthogonal if the inner product of and is 0.

Row space is orthogonal to nullspace

$$\begin{bmatrix} \text{row 1 of } A \\ \text{row 2 of } A \\ \dots \\ \text{row } m \text{ of } A \end{bmatrix} \begin{bmatrix} \vdots \\ x \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

and column space is orthogonal to nullspace of A^T

$$N(ATA) = N(A)$$

rank of $ATA = \text{rank of } A$

If A has independent columns then ATA is invertible.

Proof:

$$\text{Suppose } ATAx = 0$$

$$x^T A^T A^T x = 0$$

$$(Ax)^T (Ax) = 0$$

$$Ax = 0$$

$$x = 0$$

$\therefore ATA$ is invertible

Projection

Because $Ax=b$ may have no solution

we solve $\hat{A}\hat{x}=p$ instead

↳ projection of b onto column space

e.g.

e is prep to plane

$P = \hat{A}\hat{x}$ Find \hat{x}

Key: $b - \hat{A}\hat{x}$ is prep. to plane

$$a_1^T(b - \hat{A}\hat{x}) = 0 \quad a_2^T(b - \hat{A}\hat{x}) = 0$$

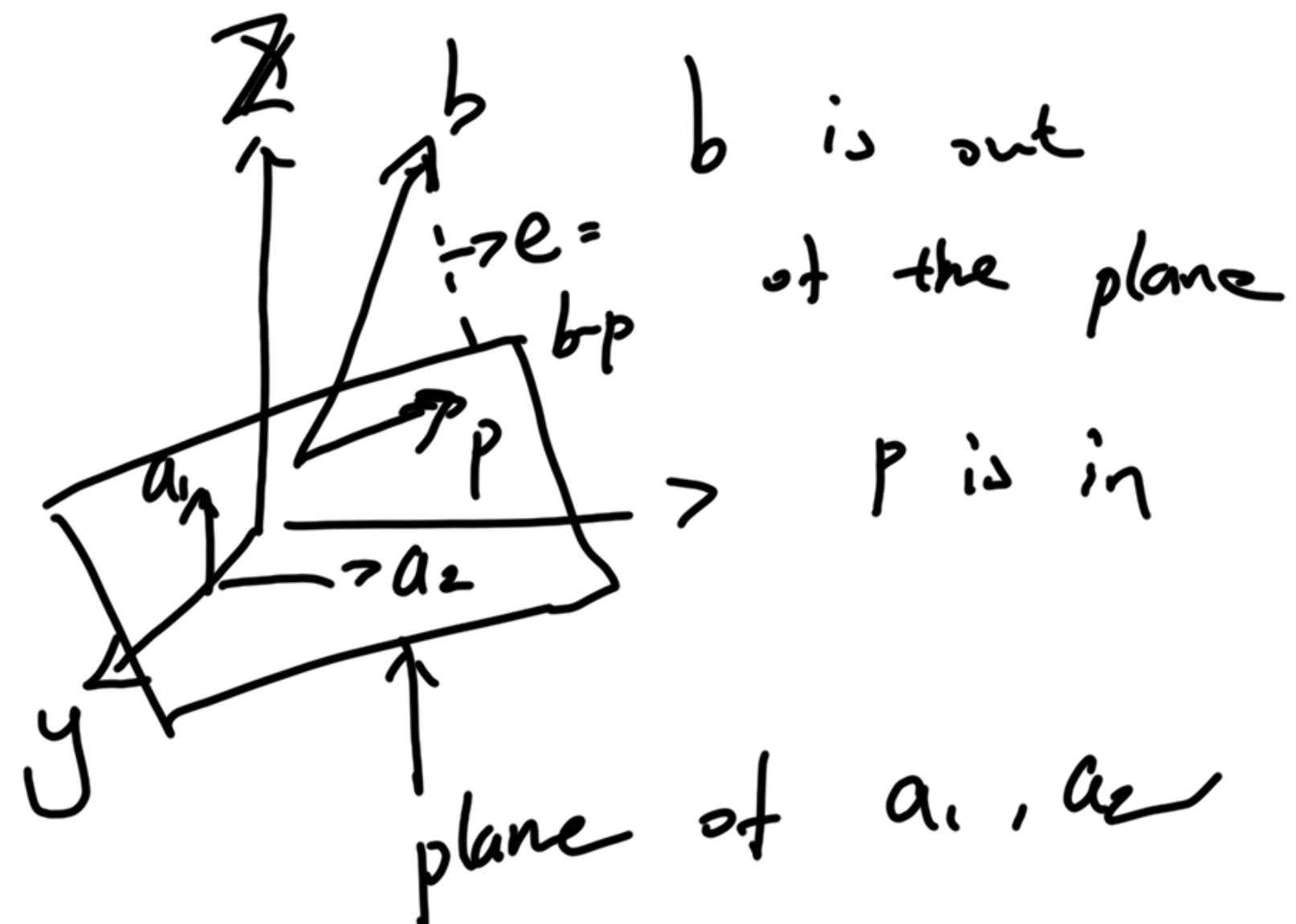
$$\begin{bmatrix} a_1^T \\ a_2^T \end{bmatrix} (b - \hat{A}\hat{x}) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$A^T(b - \hat{A}\hat{x}) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$\downarrow e$

e in $N(A^T)$

$e \perp (A)$



$$\text{column space of } A = \begin{bmatrix} a_1 & a_2 \end{bmatrix}$$

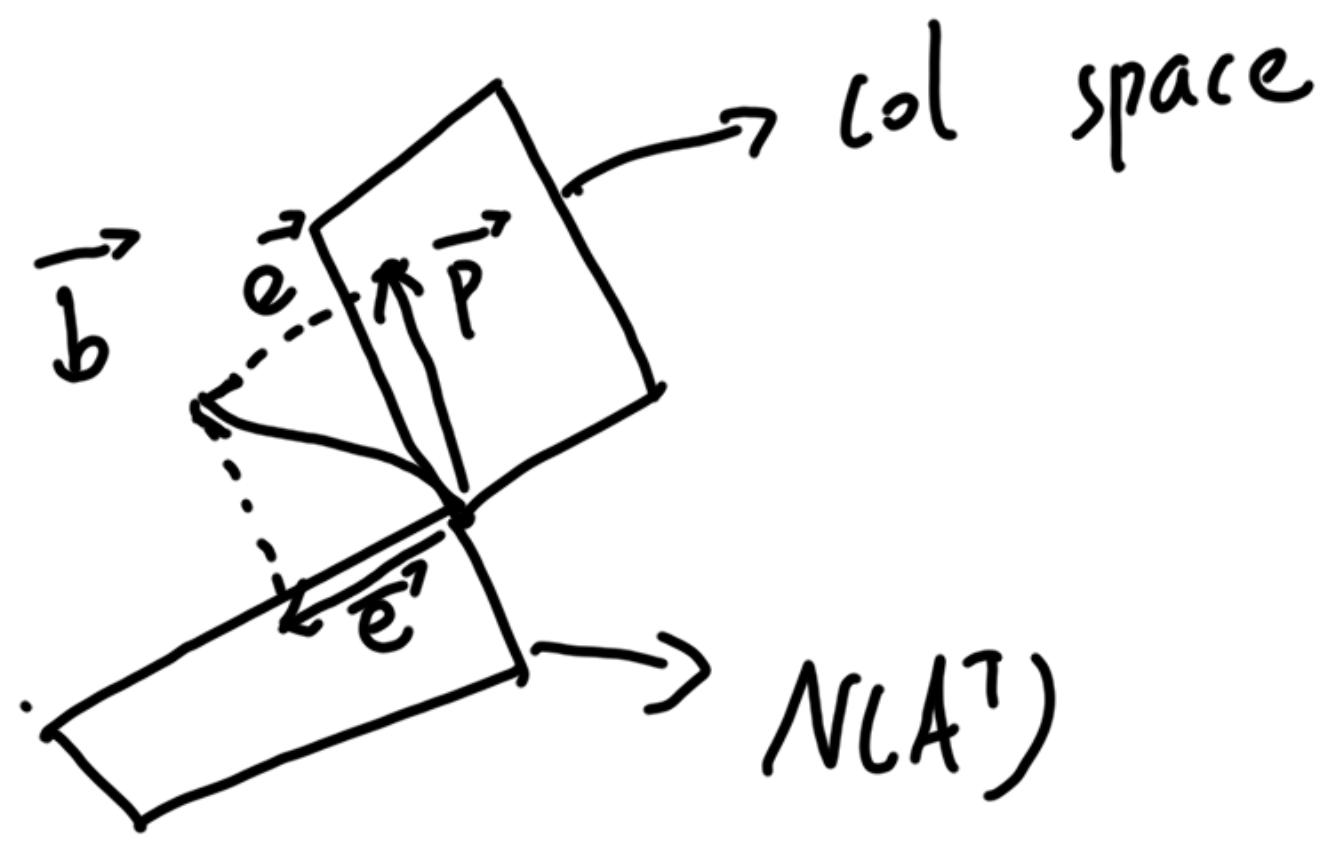
$$A^T A \hat{x} = A^T b$$

$$\hat{x} = (A^T A)^{-1} A^T b$$

$$P = \hat{A}\hat{x} = A (A^T A)^{-1} A^T b$$

$$P^T = P \quad P^2 = P$$

$$P = Pb$$



$$\vec{p} + \vec{e} = \vec{b}$$

↓

$$P\vec{b} \quad (I-P)\vec{b}$$

Key: $A^T A x = A^T b$

property of projection matrix P : $P^2 = P$

$$\left(\frac{AA^T}{A^TA} \right)^2 = \frac{AA^T}{A^TA}$$

Exercise:

$$(1,1) \quad (2,2) \quad (3,2)$$

$$y = Ax + b$$

$$A + b = 1$$

$$2A + b = 2$$

$$3A + b = 2$$

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

$$A^T A x = A^T b$$

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

$$\begin{bmatrix} 6 & 3 \\ 14 & 6 \end{bmatrix} \begin{bmatrix} A \\ b \end{bmatrix} = \begin{bmatrix} 5 \\ 11 \end{bmatrix}$$

$$A = \frac{1}{2}$$

$$b = \frac{2}{3}$$

$$A^T A = \begin{bmatrix} 1 & \cdots & 1 \\ t_1 & \cdots & t_m \end{bmatrix} \begin{bmatrix} 1 & t_1 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} = \begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix}$$

$$A^T b = \begin{bmatrix} 1 & \cdots & 1 \\ t_1 & \cdots & t_m \end{bmatrix} \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

$$\begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

Problem: Fit height b_1, \dots, b_m at times t_1, \dots, t_m by a parabola $C + Dt + Et^2$

Solution: $C + Dt_1 + Et_1^2 = b_1$
⋮

$$C + Dt_m + Et_m^2 = b_m$$

is $Ax = b$ with m by 3 matrix

$$\begin{bmatrix} 1 & t_1 & t_1^2 \\ \vdots & \vdots & \vdots \\ 1 & t_m & t_m^2 \end{bmatrix} \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix}$$

The closest parabola $C + Dt + Et^2$ chooses $\hat{x} = (C, D, E)$ to satisfy the three normal equations $A^T A \hat{x} = A^T b$

Orthonormal Bases and Gram-Schmidt

Def:

The vectors q_1, \dots, q_n are orthonormal if

$$q_i^T q_j = \begin{cases} 0 & \text{when } i \neq j \\ 1 & \text{when } i=j \quad \|q_i\|=1 \end{cases}$$

A matrix with orthonormal columns satisfies $(Q^T Q = I)$
When matrix is square: $Q^T = Q^{-1}$

- Every permutation matrix is an orthogonal matrix

Reflection: If u is any unit vector, set $Q = I - 2uu^T$. Notice
that uu^T is a matrix while u^Tu is a number $\|u\|^2 = 1$

$$Q^T = I - 2uu^T = Q \quad Q^T Q = I - 4uu^T + 4uu^T u u^T = I \quad (Q^T = Q^{-1})$$

$$\text{e.g. } u = \left(-\frac{\sqrt{2}}{2}, \frac{\sqrt{2}}{2} \right) \quad Q = I - 2 \begin{bmatrix} 0.5 & -0.5 \\ 0.5 & 0.5 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} y \\ x \end{bmatrix}$$

When (x,y) goes to (y,x) a vector like $(3,3)$ doesn't
move it's on the mirror line

If Q has orthonormal columns ($Q^T Q = I$), it leaves lengths unchanged:

$$\|Qx\| = \|x\| \quad (Qx)^T(Qy) = x^T Q^T Q y = x^T y$$

property of orthogonal matrix: $(\lambda) = |$

$$Ax = \lambda x$$

$$AA^T = A^T A = E$$

$$\|A\| \|x\| = |\lambda| \|x\|$$

$$Ax = \lambda x$$

$$|\lambda| = |$$

$$x^T A^T = \lambda x^T$$

$$x^T A^T A x = \lambda^2 x^T x$$

$$\lambda^2 = |$$

Gram - Schmidt

- ① Begin by choosing $A = a$
- ② start with b and subtract its projection along A

$$B = b - A \frac{A^T b}{A^T A}$$

A and B are orthogonal

$$C = c - A \frac{A^T c}{A^T A} - B \frac{B^T c}{B^T B}$$

Example of Gram - Schmidt

$A = QR$:

first step: $q_1 = \frac{a}{\|a\|}$

$$\begin{bmatrix} 1 & 1 & 1 \\ a & b & c \end{bmatrix} = \begin{bmatrix} q_1 & q_2 & q_3 \end{bmatrix} \begin{bmatrix} q_1^T a & q_1^T b & q_1^T c \\ q_2^T b & q_2^T c \\ q_3^T c \end{bmatrix}$$

$$\therefore b = \|b\|q_2 + q_1 \frac{q_1^T b}{\|q_1\|^2}$$

$$c = \|c\|q_3 + q_1 \frac{q_1^T c}{\|q_1\|^2} + q_2 \frac{q_2^T c}{\|q_2\|^2}$$

$$A^T A \hat{x} = A^T b$$

$$R^T R \hat{x} = R^T Q^T b$$

$$R \hat{x} = Q^T b$$

$$A^{-1} = \frac{1}{\det A} C$$

$$A = \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ -1 & 0 & 3 \\ 0 & -2 & 3 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ 0 & -\frac{2}{\sqrt{6}} & \frac{1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} \sqrt{2} & \sqrt{2} & \sqrt{8} \\ 0 & \sqrt{6} & -\sqrt{6} \\ 0 & 0 & \sqrt{3} \end{bmatrix} = QR$$

$$q_1 = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \\ -\frac{\sqrt{2}}{2} \\ 0 \end{bmatrix}$$

$$q_2 = \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix} - \frac{a^T b}{a^T a} a$$

$$= \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix} - \frac{2}{2} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ -2 \end{bmatrix}$$

$$= \sqrt{6} \begin{bmatrix} \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \\ -\frac{2}{\sqrt{6}} \end{bmatrix}$$

$$q_3 = \begin{bmatrix} 3 \\ -3 \\ 3 \end{bmatrix} - \frac{a^T c}{a^T a} a - \frac{b^T c}{b^T b} b$$

$$= \begin{bmatrix} \frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{3}} \end{bmatrix}$$

Eigenvalues - Eigen vectors

$$Ax = \lambda x$$

↓ ↓
Eigenvalues Eigen vectors

$$(A - \lambda I)x = 0$$

$$\therefore \det(A - \lambda I) = 0$$

$$\text{Trace: } \lambda_1 + \lambda_2 + \cdots + \lambda_n = a_{11} + a_{22} + \cdots + a_{nn}$$

$$\det A = \lambda_1 \cdot \lambda_2 \cdots \lambda_n$$

$$\begin{cases} Ax = \lambda x \\ (A + \beta I)x = (\lambda + \beta)x \end{cases}$$

Every matrix $C = B^{-1}AB$ has the same eigenvalue as A
 C 's are "similar" to A

proof

Suppose $x = \lambda x$ $B(B^{-1})$ has the same eigenvalue λ with the new eigenvector Bx :

$$(B(B^{-1}))(Bx) = B(x = B\lambda x = \lambda(Bx))$$

eigenvalues might be complex number

e.g.

$$Q = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \quad \text{trace} = 0 \quad \det = 1$$

$$\det(Q - \lambda I) = \begin{vmatrix} -\lambda - 1 & 1 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 + 1 = 0$$

$$\therefore \lambda_1 = i$$

$$\lambda_2 = -i$$

Suppose n independent eigenvectors of A

put them in columns of S

$$AS = A \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} = \begin{bmatrix} \lambda_1 x_1 & \cdots & \lambda_n x_n \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & & 0 \\ 0 & \ddots & & 0 \\ & & \ddots & 0 \\ & & & \lambda_n \end{bmatrix} = S\Lambda$$

$$S^{-1}AS = \Lambda$$

$$A = S\Lambda S^{-1}$$

$$\text{If } Ax = \lambda x$$

$$A^2x = \lambda Ax = \lambda^2 x$$

$$A^2 = S\Lambda^2 S^{-1}$$

A^2 eigenvector is same eigenvalue is λ^2

$$A^k = S\Lambda^k S^{-1}$$

Theorem

$$A^k \rightarrow 0 \text{ as } k \rightarrow \infty$$

$$\text{if all } |\lambda_i| < 1$$

A is sure to have n independent eigenvectors (and be diagonalizable) if all the λ are different

Repeated eigenvalues may or may not have

e.g. I $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ n independent eigenvector

Proof:

Suppose $c_1x_1 + c_2x_2 = 0$

Multiply by A : $c_1\lambda_1x_1 + c_2\lambda_2x_2 = 0$

Multiply by λ_2 : $c_1\lambda_2x_1 + c_2\lambda_2x_2 = 0$

$$\therefore (c_1 - c_2)\lambda_2x_1 = 0$$

$$\therefore c_1 = c_2 = 0$$

Similarly $c_2 = 0$

$$\therefore c_1 = c_2 = 0 \quad c_1x_1 + c_2x_2 = 0$$

$\therefore x_1, x_2$ must be independent

This proof extends directly to j eigenvectors.

If x_1, x_2 is symmetric matrix A's two
eigen vectors : $Ax_1 = \lambda_1 x_1$ $Ax_2 = \lambda_2 x_2$ and

$$\lambda_1 \neq \lambda_2$$

we can have : $x_1^T x_2 = 0 \Rightarrow x_1, x_2$ are
orthogonal

When things are evolving in time by a first-order system

$$U_{k+1} = AU_k$$

$$U_k = A^k U_0$$

$$U_0 = C_1 X_1 + C_2 X_2 + \dots + C_n X_n = S_C$$

$$A^{100} U_0 = C_1 \lambda_1^{100} X_1 + C_2 \lambda_2^{100} X_2 + \dots + C_n \lambda_n^{100} X_n = A^{100} S_C$$

e.g. Fibonacci sequence 0, 1, 1, 2, 3, 5 ... $F_{100} = ?$

$$F_{k+2} = F_{k+1} + F_k$$

$$F_{k+1} = F_{k+1}$$

$$A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

$$\lambda = \frac{1 \pm \sqrt{5}}{2}$$

$$\lambda_1 = \frac{1 + \sqrt{5}}{2}$$

$$\lambda_2 = \frac{1 - \sqrt{5}}{2}$$

$$U_k = \begin{bmatrix} F_{k+1} \\ F_k \end{bmatrix} U_{k+1} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \hat{F}_{k+1} \\ \hat{F}_k \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}^A U_k$$

$$X_1 = \begin{bmatrix} \lambda_1 \\ 1 \end{bmatrix}$$

$$X_2 = \begin{bmatrix} \lambda_2 \\ 1 \end{bmatrix}$$

$$[U_{k+1}] = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} [U_k]$$

$$C_1 X_1 + C_2 X_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\text{e.g. } \frac{du_1}{dt} = -u_1 + 2u_2$$

$$U_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\frac{du_2}{dt} = u_1 - 2u_2$$



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

$$\lambda_1 = 0 \quad \lambda_2 = -3$$

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

$$u(t) = C_1 e^{\lambda_1 t} x_1 + C_2 e^{\lambda_2 t} x_2$$

$$= C_1 \cdot 1 \cdot \begin{bmatrix} 2 \\ 1 \end{bmatrix} + C_2 e^{-3t} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$= \frac{1}{3} \begin{bmatrix} 2 \\ 1 \end{bmatrix} + \frac{1}{3} e^{-3t} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Differential equations 微分方程

$$\frac{du}{dt} = Au$$

set $U = S V \xrightarrow{\text{eigenvector matrix}}$

$$\frac{du}{dt} = Au$$

↓

$$\frac{dv}{dt} = S^{-1} A S v = \Lambda v$$

$$\frac{dV_1}{dt} = \lambda_1 V_1$$

⋮

$$\therefore V(t) = e^{\Lambda t} V(0)$$

$$U(t) = S e^{\Lambda t} S^{-1} U(0)$$

$$\text{If } f(x) = C e^{\lambda x}$$

$$f'(x) = (\lambda x) e^{\lambda x} = \lambda (C e^{\lambda x})$$

$$f(x) = f(0) \cdot e^{\lambda x}$$

↓
★

$$e^{\Lambda t} = S e^{\Lambda t} S^{-1}$$

Matrix exponential

$$e^{At} = I + At + \frac{(At)^2}{2} + \frac{(At)^3}{6} + \dots + \frac{(At)^n}{n!} + \dots$$

$$= S \cdot S^{-1} + \lambda_1 S^{-1} t + \frac{\lambda_1^2 S^{-1}}{2} t^2 + \dots$$

$$= S e^{\lambda t} S^{-1}$$

$$\lambda = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$$

$$e^{\lambda t} = \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix}$$

$$u(t) = e^{At} u(0) = S e^{\lambda t} S^{-1} u(0)$$

$$= c_1 e^{\lambda_1 t} x_1 + \dots + c_n e^{\lambda_n t} x_n$$

$$= [x_1 \dots x_n] \begin{bmatrix} e^{\lambda_1 t} & & \\ & \ddots & \\ & & e^{\lambda_n t} \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix}$$

if $\operatorname{Re} \lambda_i < 0$
the exponential goes to 0
 $u(t)$ is steady

$u(t)$ approaches zero (stability) if every λ has negative real part : All $e^{\lambda t} \rightarrow 0$

$$\therefore |e^{(-3+6i)t}| = e^{-3t} \quad |e^{6it}| = 1$$

$$y'' + by' + ky = 0$$

$$y' = y'$$

$$u = \begin{bmatrix} y' \\ y \end{bmatrix} \quad u' = \begin{bmatrix} -b & -k \\ 1 & 0 \end{bmatrix} [u]$$

if we have a matrix goes from

a n order, we can put it to

first order

Markov matrix

Two properties:

1. every entry is greater equal zero
2. all columns add to 1

so the powers of Markov matrix are all Markov

the matrix has an eigenvalue of 1

1. $\lambda=1$ is an eigenvalue

2. All other $|\lambda_i| < 1$

$$U_k = A^k U_0 = c_1 \lambda_1^k x_1 + c_2 \lambda_2^k x_2 + \dots$$

$\xrightarrow{\lambda_2 \rightarrow 0}$

$$= c_1 \lambda_1^k x_1$$

$$= c_1 x_1$$

proof:

$$A - I = \begin{bmatrix} -0.1 & 0.01 & 0.3 \\ 0.2 & -0.01 & 0.3 \\ 0.7 & 0 & -0.6 \end{bmatrix}$$

because $(1,1,1)$ is in $N(A^T)$

$$\therefore \det(A - I) = 0$$

eigenvalue of A = eigenvalue of A^T

e.g. Application of Markov matrix

$$\begin{bmatrix} U_{cal} \\ U_{mass} \end{bmatrix}_{t=k+1} = \begin{bmatrix} 0.9 & 0.2 \\ 0.1 & 0.8 \end{bmatrix} \begin{bmatrix} U_{cal} \\ U_{mass} \end{bmatrix}_k$$

$$\begin{bmatrix} U_{cal} \\ U_{mass} \end{bmatrix}_0 = \begin{bmatrix} 0 \\ 1000 \end{bmatrix}$$

$$U_k = c_1 1^k \begin{bmatrix} 2 \\ 1 \end{bmatrix} + c_2 (0.7)^k \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \frac{1000}{3} \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$= \frac{1000}{3}$$

Fourier Series

$$f(x) = a_0 + a_1 \cos x + b_1 \sin x + a_2 \cos 2x + b_2 \sin 2x + \dots$$

dot product of vectors / functions

vector function

$$\nabla^T W = v_1 W_1 + \dots + v_n W_n$$

$$f^T g = \int_0^{2\pi} f(x) g(x) dx$$

$$\int_0^{2\pi} f(x) \cos x dx = a_1 \int_0^{2\pi} \cos^2 x = a_1 \pi$$

$$a_1 = \frac{1}{\pi} \int_0^{2\pi} f(x) \cos x$$

eigenvalues of A^{-1} are $\frac{1}{\lambda_1} \frac{1}{\lambda_2} \dots$

$$|A - \lambda I| = 0 \Rightarrow |A^{-1}| |A - \lambda I| = 0 \Rightarrow |A^{-1}A - \lambda A^{-1}| = 0$$

$$|I - \lambda A^{-1}| = 0 \Rightarrow |\frac{1}{\lambda} I - A^{-1}| = 0$$

Symmetric matrix

$$A = A^T$$

① The eigenvalues are real

② The eigenvectors are perpendicular

usual

$$A = S \Lambda S^{-1}$$

symmetric:

$$A = Q \Lambda Q^{-1}$$

Why eigenvalues real?

$$Ax = \lambda x \xrightarrow{\text{always}} A\bar{x} = \bar{\lambda}\bar{x} \Rightarrow \bar{x}^T A = \bar{x}^T \bar{\lambda}$$

$$\bar{x}^T A x = \bar{\lambda} \bar{x}^T x$$

$$\bar{x}^T A x = \overline{\bar{x}^T \lambda x}$$

GOOD MATRIX:

Real λ 's

Perpendicular x 's

$$A = \bar{A}^T$$

if A is complex : $A = \bar{A}^T \Rightarrow \lambda = \bar{\lambda}$

Eigenvectors of a real symmetric matrix (when they correspond to different λ 's) are perpendicular

Proof:

Suppose $Sx = \lambda_1 x$ and $Sy = \lambda_2 y$ $\lambda_1 \neq \lambda_2$

$$(\lambda_1 x)^T y = (Sx)^T y = x^T S^T y = x^T Sy = x^T \lambda_2 y$$

$$x^T \lambda_1 y = x^T \lambda_2 y$$

$$\therefore x^T y = 0$$

If $A^{(n \times n)}$ is symmetric, $P = T^T A T$ is diagonal

T is orthogonal matrix

prove by mathematical induction ~~數子法~~

$n=1$ easy

when $n=t$ suppose it's right

when $n=t+1$

suppose λ_1 is an eigenvalue of A , $Ax_1 = \lambda_1 x_1$ let $\|x_1\|=1$
span x_1 into a orthonormal basis in \mathbb{R}^t $\{x_1, \dots, x_t\}$

$T_0 = (x_1 \ x_2 \ \dots \ x_t)$ T_0 is orthogonal matrix $T_0^{-1} = T_0^T$

$$T_0^{-1} A T_0 = \begin{pmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_t^T \end{pmatrix} A (x_1 \ x_2 \ \dots \ x_t) = \begin{pmatrix} x_1^T A x_1 & x_1^T A x_2 & \dots & x_1^T A x_t \\ x_2^T A x_1 & x_2^T A x_2 & \dots & x_2^T A x_t \\ \vdots & \vdots & \ddots & \vdots \\ x_t^T A x_1 & x_t^T A x_2 & \dots & x_t^T A x_t \end{pmatrix}$$

$\therefore \exists$ orthogonal matrix T_1
s.t. $T_1^{-1} A_1 T_1 = P_1$ P_1 is diagonal

$$= \begin{pmatrix} 1 & 0 \\ 0 & T_1 \end{pmatrix} \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_t \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & T_1 \end{pmatrix}^{-1}$$

$$= \begin{pmatrix} \lambda_1 & & & \\ \vdots & \ddots & & \\ 0 & & A_1 & \\ \vdots & & & \ddots & 0 \end{pmatrix}$$

A_1 is symmetric

$$T = T_0 \begin{pmatrix} 1 & 0 \\ 0 & T_1 \end{pmatrix}$$

$$T^T T = I \quad \because T \text{ is } \begin{cases} \text{orthogonal} \\ \text{or...} \end{cases}$$

Schur's Theorem

Every square A factor into QTQ^{-1} where T is upper triangular and $\bar{Q}^T = Q^{-1}$. If A has real eigenvalues then Q and T can be chosen real: $Q^T Q = I$

Proof: mathematical induction

$$A = A^T$$

$$A = Q \Lambda Q^T$$

$$= [q_1 \ q_2 \dots \ q_n] \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} \begin{bmatrix} q_1^T \\ \vdots \\ q_n^T \end{bmatrix}$$

$$= \lambda_1 q_1 q_1^T + \lambda_2 q_2 q_2^T + \dots$$

Symmetric matrix:

signs of pivots same as signs of λ 's

pivots = # positive λ 's
(positive)

If $AA^T = A^TA$ the eigenvectors of A are orthogonal

A : symmetric

anti-symmetric

orthonormal

$$Qx = \lambda_1 x \quad ①$$

$$Qy = \lambda_2 y$$

$$y^T Q^T = \lambda_2 y^T \quad ②$$

$\textcircled{2} \times \textcircled{1}$

$$y^T x = \lambda_1 \lambda_2 y^T x$$

$$\therefore |\lambda| = 1$$

$$\therefore y^T x = 0$$

Complex matrix

inner product :

$$\bar{z}^T \cdot z \quad z^H z$$

Symmetric

$$A^H = A \quad \text{e.g.: } \begin{bmatrix} 2 & 3+i \\ 3-i & 5 \end{bmatrix}$$

Orthnormal

$$q_1, q_2, \dots, q_n$$

$$\bar{q}_i^T \cdot q_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases}$$

Fouier

$$F_n = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & W & W^2 & \dots & W^{n-1} \\ 1 & W^2 & W^4 & \dots & W^{2(n-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & W^{n-1} & W^{2(n-1)} & \dots & W^{(n-1)^2} \end{bmatrix} \quad (F_n)_{ij} = W^{ij}$$

$i, j = 0, \dots, n-1$

$$W^n = 1 \quad W = e^{\frac{2\pi}{n}}$$

$$F_4 : \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & i & i^2 & i^3 \\ 1 & i^2 & i^4 & i^6 \\ 1 & i^3 & i^6 & i^9 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & i & -1 & -i \\ 1 & -1 & 1 & 1 \\ 1 & -i & -1 & i \end{bmatrix}$$

$$F_4^H \cdot F_4 = I$$

Fast Fourier Transform

takes the even (0, 2, 4...)

by

numbered

$$[F_{64}] = [I \ D] [F_{32} \ 0] [0 \ F_{32}] [\cdot \ \cdot \ \cdot \ \cdot]$$

↑ numbered
components first
and then the odds

$$D = \begin{bmatrix} 1 & w & w^2 & \dots & w^{31} \end{bmatrix}$$



$$\begin{bmatrix} I & D \\ I-D & 0 \\ 0 & I-D \end{bmatrix} \begin{bmatrix} F_6 & & & \\ & F_6 & & \\ & & F_6 & \\ & & & F_6 \end{bmatrix} \begin{bmatrix} P_{32} & & \\ & P_{32} & \end{bmatrix}$$

only need $\frac{n}{2} \log_2 n$ multiply

Positive Definite Matrix

① $\lambda_1 > 0 \quad \lambda_2 > 0 \dots$

② $\det A > 0$

③ pivot > 0

④ $x^T A x > 0$

If A, B are pos def $A+B$ is pos def

$A^T A$ is pos def

Similar Matrix

A and B are similar

means: for some M

$$B = M^{-1}AM$$

A, B have same eigenvalues

eigenvector of A = M^{-1} (evector of A)

ATTENTION: If A, B have same eigenvalues

they probably not similar

The Singular Value Decomposition (SVD)

$$A = U \Sigma V^T$$

$$⑥, u_i = A v_i \xrightarrow{\text{orthonormal}}$$

v_1, v_2, \dots in row space

u_1, u_2, \dots in col space

Idea: We want to find an orthonormal basis in row space
and A multiply it can get a orthogonal basis in col space

If there's some null space, then we want to stick
in a basis for that

$$\underbrace{v_1, v_2, \dots, v_r}_{\text{row}}, \underbrace{v_{r+1}, \dots, v_n}_{\text{null}}$$

$$\underbrace{u_1, u_2, \dots, u_r}_{\text{col}}, \underbrace{u_{r+1}, \dots, u_n}_{\text{null of } A^T}$$

$$A^T A = V \Sigma^T \Sigma V^T$$

$$A A^T = U \Sigma \Sigma^T U^T$$

$$= V \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_r^2 \end{bmatrix} V^T$$

\downarrow
 $Q \Lambda Q^T$ of $A^T A$

$$\text{e.g. } \begin{bmatrix} 4 & 4 \\ -3 & 3 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 25 & 7 \\ 7 & 25 \end{bmatrix}$$

$$X_1 = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix} \quad 32$$

$$X_2 = \begin{bmatrix} \frac{\sqrt{2}}{2} \\ -\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} \end{bmatrix} \quad 18$$

$$\begin{bmatrix} 4 & 4 \\ -3 & 3 \end{bmatrix} = U \begin{bmatrix} \sqrt{32} & 0 \\ 0 & \sqrt{18} \end{bmatrix} V^T \begin{bmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{bmatrix}$$

$$U = \begin{bmatrix} \frac{1}{\sqrt{32}} & 0 \\ 0 & \frac{1}{\sqrt{18}} \end{bmatrix} \begin{bmatrix} 4 & 4 \\ -3 & 3 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & -\frac{\sqrt{2}}{2} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{32}} & 0 \\ 0 & \frac{1}{\sqrt{18}} \end{bmatrix} \begin{bmatrix} 4\sqrt{2} & 0 \\ 0 & -3\sqrt{2} \end{bmatrix}$$

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

$$\text{e.g. } \begin{bmatrix} 4 & 3 \\ 8 & 6 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 8 & 60 \\ 60 & 45 \end{bmatrix}$$

$$\lambda_1 = 125 \quad \lambda_2 = 0$$

$$x_1 = \begin{bmatrix} 0.8 \\ 0.6 \end{bmatrix} \quad x_2 = \begin{bmatrix} 0.6 \\ -0.8 \end{bmatrix}$$

$$\begin{bmatrix} 4 & 3 \\ 8 & 6 \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{5}}{5} & \frac{2\sqrt{5}}{5} \\ \frac{2\sqrt{5}}{5} & -\frac{\sqrt{5}}{5} \end{bmatrix} \begin{bmatrix} \sqrt{45} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0.8 & 0.6 \\ 0.6 & -0.8 \end{bmatrix}$$

Linear Transform

$$T(cv + dw) = cT(v) + dT(w)$$

T : with respect to $v_1 \dots v_n$ it has matrix A

with respect to $w_1 \dots w_g$ has matrix B

$$B = M^{-1} A M$$

similar

2-sided inverse

$$AA^{-1} = I = A^{-1}A$$

condition: full rank $r=m=n$

left inverse

$$\text{nullspace} = \{0\}$$

full column rank

$$r=n$$

$A^T A$ is full rank

$$(A^T A)^{-1} A^T$$

↓
left inverse

$$(A^T A)^{-1} A^T A = I$$

right inverse

full row rank

$$r=m$$

$$\text{nullspace of } A^T = \{0\}$$

$A A^T$ is full rank

$$A^T (A A^T)^{-1}$$

↓
right inverse

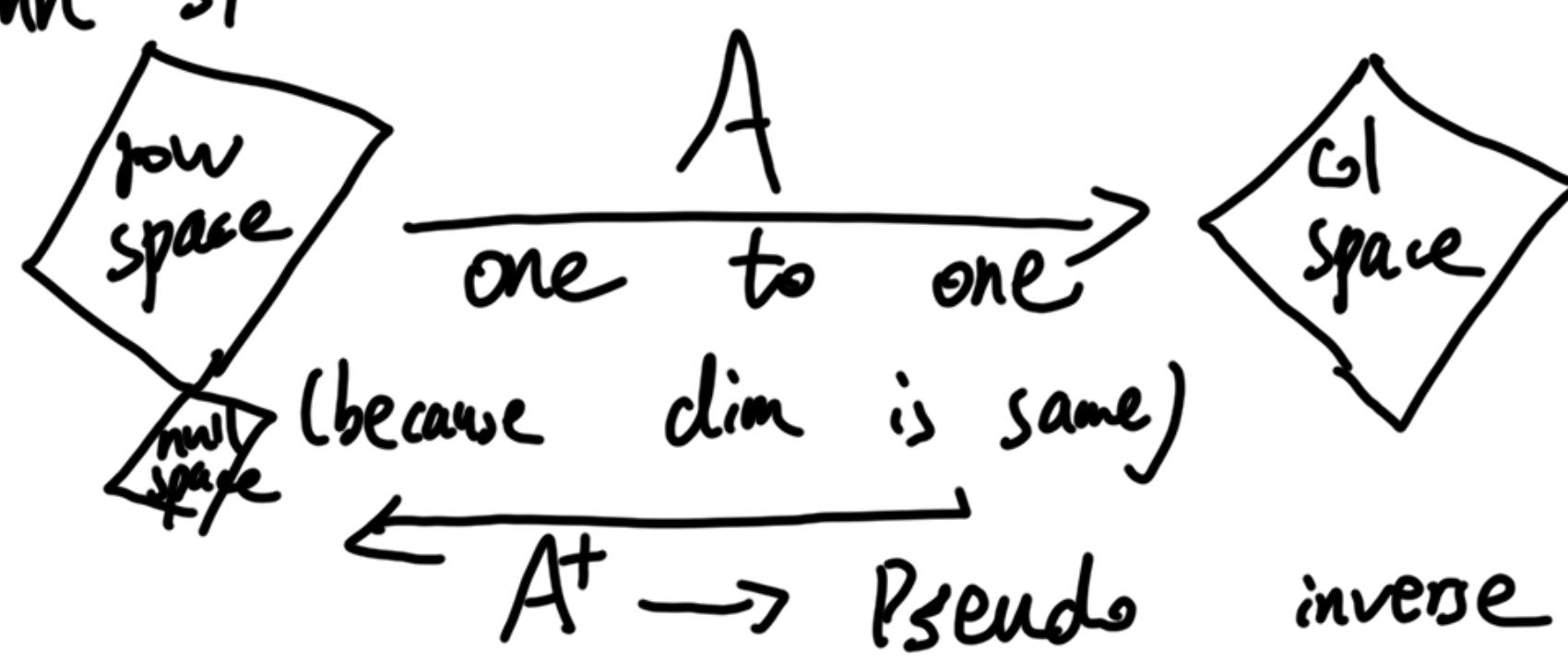
$$A A^T (A A^T)^{-1} = I$$

* if A (left inverse), $(\text{right inverse}) A$

they are projection matrix

Pseudo inverse

key idea: $Ax = b$ b is a combination of column vector, b is in column space



If $x \neq y$ both in row space the col space

$$Ax \neq Ay$$

Proof

Suppose $Ax = Ay$

$$\underline{A(x-y)} = 0 \quad \text{in nullspace}$$

$\therefore (x-y)$ is in nullspace

\therefore nullspace and nullspace are orthogonal

\therefore contradict

The way to find Pseudo inverse A^+

① SVD

$$A = U \Sigma V^T$$
$$\Sigma = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_m \end{bmatrix}_{n \times m}$$

$$\Sigma^+ = \begin{bmatrix} \sigma_1^{-1} & & 0 \\ & \ddots & \\ 0 & & \sigma_m^{-1} \end{bmatrix}_{m \times n}$$

idea:

$$\Sigma x = b$$
$$\Sigma^+ b = x$$

because U, V^T are orthonormal

$$A^+ = V \Sigma^+ U^T$$