

Introduction to Linear Algebra
- Gilbert Strang

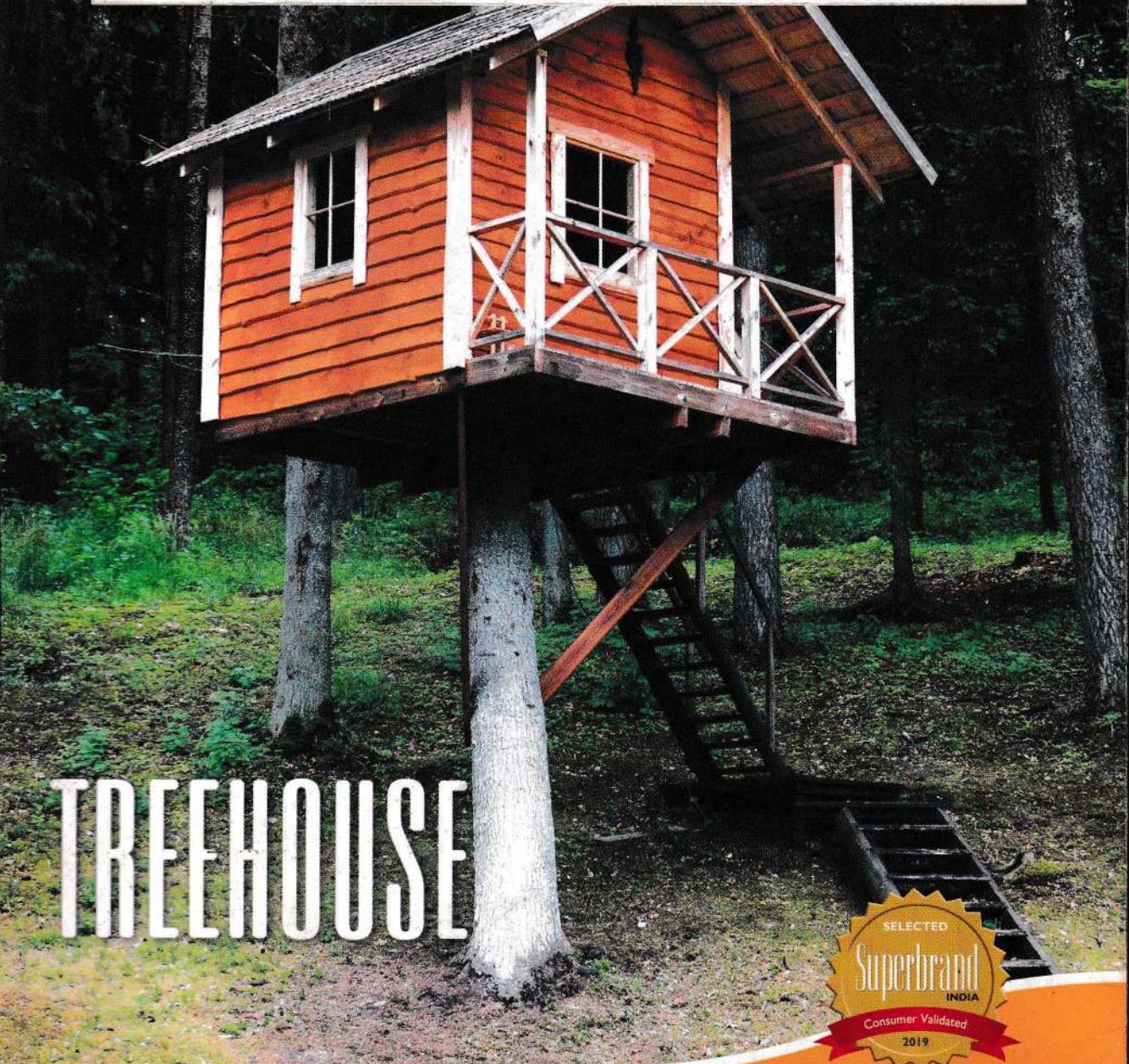
5

Vector Spaces & Subspaces

Orthogonality

Ende

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I N D E X

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		<p>INTRODUCTION TO LINEAR ALGEBRA — Gilbert Strang, MIT (5th Edition)</p>		

$$\dim(\text{outputs}) + \dim(\text{null space}) = \dim(\text{inputs})$$

For an $m \times n$ matrix of rank γ ,

$$A_{m \times n}$$

outputs = column space

$$\dim(\text{outputs}) = \gamma = \dim(C(A))$$

$$\dim(\text{inputs}) = n$$

$$\dim(\text{null space}) = n - \gamma$$

$$(*) \quad \gamma + (n - \gamma) = n$$

45. Inside \mathbb{R}^n , suppose $\dim(V) + \dim(W) > n$.

Show that some non-zero vector is in both V and W .

Ans:

$$\dim(V) + \dim(W) = \dim(V \cap W) + \dim(V + W) > n$$

$$\dim(V + W) \leq n$$

$$\implies \dim(V \cap W) > 0$$

$V \cap W$ is non-zero

$$V \cap W \neq \emptyset \iff 0 \in V \cap W$$

46 Suppose A is 10×10 and $A^2 = 0$.

~~Ans~~

$$A^2 = AA = A \begin{bmatrix} \vec{q}_1 & \vec{q}_2 & \dots & \vec{q}_{10} \end{bmatrix} = \begin{bmatrix} A\vec{q}_1 & A\vec{q}_2 & \dots & A\vec{q}_{10} \end{bmatrix} = \begin{bmatrix} \vec{0} & \vec{0} & \dots & \vec{0} \end{bmatrix}$$

~~Ques~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~ ~~Ans~~

A multiplies each column of ' A ' to give the zero vector.

$$A\vec{q}_1 = \vec{0}, A\vec{q}_2 = \vec{0}, \dots, A\vec{q}_{10} = \vec{0}$$

$$\boxed{A^2 = 0 \Rightarrow C(A) \subset N(A)}$$

$$\dim(C(A)) = 8$$

$$\dim(N(A)) = n - r = 10 - 8$$

$$C(A) \subset N(A) \implies r \leq 10 - 8$$

, $2r \leq 10 \implies \boxed{\boxed{r \leq 5}}$

46 Suppose A is 10×10 and $A^2 = 0$.

$$A^2 = AA = A \begin{bmatrix} \vec{q}_1 & \vec{q}_2 & \dots & \vec{q}_{10} \end{bmatrix} = \begin{bmatrix} A\vec{q}_1 & A\vec{q}_2 & \dots & A\vec{q}_{10} \end{bmatrix} = \begin{bmatrix} \vec{0} & \vec{0} & \dots & \vec{0} \end{bmatrix}$$

A multiplies each column of ' A ' to give the zero vector.

$$A\vec{q}_1 = \vec{0}, A\vec{q}_2 = \vec{0}, \dots, A\vec{q}_{10} = \vec{0}$$

$$A^2 = 0 \Rightarrow C(A) \subset N(A)$$

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

$$\dim(N(A)) = n - r = 10 - r$$

$$C(A) \subset N(A) \implies r \leq 10 - r \\ , \quad 2r \leq 10 \implies r \leq 5$$

3.5

Q. Find bases & dimensions for the 4 subspaces associated with

$$\textcircled{2} \quad A = \begin{bmatrix} 1 & 2 & 4 \\ 2 & 4 & 8 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & 4 \\ 0 & 0 & 0 \end{bmatrix} = R_A$$

$$x+2y+4z=0$$

Ans: Row space - Dimension: 1
Basis: $(1, 2, 4)$

Null space - Dimension: 2
Basis: $(-2, 1, 0), (-4, 0, 1)$

Column space - Dimension: 1
Basis: $(1, 2)$

$$A^T y = 0 \\ y^T A = 0^T$$

Left null space - Dimension: 1
Basis: $(-2, 1)$

$$A^T = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 4 & 8 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \Rightarrow y_1 + 2y_2 = 0 \\ \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = y_2 \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$

$$⑥ B = \begin{bmatrix} 1 & 2 & 4 \\ 2 & 5 & 8 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & 4 \\ 0 & 1 & 0 \end{bmatrix}$$

Ans:

$$\rightarrow \begin{bmatrix} 1 & 0 & 4 \\ 0 & 1 & 0 \end{bmatrix} = R_B$$

$$x+4z=0 \\ y=0$$

Row space basis: $(1, 2, 4), (2, 5, 8)$

Column space basis: $(1, 2), (2, 5)$

Null space basis: $(-4, 0, 1)$

$$m-r = 2-2=0$$

left null space basis is empty

only $y=0$ is the solution to $A^T y = 0$

\therefore the rows of B are independent

3. Find a basis for each of the 4 subspaces associated with A:

$$A = \begin{bmatrix} 0 & 1 & 2 & 3 & 4 \\ 0 & 1 & 2 & 4 & G \\ 0 & 0 & 0 & 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 & 2 & 3 & 4 \\ 0 & 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$A = L \cup$

Row:

Rowspace Basis: $(0, 1, 2, 3, 4), (0, 0, 0, 1, 2)$

row operations does not change row space

Column space Basis: Pivot columns of A not U.

$(1, 1, 0), (3, 4, 1)$

$$3d = 3(-2e) = -6e.$$

~~$b + 2c + 3d + 4e = 0$~~

$$d + 2e = 0.$$

$$\begin{bmatrix} a \\ b \\ c \\ d \\ e \end{bmatrix} = a \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + c \begin{bmatrix} 0 \\ -2 \\ 1 \\ 0 \\ 0 \end{bmatrix} + e \begin{bmatrix} 0 \\ +2 \\ 0 \\ -2 \\ 1 \end{bmatrix}$$

Nullspace Basis: $(1, 0, 0, 0, 0), (0, 2, -1, 0, 0),$

$(0, 2, 0, -2, 1)$

$$A^T = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 0 \\ 2 & 2 & 0 \\ 3 & 4 & 1 \\ 4 & 6 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 2 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Ans:-

$$x+y=0$$

$$y+z=0$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = z \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

(d)

Ans:

4. Construct a matrix with the required property

(a)

- ① Column space contains $\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$, row space contains $\begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 5 \\ 1 \end{bmatrix}$

(e)

Ans:-

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

Ans:

③ Dimension

~~c) $\dim(N(A^T)) = 1 + \dim(N(A))$~~

Aus:

$$n-r = 1 + m-r \Rightarrow \underline{\underline{n-m=1}}$$

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

d) $N(A)$ contains $\begin{bmatrix} 1 \\ 3 \end{bmatrix}$, column space contains $\begin{bmatrix} 3 \\ -1 \end{bmatrix}$

Aus: A is 2×2

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

e) Row space = column space, $N(A) \neq N(A^T)$

Aus:

$$m=n$$

$$\Rightarrow n-r = m-r$$

$$\dim(\text{col}(A)) = \dim(N(A^T))$$

N.P.

Next chapter

7. Suppose the 3×3 matrix A is invertible.

Write down bases for the 4 subspaces for A ,
and also for the 3×6 matrix $B = [A \ A]$.

(The basis for Z is empty)

(B)

Ans. Row space basis: $\{(1,0,0), (0,1,0), (0,0,1)\}$

(A)

$$n=m=r=3$$

$$C(A) = \mathbb{R}^3 = C(A^T)$$

Column & Row space basis: $\{(1,0,0), (0,1,0), (0,0,1)\}$

check
29(3.2) \rightarrow

$$N(A) = N(A^T) = Z$$

Nullspace & left nullspace basis are empty

(B) Rowspace basis: $(1, 0, 0, 1, 0, 0)$, $(0, 1, 0, 0, 1, 0)$
 $(0, 0, 1, 0, 0, 1)$

$$C(B) = \mathbb{R}^3$$

column space basis : $(1, 0, 0)$, $(0, 1, 0)$, $(0, 0, 1)$

$$BX = \begin{bmatrix} A & A \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = Ax_1 + Ax_2 = 0$$

$$\implies x_1 = -x_2$$

check
aq(3,2) Nullspace basis: $(1, 0, 0, 1, 0, 0)$, $(0, 1, 0, 0, 1, 0)$,
 $(0, 0, 1, 0, 0, 1)$

$$m - r = 3 - 3 = 0$$

Nullspace basis is empty

8. What are the dimensions of the 4 subspaces for A, B, C , if I is the 3×3 identity matrix and O is the 3×2 zero matrix

Ans: $\textcircled{a} \quad A = [I \ O]$

$$I_{3 \times 3}, \quad O_{3 \times 2}$$

Ans: $\dim(C(A)) = 3; \dim(C(A^T)) = 3;$
 $\dim(N(A)) = 5 - 3 = 2; \dim(N(A^T)) = 0$

b) $B = \begin{bmatrix} I & I \\ O^T & O^T \end{bmatrix}$

Ans: $\dim(C(B)) = \dim(C(B^T)) = 3$

$$\dim(N(A)) = 6 - 3 = 3$$

$$\dim(N(A^T)) = 5 - 3 = 2$$

c) $C = [O] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

Ans: $\dim(C(C^T)) = \dim(C(C)) = 0$

$$C = [O] = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\dim(N(I)) = 2 - 0 = 2$$

$$\dim(N(C^T)) = 3 - 0 = 3$$

9. Which subspaces are the same for these matrices of different sizes?

Show that all 3 of those matrices have the same rank?

Ans:

(a) $\begin{bmatrix} A \\ A \end{bmatrix}$ and $\begin{bmatrix} A \\ A \end{bmatrix}$

Ans: same row space & null space

(b) $\begin{bmatrix} A \\ A \end{bmatrix}$ and $\begin{bmatrix} A & A \\ A & A \end{bmatrix}$

Ans: $\begin{bmatrix} A^T & A^T \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = A^T x + A^T y = 0 \Rightarrow x + y = 0$

$$\begin{bmatrix} A^T & A^T \\ A^T & A^T \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} A^T x + A^T y \\ A^T x + A^T y \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow x + y = 0.$$

Same column space & left null space.

10.

If the entries of a 3×3 matrix are chosen randomly b/w 0 and 1, what are the most likely dimensions of the 4 subspaces?

Start 15/9/2020

What if the random matrix is 3×5 ?

Ans:

Suppose,

each column of the 3×3 matrix is drawn independently from the uniform distribution on the cube $[0,1]^3$.

The probability that each column lies in the region \mathbb{R} of the cube is equal to the volume of \mathbb{R} .

~~1st~~ 1st column is drawn.

After drawing the 1st column, you need to draw the 2nd column so that it does not lie on the subspace spanned by the 1st column. This subspace is a line inside the cube $[0,1]^3$, that has zero volume.

\therefore The probability that the 2nd column lies in this subspace is zero.

i.e., the probability that the 2nd column is linearly independent of the 1st column is 1.

After drawing the 1st & 2nd columns (where the 2nd column is linearly independent of the 1st column), you need the 3rd column to lie outside the subspace spanned by the 1st two columns. This subspace is a plane inside the cube, and this plane also has zero volume.

So again, the probability that the 3rd column lies in this subspace is zero.

i.e., the probability that the 3rd column lies in this subspace is zero.

i.e., the probability that the 3rd column is linearly independent of the 1st two columns is 1.

→ For all distributions of $[0,1]^3$ that has a density function,

the prob. of lying in a 1-D or 2-D subspace is zero.

So,

the probability that a given column is linearly independent of the previous columns is 1.

~~for~~ for $A_{3 \times 5}$, rank is 3.

12.

- ii. A is an $m \times n$ matrix of rank r . Suppose there are right sides b for which $Ax=b$ has no solution.

- Ques: When are all inequalities that must be true between m, n & r ?

Ans:

Ans: No solution $\rightarrow \text{ref}(Ab)$ has a row $[0, 0, \dots, 0 | 1]$

$$\therefore \underline{r < m}$$

$$\& \quad r \leq n$$

Can't compare m & n .

- ⑤ How do you know that $A^T y = 0$ has solutions other than $y=0$?

Ans: $m > r \Rightarrow \underline{m - r > 0}$

\therefore left null space must contain a non-zero vector.

12. Construct a matrix with $(1,0,1)$ and $(1,2,0)$ as a basis for its row space and its column space. Why can't this be a basis for the row space and null space?

Ans:

$$A = \begin{bmatrix} 1 & 1 \\ 0 & 2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 1 \\ 1 & 2 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 2 & 1 \\ 2 & 4 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 2 & 1 \\ 2 & 4 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

$n = 3 = (n-2) + 0$

But $2+2=4$ ~~X~~

$$(1,0,1) \times (1,0,1) = (1,0,1) = (1,0,1)$$

$$x = (1,0,1)u^T = 1u$$

$$x = (1,2,0)u = (1,2,0)$$

13. True / False

- ③ If $A \& B$ share the same 4 subspaces
then A is a multiple of B .

Ans: Consider 2 matrices $A \& B$ of same size 3×3 invertible

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

(column space $(A) \subset$ column space (B))

$$C(A) = C(B) = C(A^T) = C(B^T) = \mathbb{R}^3.$$

$$N(A) = N(B) = \mathbb{Z}$$

$$N(A^T) = N(B^T) = \mathbb{Z}$$

14. Without computing A , find bases for its 4 fundamental subspaces

$$A = \begin{array}{|ccc|} \hline & 1 & 0 & 0 \\ & 0 & 1 & 0 \\ & 0 & 8 & 1 \\ \hline \end{array} \begin{array}{|cccc|} \hline & 1 & 2 & 3 & 4 \\ & 0 & 1 & 2 & 3 \\ & 0 & 0 & 1 & 2 \\ \hline \end{array} = BC$$

$\downarrow 3 \times 3$

for column.

Ans: Rows each row of A is a linear combination of the rows of C .

\Rightarrow Row space basis: $(1, 2, 3, 4), (0, 1, 2, 3), (0, 0, 1, 2)$

$$\begin{array}{l} c+2d=0 \\ b+2c+3d=0 \\ a+2b+3c+4d=0 \\ \hline b=-3d-2c \\ = -3d - 2 \begin{bmatrix} -2d \\ d \end{bmatrix} = -3d + 4d = d \\ a = -2d + 6d - 4d = 0 \end{array} \quad \left\{ \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = d \begin{bmatrix} 0 \\ 1 \\ -2 \\ 1 \end{bmatrix} \right.$$

Null space basis is same as that of C : $(0, 1, -2, 1)$

Each column of A is a linear combination of the columns of B .

$$C(A) = C(B) = \mathbb{R}^3 \quad \leftarrow B_{3 \times 3} \text{ is invertible}$$

Column space basis: $(1, 0, 0), (0, 1, 0), (0, 0, 1)$

13. True / False

- ③ If $A \& B$ share the same 4 subspaces
then A is a multiple of B

Ans: Consider 2 matrices $A \& B$ of same size & invertible

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

column space (A) \cap column space

$$C(A) = C(B) = C(A^T) = C(B^T) = \mathbb{R}^3$$

$$N(A) = N(B) = \mathbb{Z}$$

$$N(A^T) = N(B^T) = \mathbb{Z}$$

14. (W)

fund

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

Ans: \mathbb{R}

q

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

$$\begin{array}{l} c+2 \\ b+2 \end{array}$$

$$\begin{array}{l} a+2b+ \\ b= - \\ = - \end{array}$$

$$a = -2$$

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

Gach

column

C

column

14. Without computing A , find bases for its 4 fundamental subspaces

$$A = \begin{array}{c} \\ \text{3x4} \end{array} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 2 \\ 0 & 8 & 1 & 3 \end{array} \right] \begin{array}{c} \\ \text{3x3} \end{array} \left[\begin{array}{cccc} 1 & 2 & 3 & 4 \\ 0 & 1 & 2 & 3 \\ 0 & 0 & 1 & 2 \end{array} \right] \begin{array}{c} \\ \downarrow \text{3x4} \end{array} = BC$$

free column.

Ans: Each row of A is a linear combination of the rows of C .

\Rightarrow Row space basis: $(1, 2, 3, 4), (0, 1, 2, 3), (0, 0, 1, 2)$

$$\begin{array}{l} c+2d=0 \\ b+2c+3d=0 \\ a+2b+3c+4d=0 \end{array} \quad \left\{ \begin{array}{l} \begin{array}{l} a \\ b \\ c \\ d \end{array} \\ \begin{array}{l} 1 \\ -2 \\ -3 \\ 1 \end{array} \end{array} \right. \quad \begin{array}{l} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = d \begin{bmatrix} 0 \\ 1 \\ -2 \\ 1 \end{bmatrix} \\ \begin{bmatrix} 1 \\ -2 \\ -3 \\ 1 \end{bmatrix} \end{array}$$

$$\begin{aligned} b &= -3d - 2c \\ &= -3d - 2[-2d] = -3d + 4d = d \\ a &= -2d + 6d - 4d = 0 \end{aligned}$$

Null space basis is same as that of C : $(0, 1, -2, 1)$

Each column of A is a linear combination of the columns of B :

$$C(A) = C(B) = \mathbb{R}^3 \quad \leftarrow B_{3x3} \text{ is invertible}$$

Column space basis: $(1, 0, 0), (0, 1, 0), (0, 0, 1)$

~~Left nullspace has empty basis since B is invertible.~~

$$\left[\begin{array}{cc|c} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right] \xrightarrow{\text{Row operations}} \left[\begin{array}{cc|c} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{array} \right]$$

16. Explain why $v = (1, 0, -1)$ can not be a
zero of A & also in the nullspace

Ans.

~~Focus~~

$$Av = 0 \Rightarrow \begin{bmatrix} \vdots \\ v^T \\ \vdots \end{bmatrix} v = 0 = \begin{bmatrix} \vdots \\ v^T v \\ \vdots \end{bmatrix}$$

$$v^T v = v \cdot v = 1 - 1 = 0 = |v|$$

$$\Rightarrow v = 0$$

Not true for $v = (1, 0, -1)$

18.

$$\bullet \quad [A|b] = \left[\begin{array}{ccc|c} 1 & 2 & 3 & b_1 \\ 4 & 5 & 6 & b_2 \\ 7 & 8 & 9 & b_3 \end{array} \right] \rightarrow \left[\begin{array}{ccc|c} 1 & 2 & 3 & b_1 \\ 0 & -3 & -6 & b_2 - 4b_1 \\ 0 & 0 & 0 & b_3 - 2b_2 + b_1 \end{array} \right]$$

What combination of the rows of 'A' has produced the zero row?

Which vectors are in $N(A^T)$ &
which vectors are in $N(A)$?

Ans. ~~$b_3 - 2b_2 + b_1 = 0$~~

$$\text{row } 3 - 2(\text{row } 2) + \text{row } 1 = 0$$

$$A^T y = 0 \implies y^T A = 0$$

linear combination of rows of $A = 0$

$$N(A^T) = \underline{c(1, -2, 1)}$$

$$N(A) = c(1, -2, 1)$$

19- reduce A to echelon form & look at zero rows. The b column tells which combinations you have taken of the rows:

(b)

From the b column after elimination, read off $(m-n)$ basis vectors in the left nullspace.

Ans:

Those y_i 's are combinations of rows that give zero rows in the same echelon form.

$$\text{Ans: } A = \begin{bmatrix} 1 & 2 & b_1 \\ 3 & 4 & b_2 \\ 0 & 6 & b_3 \end{bmatrix}$$

$$\rightarrow \begin{bmatrix} 1 & 2 & b_1 \\ 0 & -2 & b_2 - 3b_1 \\ 0 & -2 & b_3 - b_1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 2 & b_1 \\ 0 & 2 & 3b_1 - b_2 \\ 0 & 0 & b_1 + b_2 + b_3 \end{bmatrix}$$

$$-b_1 - b_2 + b_3 = 0 \Rightarrow (\text{row 1}) - (\text{row 2}) + \text{row 3} = 0$$

$\therefore (-1, -1, 1)$ is in $N(A^T)$

$$(b) \begin{bmatrix} 1 & 2 & b_1 \\ 2 & 3 & b_2 \\ 2 & 4 & b_3 \\ 2 & 5 & b_4 \end{bmatrix}$$

$\xrightarrow{\text{Row}} \begin{bmatrix} 1 & 2 & b_1 \\ 0 & -1 & b_2 - 2b_1 \\ 0 & 0 & b_3 - 2b_1 \\ 0 & 1 & b_4 - 2b_1 \end{bmatrix} \xrightarrow{\quad} \begin{bmatrix} 1 & 2 & b_1 \\ 0 & 1 & 2b_1 - b_2 \\ 0 & 0 & b_3 - 2b_1 \\ 0 & 0 & -4b_1 + b_2 + b_4 \end{bmatrix}$

$$\begin{aligned} -2b_1 + b_3 &= 0 \\ -4b_1 + b_2 + b_4 &= 0 \end{aligned} \quad \left\{ \begin{array}{l} -2(\text{row } 1) + (\text{row } 3) = 0 \\ -4(\text{row } 1) + (\text{row } 2) + (\text{row } 4) = 0 \end{array} \right.$$

$(-2, 0, 1, 0), (-4, 1, 0, 1)$ case in $N(B)$

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

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

25. C

Ans.

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & 6 \\ 3 & 6 & 9 \end{bmatrix}$$

- Q2. Construct $A = UV^T + WZ^T$ whose column space has basis $(1, 2, 4)$, $(2, 4, 6)$ and whose row space has basis $(1, 0), (1, 1)$.

Write A as (3×2) times (2×2)

Ans:

$$A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 2 \\ 4 & 2 \\ 5 & 1 \end{bmatrix}$$

$$= UV^T + WZ^T = \begin{bmatrix} u & w \end{bmatrix} \begin{bmatrix} V^T \\ Z^T \end{bmatrix}$$

25.

(C) If $C(A^T) = C(A)$ then $A^T = A$

Ans.

False

$$\begin{array}{|ccc|} \hline & 1 & 2 \\ \hline 1 & 1 & 3 \\ 2 & 2 & 3 \\ \hline \end{array}$$

$$\text{Ex: } A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & -2 \\ 2 & 4 \end{bmatrix} \neq A.$$

$$C(A) = R(A^T) = \text{span}\left(\begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ -2 \end{bmatrix}\right)$$

27. Find the ranks of the 8×8 checkerboard matrix B & the chess matrix C:

$$B = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ \vdots & \vdots \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$$C = \begin{bmatrix} r & n & b & q & k & b & n & r \\ p & p & p & p & p & p & p & p \\ \dots & \dots \\ p & p & p & p & p & p & p & p \\ r & n & b & q & k & b & n & r \end{bmatrix}$$

The #'s r, n, b, q, k, p are all different.

Find bases for the row space & left null space of B & C.

Find a basis for the nullspace of C.

Ans: $\begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} = 1 \implies \text{rank}(B) = 2$

$$\begin{vmatrix} r & ? \\ p & p \end{vmatrix} = p(r-p) \neq 0 \text{ if } p \neq 0$$

$$\text{rank}(C) = 2 \text{ if } p \neq 0$$

row 1 & row 2 are a basis for the row space
of C.

$$m-r = 8-2 = 6 = n-r$$

$$(1, 0, -1, 0, 1, 0, 0, 0), (1, -1, 1, 0, -1, 1)$$

$$\begin{array}{l} a+c+e+g = 0 \\ b+d+f+h = 0 \end{array}$$

$$\begin{matrix} \left[\begin{matrix} a \\ b \\ c \\ d \\ e \\ f \\ g \\ h \end{matrix} \right] = \left[\begin{matrix} -1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{matrix} \right] + d \left[\begin{matrix} 0 \\ -1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{matrix} \right] + e \left[\begin{matrix} -1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{matrix} \right] + f \left[\begin{matrix} 0 \\ -1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{matrix} \right] + g \left[\begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -1 \\ 0 \end{matrix} \right] + h \left[\begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{matrix} \right] \end{matrix}$$

are the bases of $N(\beta)$ & $N(\beta^T)$

$$\boxed{r\alpha_1 + m\alpha_2} = b\alpha_3 + q\alpha_4 + k\alpha_5 + l\alpha_6 + n\alpha_7 + s\alpha_8 = 0$$

$$P(\alpha_1 + \alpha_2) = 0$$

$$\cancel{\alpha_1 + \alpha_2} C^T = \begin{bmatrix} r & p & 0 & \dots & 0 & p & r \\ n & p & 0 & \dots & 0 & p & n \\ b & p & 0 & \dots & 0 & p & b \\ q & p & 0 & \dots & 0 & p & q \\ k & p & 0 & \dots & 0 & p & k \\ b & p & 0 & \dots & 0 & p & b \\ n & p & 0 & \dots & 0 & p & n \\ r & p & 0 & \dots & 0 & p & r \end{bmatrix}$$

$$\rightarrow \begin{bmatrix} r & p & 0 & \dots & 0 & p & r \\ 1 & 0 & 0 & \dots & 0 & 0 & 0 \\ 1 & 0 & 0 & \dots & 0 & 0 & 1 \\ 1 & 0 & 0 & \dots & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \dots & 0 & 0 & 1 \end{bmatrix}$$

$$\cancel{\alpha_1 + \alpha_2} \cancel{+ \alpha_7 + \alpha_8 = 0}$$

$$\cancel{\alpha_1 + \alpha_8 = 0}$$

Basis of $N(C)$:

$$(-1, 0, 0, 0, 0, 0, 0, 1), (0, -1, 0, 0, 0, 0, 1, 0),$$
$$(0, 0, -1, 0, 0, 0, 0, 0), (0, 0, 0, -1, 1, 0, 0, 0)$$
$$\nearrow (0, 0, 0, 0, 1, 0, 0, 0), (0, 0, 0, 1, 1, 0, 0, 0)$$

Basis of $N(C)$:

$$(-1, 0, 0, 0, 0, 0, 0, 1), (0, -1, 0, 0, 0, 0, 1, 0)$$
$$(0, 0, -1, 0, 0, 1, 0, 0), ($$

?

29. If $A = uv^T$ is a 2×2 matrix of rank 1,
 draw figure to show the 4 fundamental
 subspaces. If B produces those same 4
 subspaces, what is the exact relation of B to A ?

Ans: $A_{2 \times 2} = uv^T$

$C(A)$ & $C(A^T)$ are lines in \mathbb{R}^2

$$uv^T x = u v^T \alpha = u(v \cdot \alpha) = 0$$

$N(A) \perp \underline{\text{row}} V$ in the row space

$$n-r=2-1=1$$

$$S = ((A)x)_m \iff$$

$R(A)$ & $N(A)$: u, v^T columns with ①

$C(A)$, & $N(A^T)$: u, u^T

If B produces those same 4 subspaces
 then $B = c A$ with $c \neq 0$

most of the time it's zeroed up

30) M is the space of 3×3 matrices.

Multiply every matrix X in M by

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

② Which matrices X lead to $AX = 0$?

$$\underline{X} = \begin{bmatrix} a & b & c \\ a & b & c \\ a & b & c \end{bmatrix}$$

Ans: $AX = 0$ if each column of X is a multiple of $(1, 1, 1)$.

$$\Rightarrow \underline{\text{dim}(N(A)) = 3}$$

③ Which matrices have the form AX for some matrix X ?

Ans: $AX = B \Rightarrow$

$$\begin{array}{c|ccc|c|c|c} 1 & 0 & -1 & b_1 \\ \hline 0 & 1 & -1 & b_2 + b_1 \\ 0 & 0 & 0 & b_1 + b_2 + b_3 \end{array} \quad \left. \begin{array}{c} c_1 \\ c_2 + c_1 \\ c_1 + c_2 + c_3 \end{array} \right| \quad \left. \begin{array}{c} d_1 \\ d_2 + d_1 \\ d_1 + d_2 + d_3 \end{array} \right|$$


all columns of B add to zero.

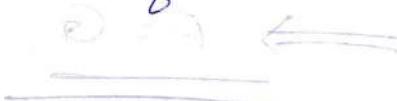
$$AX = B \text{ iff } B = \begin{bmatrix} a & b & c \\ d & e & f \\ -a-d & -b-e & -c-f \end{bmatrix}$$

$$Ax = b \Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = 0, \quad x + y + z = 0$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = y \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} + z \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

$$\dim(C(s)) = 6$$

$3+6=9$, which is the dimension of the space of inputs of this matrix



31.

Suppose the $m \times n$ matrices A & B have the same 4 subspaces. If they are both in ref , prove that $F = G$,

$$A = \begin{bmatrix} I & F \\ 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} I & G \\ 0 & 0 \end{bmatrix}$$

Ans: $\text{Rowspace}(A) = \text{Rowspace}(B)$

Row 1 of A = combination of the rows of B

\Rightarrow Only possible combination is

$$\text{If } [I \ F] = [I \ G]$$

$$\underline{\underline{\Rightarrow F = G}}$$

4

ORTHOGONALITY

Orthogonal vectors: $\mathbf{v}^T \mathbf{w} = \mathbf{v} \cdot \mathbf{w} = 0$ & $|\mathbf{v}|^2 |\mathbf{w}|^2 = |\mathbf{v} + \mathbf{w}|^2$

number of v and w for V complete iff v and w

v and w basis for V

$0 = \mathbf{w}^T \mathbf{v}$: component of \mathbf{w} in \mathbf{v}

\mathbf{w}, \mathbf{v} orthogonal

- * Two subspaces V and W of a vector space are orthogonal if every vector v in V is \perp to every vector w in W .

Ex: 1

Orthogonal subspaces : $V^T W = 0$ for all $v \in V$ and all $w \in W$

Ex: 2

Test

Put bases for the subspaces V and W into the columns of V and W .

Orthogonal subspaces V & W : $V^T W = 0$

Ex:1 The floor of your room (extended to ∞) is a subspace V . The line where 2 walls meet is a subspace W ($1D$). Those subspaces are orthogonal. Every vector \perp the meeting line of the walls is \perp to every vector in the floor.

Ex:2 2 walls look \perp but those 2 subspaces are not orthogonal.

The meeting line is in both V and W . & this line is not \perp to itself.

Two planes (dimensions 2 and 2 in \mathbb{R}^3) can't be orthogonal subspaces.

→ When a vector is in 2 orthogonal subspaces, it must be zero. It is \perp to itself.

- Zero is the only point where the nullspace meets the row space.

P

* The nullspace $N(A)$ and the row space $C(A^T)$ are orthogonal subspaces of \mathbb{R}^n .

Every vector α in the nullspace is \perp to every row of A ; because $A\alpha = 0$.

Denote α as $\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}$

Proof:

$$A\alpha = \begin{bmatrix} \text{row 1} \\ \vdots \\ \text{row } m \end{bmatrix} \cdot \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} (\text{row 1}) \cdot \alpha \\ \vdots \\ (\text{row } m) \cdot \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

= sum of zero products

$\rightarrow \alpha$ is \perp to every combination of the rows.

\therefore The whole row space $C(A^T)$ is

orthogonal to $N(A)$.

Proof 2:

Vectors in the row space are combinations of the rows. Take the dot product of $A^T y$ with any x in the nullspace, i.e., $Ax = 0$

$$x \cdot (A^T y) = x^T (A^T y) = (Ax)^T y = 0^T y = 0$$

$$\text{Left Nullspace} \subset \text{Row Space}$$

* The left nullspace $N(A^T)$ and the column space $C(A)$ are orthogonal in \mathbb{R}^m .

$$(A)N \perp (A)C$$

P

Proof 1:

$$A^T y = \begin{bmatrix} (\text{column } 1)^T \\ \vdots \\ (\text{column } n)^T \end{bmatrix} y = \begin{bmatrix} (\text{column } 1) \cdot y \\ \vdots \\ (\text{column } n) \cdot y \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

Proof 2:

Vectors in $C(A)$ are combinations

of the columns.

$$y \in N(A^T) \implies A^T y = 0 \iff y^T A = 0^T$$

$$y \cdot (A\alpha) = y^T (A\alpha) = (A^T y)^T \alpha = 0^T \alpha = 0$$

$$C(A^T) \perp N(A)$$

in \mathbb{R}^n

$$C(A) \perp N(A^T)$$

in \mathbb{R}^m

$$C(A^T) \oplus N(A) = \mathbb{R}^n$$

(or another)

$$C(A) \oplus N(A^T) = \mathbb{R}^m$$

(or another)

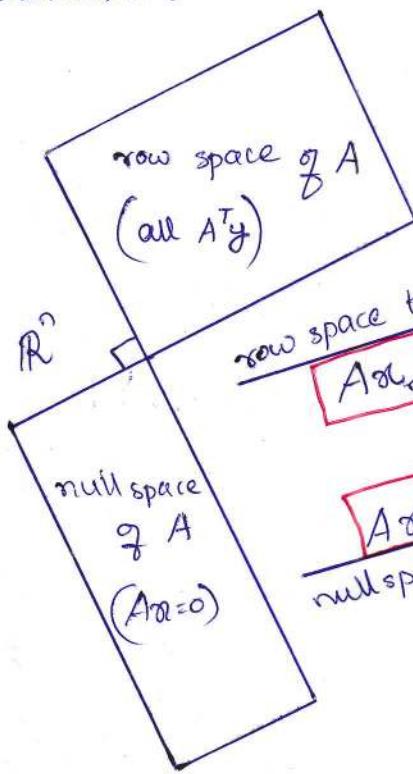
$C(A^T)$
dimension

\mathbb{R}^n
number

N
dimension

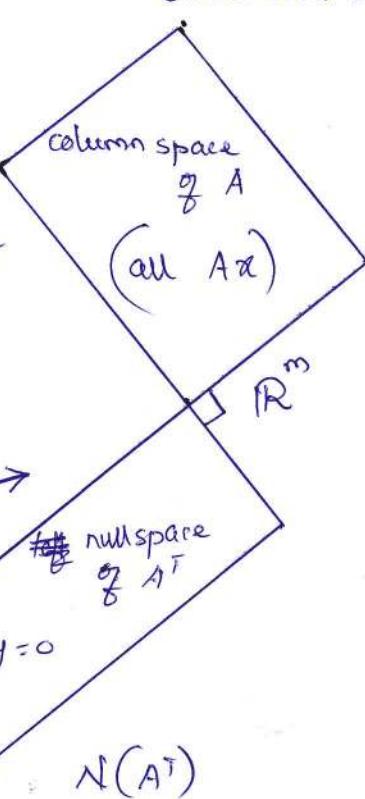
$C(A^T)$

dimension = r



$C(A)$

dimension = r



$N(A)$

dimension = $n-r$

$$A\mathbf{x}_{\text{row}} = \mathbf{b}$$

$$A\mathbf{x}_{\text{null}} = \mathbf{0}$$

dimension = $m-r$

$$A^T \mathbf{y} = \mathbf{0}$$

$N(A^T)$

Orthogonal Complements

$$\mathbb{R}^n: \text{rank } (n-r) = r$$

Two lines could be \perp in \mathbb{R}^3 , but those lines could not be the row space and null space of a 3×3 matrix.

- * The orthogonal complement of a subspace V contains every vector that is \perp to V .

This orthogonal subspace is denoted by V^\perp (" V perp").

$$V^\perp \cap V = \{0\}$$

Every α that is \perp to the rows satisfies $A\alpha = 0$, and lies in the null space.

If V is orthogonal to the null space, it must be in the row space. Otherwise we could add this V as an extra row of the matrix, without changing its null space. The rowspace could grow, which breaks the law $r + (n - r) = n$.

$$V \rightarrow N(A)^\perp = C(A^\top)$$

* If a subspace S is contained in a subspace V , S^\perp contains V^\perp .

$$S \subset V \rightarrow V^\perp \subset S^\perp$$

Fundamental Theorem of Linear Algebra

- Part 2

$N(A)$ is the orthogonal complement of the row space $C(A^T)$ in \mathbb{R}^n .

$N(A^T)$ is the orthogonal complement of the column space $C(A)$ in \mathbb{R}^m .

"complements" \rightarrow every ' α ' can be split into
a row space component α_r & a
nullspace component α_n .

$$A\alpha = A(\alpha_r + \alpha_n) = A\alpha_r + A\alpha_n$$

$A\alpha_n = 0$: The nullspace component goes to zero

$A\alpha_r = A\alpha$: The rowspace component goes
to the column space

\Rightarrow Every vector goes to the column space.
Multiplying by A can not do anything else

- Every vector b in the column space comes from one & only one vector α_s in the row space.

Proof

$$\text{If } A\alpha_s = A\alpha'_s \Rightarrow A(\alpha_s - \alpha'_s) = 0$$

$\alpha_s - \alpha'_s$ is in the $N(A)$

It is also in the row space, since α_s, α'_s are in the row space of A .

$$N(A) \perp C(A^T) \Rightarrow \alpha_s - \alpha'_s \text{ must be the zero vector.}$$

$$\underline{\alpha_s = \alpha'_s}$$

- There is an $n \times n$ invertible matrix hiding inside A , if we throw away the 2 null spaces ($N(A)$ & $N(A^T)$).

From the row space to the column space, A is invertible.

The "pseudo inverse" will invert that part of A .
in section 7.4.

Ex:4 Every matrix of rank r has an $r \times r$ invertible submatrix:

$$A = \begin{bmatrix} 3 & 0 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{contains the submatrix} \quad \begin{bmatrix} 3 & 0 \\ 0 & 5 \end{bmatrix}.$$

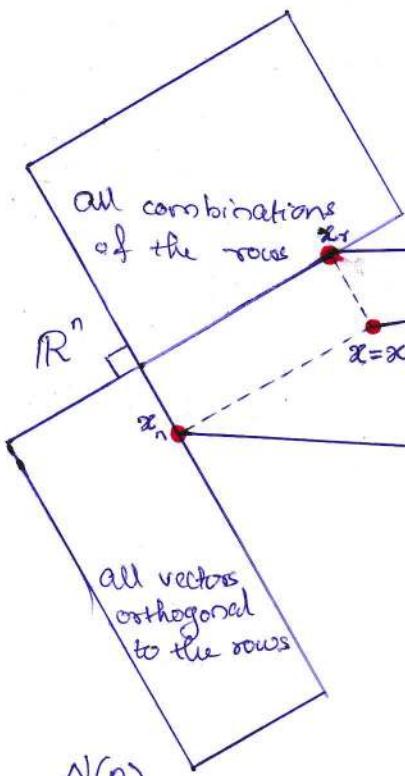
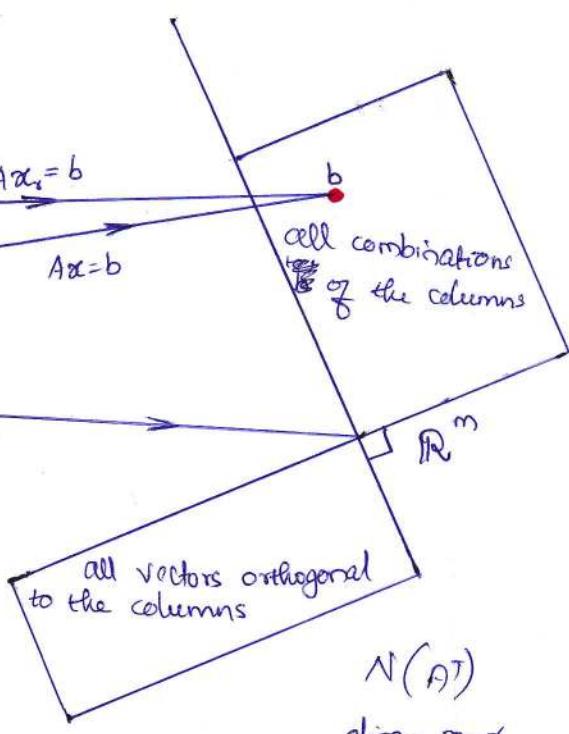
The other "0"s are responsible for the nullspaces. The rank of B is also $\cancel{r=2}$.

$$B = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 \\ 1 & 2 & 4 & 5 & 6 \\ 1 & 2 & 4 & 5 & 6 \end{bmatrix} \quad \text{contains} \quad \begin{bmatrix} 1 & 3 \\ 1 & 4 \end{bmatrix} \text{ in}$$

the pivot rows & columns.

Every matrix can be diagonalized, when we choose the right bases for \mathbb{R}^n and \mathbb{R}^m .

→ Singular Value Decomposition.

$C(A^\top)$ $\dim = r$  $C(A)$ $\dim = r$  $N(A^\top)$ $\dim = n - r$ $N(A)$ $\dim = n - r$

Combining Bases from Subspaces with \oplus

• consider how to add two bases together if
they don't have common elements.

* [Any n independent vectors in \mathbb{R}^n must span \mathbb{R}^n .
So they are a basis.]

[Any n vectors that span \mathbb{R}^n must be independent.
So they are a basis.]

[If the n columns of A are independent,
they span \mathbb{R}^n . So $Ax=b$ is solvable.]

[If the n columns span \mathbb{R}^n , they are independent.
So $Ax=b$ has only one solution.]

If there are no free variables, the solution is unique. There must be n pivot columns.

Then the back-substitution solves $Ax=b$. (The solution exists).

Suppose that $Ax=b$ can be solved for every ' b ' (existence of solutions). Then elimination produces no zero rows. There are n pivots & no free variables. The nullspace contains only $x=0$ (uniqueness of solutions).

Uniqueness \Rightarrow Existence }
A is invertible.

Existence \Rightarrow Uniqueness

$$\text{row } \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \text{ is not linearly independent}$$

$$\left[\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right] \text{ is not linearly independent}$$

$$\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \text{ is linearly independent}$$

- * Each x is the sum of $x_r + x_n$ of a rowspace vector x_r and a nullspace vector x_n .

$$x = x_r + x_n$$

Ex: 5. For $A = \begin{bmatrix} 1 & 2 \\ 3 & 6 \end{bmatrix}$ split $\alpha = \begin{bmatrix} 4 \\ 3 \end{bmatrix}$ into

$$\alpha_s + \alpha_n = \begin{bmatrix} 2 \\ 4 \end{bmatrix} + \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

$$\alpha_1 + 2\alpha_2 = 0$$

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

$$m^2 + 2m = 0$$

□ Projection

The prototype of an oblique projection is the shadow cast by objects on the ground (when the sun is not vertical). Mathematically, we have a plane (the ground), a direction (direction of the rays of light, which are approximately parallel, since the sun is very far), and the projection of a person along the light rays is its shadow on the ground.

More generally,

we can have projections \parallel to higher dimensional subspaces.

$$v^{\perp} = vR = v^{\perp}R + v^{\parallel}R, \quad vR = v^{\parallel}$$

$$v^{\perp} = v(-s)R = v(s^2R)$$

$$\underline{s^2R(v^{\perp}) = s^2R(-s)R \iff -s = s \iff s = 0}$$

* Given a vector space V , a projection is a linear transformation $P: V \rightarrow V$ such that $P^2 = P$.

- In the finite dimensional case, a square matrix P is called a projection matrix if it is equal to its square.

$$\text{i.e., } P^2 = P \rightarrow \underline{\text{idempotent}}$$

- The eigenvalues of a projection matrix must be 0 or 1.

$$\text{i.e., } \lambda = 0 \text{ or } 1$$

Proof

$$Pv = \lambda v, P^2v = \lambda^2 v = \lambda v = Pv$$

$$(\lambda^2 - \lambda)v = \lambda(\lambda - 1)v = 0$$

$$v \neq 0 \Rightarrow \lambda(\lambda - 1) = 0 \Rightarrow \underline{\lambda = 0 \text{ or } \lambda = 1}$$

* Let V be a finite dimensional vectorspace and $P: V \rightarrow V$ be a projection on V .

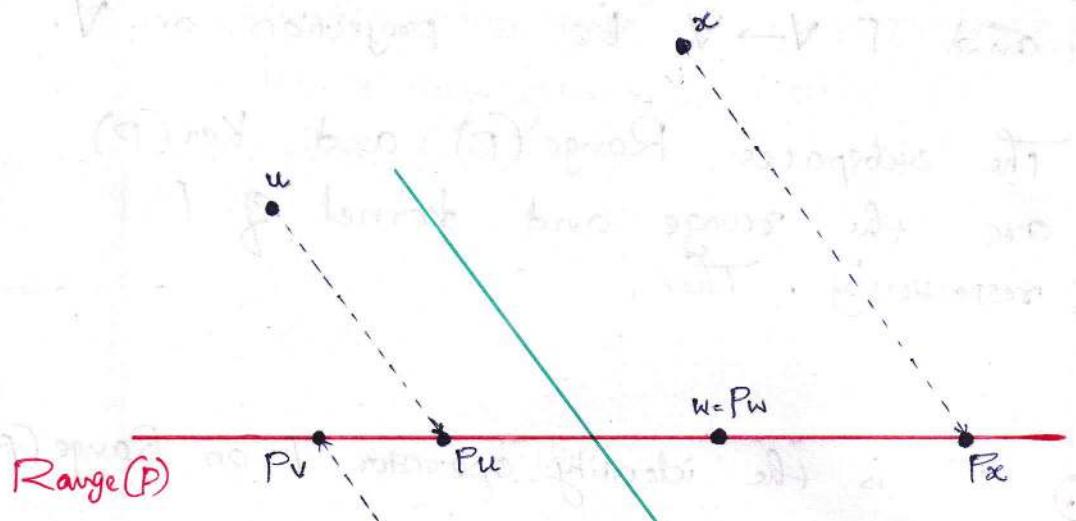
The subspaces $\text{Range}(P)$ and $\text{Ker}(P)$ are the range and kernel of P , respectively. Then,

① P is the identity operator I on $\text{Range}(P)$.

$$\text{i.e., } Px = x \quad \forall x \in \text{Range}(P)$$

$$Py = 0 \quad \forall y \in \text{Ker}(P)$$

\Rightarrow $\text{Range}(P)$ is the subspace on which P projects, and the projection is parallel to (or, along) the subspace $\text{Ker}(P)$.



$\text{Ker}(P)$

② The vector space V can be written as the direct sum, $V = \text{Range}(P) \oplus \text{Ker}(P)$

→ The range and the kernel of a projection P are complementary, as are P and $I-P$. $\text{Range}(P) \cap \text{Ker}(P) = \{0\}$

Every vector $x \in V$ may be decomposed uniquely as, $x = x_R + x_N$ with

$$x_R = Px \in \text{Range}(P) \text{ and}$$

$$x_N = (I-P)x = x - Px \in \text{Ker}(P).$$

Proof

$$Px_N = P(x - Px) = Px - P^2x = Px - Px = 0 \implies x_N \in \text{Ker}(P)$$

⇒ Let U and W be subspaces of a vector space V . A linear transformation $T: V \rightarrow V$ is called the projection of V onto the subspace U along W if $V = U \oplus W$ and $Tx = u$ for $x = u + w \in U \oplus W$.

* If $P: V \rightarrow V$ is a projection, then

$$V = \text{Range}(P) \oplus \text{Ker}(P)$$

Proof.

Step 1 : $V = \text{Range}(P) + \text{Ker}(P)$

$$\text{Ker}(P) \subseteq V \text{ & } \text{Range}(P) \subseteq V$$

$$\xrightarrow{\quad} \text{Range}(P) + \text{Ker}(P) \subseteq V$$

Let $x \in V$,

Let, $y = P(x) \in \text{Range}(P)$ and $z = x - y$ * for some $x \in V$.

then $x = y + z$ and

$$P(z) = P(x-y) = P(x) - P(y) = y - y = 0$$

$$\Rightarrow z \in \text{Ker}(P)$$

$$\therefore x = y + z \in \text{Range}(P) + \text{Ker}(P)$$

$$\xrightarrow{\quad} V \subseteq \text{Range}(P) + \text{Ker}(P)$$

$$\text{Range}(P) + \text{Ker}(P) \subseteq V$$

&

$$V \subseteq \text{Range}(P) + \text{Ker}(P)$$

$$\left. \begin{array}{c} \text{Range}(P) + \text{Ker}(P) \\ \subseteq \\ V \end{array} \right\} \xrightarrow{\quad} V = \text{Range}(P) + \text{Ker}(P)$$

Step 2 : $\text{Range}(P) \cap \text{Ker}(P) = \{0\}$

$$(1) \text{ and } (2) \text{ imply } V$$

Let $x \in \text{Range}(P) \cap \text{Ker}(P)$,

$$x = P(x) = 0 \implies x = 0$$

$$x \in \text{Range}(P) \quad x \in \text{Ker}(P)$$

$$\implies \text{Range}(P) \cap \text{Ker}(P) = \{0\}$$

$$V = \text{Range}(P) + \text{Ker}(P)$$

$$V = \text{Range}(P) \oplus \text{Ker}(P)$$

$$\text{Range}(P) \cap \text{Ker}(P)$$

$$(1) \text{ and } (2) \text{ imply } V = \text{Range}(P) \oplus \text{Ker}(P)$$

$$(1) \text{ and } (2) \text{ imply } V = \text{Range}(P) \oplus \text{Ker}(P)$$

$$(1) \text{ and } (2) \text{ imply } V = \text{Range}(P) \oplus \text{Ker}(P)$$

$$\left. \begin{array}{l} V = (1) \text{ and } (2) \text{ imply } V \\ (1) \text{ and } (2) \text{ imply } V \end{array} \right\} V = \text{Range}(P) \oplus \text{Ker}(P)$$

* If V is a vectorspace and $W_1, W_2 \subseteq V$ are subspaces such that $V = W_1 \oplus W_2$, then there exists a unique projection $P: V \rightarrow V$ such that $\text{Range}(P) = W_1$ and $\text{Ker}(P) = W_2$.

Proof

$$V = W_1 \oplus W_2$$

Any $x \in V$ has a unique expression $x = y + z$ where $y \in W_1$ and $z \in W_2$

∴ The transformation $P: V \rightarrow V$ defined by
 $P(x) = y$ is well defined.
 $y \in \text{Range}(P) = W_1$

The zero element is uniquely expressed as $0 = 0 + 0$,
so $P(0) = 0$

If $x, x' \in V$, they have unique expressions.

$$x = y + z \quad \& \quad x' = y' + z'$$

where $y, y' \in W_1$ and $z, z' \in W_2$

$$\Rightarrow x + x' = y + y' + z + z'$$

By uniqueness, this must be the expression for $x + x'$ by uniqueness.

$$\therefore P(x + x') = y + y' = P(x) + P(x')$$

By the same reasoning, P is a linear transformation.

$$x = y + z \implies cx = cy + cz \text{ for any scalar } c.$$

where $cy \in W_1$ & $cz \in W_2$.

$$P(cx) = cy = cP(x).$$

$\implies P: V \rightarrow V$ is a linear transformation.

If $P(x) = y$, where $y \in W_1$,

then y has a unique sum $y = y + 0$

$$P^2(x) = P(P(x)) = P(y) = y = P(x)$$

$\implies P = P^2$, P is a projection.

By choice, $\text{Range}(P) \subseteq W_1$,

if $y \in W_1$, its unique sum is $y = y + 0$

$$\text{so, } P(y) = y \in \text{Range}(P).$$

$$\implies \underline{\text{Range}(P) = W_1}$$

If $z \in W_2$, then

(its) unique sum is $z = 0 + z$.

so, $P(z) = 0 \rightarrow z \in \text{Ker}(P)$.

$\therefore W_2 \subseteq \text{Ker}(P)$

If $x \in \text{Ker}(P)$,

$$P(x) = 0$$

Let x can be uniquely written as $x = y + z$
where $y \in W_1$ and $z \in W_2$

Then, $P(x) = y = 0 \rightarrow x = z \in W_2$

$$\Rightarrow \text{Ker}(P) = W_2$$

* Let $P, Q: V \rightarrow V$ be projections. Then
 $P+Q: V \rightarrow V$ is a projection iff
 $\text{Range}(P) \subset \text{Ker}(Q)$ and $\text{Range}(Q) \subset \text{Ker}(P)$

Step 2:
that
i.e.,

and

Proof

Step 1:

Assume that,

$$\text{Range}(P) \subset \text{Ker}(Q) \text{ & } \text{Range}(Q) \subset \text{Ker}(P)$$

Let

$a+$

Let $z \in \text{Range}(P+Q)$ then $z = x+y$

for some $x \in \text{Range}(P)$ and $y \in \text{Range}(Q)$
 $y \in \text{Ker}(P)$ and $x \in \text{Ker}(Q)$

Since $(P+Q)v = Pv + Qv$, $P(v) = x$, $Q(v) = y$

\therefore

$$\begin{aligned} (P+Q)z &= P(z) + Q(z) = P(x) + P(y) + Q(x) + Q(y) \\ &= x + 0 + 0 + y = x + y = z \end{aligned}$$

$\therefore P+Q$ is a projection on its image.

$\implies P+Q$ is a projection.

Step 2: Suppose that there exists $\alpha \in \text{Range}(P)$ that does not belong to $\text{Ker}(Q)$.

i.e., $\alpha \in \text{Range}(P) \text{ & } \alpha \notin \text{Ker}(Q)$

and $P+Q$ is a projection.

Let, $y = Q\alpha \neq 0$

$$\alpha + y = P(\alpha) + y = P(\alpha) + Q(\alpha)$$

$$= (P+Q)(\alpha) = (P+Q)^2(\alpha)$$

$$= (P+Q)(\alpha+y) = P(\alpha) + P(y) + Q(\alpha) + Q(y)$$

$$= \alpha + P(y) + y + \gamma = \alpha + P(y) + Qy$$

$$\implies P(y) = -\gamma$$

$$y \neq 0 \implies y \in \text{Range}(P) \text{ but } P(y) = y$$

Contradiction that P is a projection.

Similarly,

* Suppose $P, Q : V \rightarrow V$ are projections.

Assume that $P+Q$ is a projection as well.

Then,

$$\text{Range}(P+Q) = \text{Range}(P) \oplus \text{Range}(Q)$$

$$\text{Ker}(P+Q) = \text{Ker}(P) \cap \text{Ker}(Q)$$

$$\Rightarrow V = \text{Range}(P) \oplus \text{Range}(Q) \oplus \text{Ker}(P) \cap \text{Ker}(Q)$$

Proof. Assume; $P, Q, P+Q$ are projections

$$P, Q, P+Q \text{ are projections} \Rightarrow \text{Range}(P+Q) = \text{Range}(P) + \text{Range}(Q)$$

$$\xrightarrow{\text{L}} \text{Range}(P) \subseteq \text{Ker}(Q) \quad \& \quad \text{Range}(Q) \subseteq \text{Ker}(P)$$

$$\{0\} \subseteq \text{Range}(P) \cap \text{Range}(Q) \subseteq \text{Ker}(Q) \cap \text{Range}(Q) = \{0\}$$

$$\therefore \text{Range}(P+Q) = \text{Range}(P) \oplus \text{Range}(Q)$$

If $z \in \text{Ker}(P) \cap \text{Ker}(Q)$, then
 $(P+Q)(z) = P(z) + Q(z) = 0 + 0 = 0$
 $\Rightarrow \text{Ker}(P) \cap \text{Ker}(Q) \subseteq \text{Ker}(P+Q).$

If $z \in \text{Ker}(P+Q)$. Then
 $0 = (P+Q)(z) = P(z) + Q(z)$
This may happen if $P(z) = -Q(z)$.
where $P(z) \in \text{Range}(P)$ & $Q(z) \in \text{Range}(Q)$.

$$\text{Range}(P) \cap \text{Range}(Q) = \{0\}$$

$$\implies P(z) = Q(z) = 0$$

$$\implies z \in \text{Ker}(P) \cap \text{Ker}(Q)$$

* Let R and N be subspaces of $V = \mathbb{R}^n$
such that $R \oplus N = V$

Let, $\{u_1, \dots, u_r\}$ be a basis for R and
 $\{v_1, \dots, v_s\}$ be a basis for N^\perp .

Let, $A = [u_1 \dots u_r]$ and $B = [v_1 \dots v_s]$

(where the vectors are expressed as their
coordinates in the standard basis).

Then the matrix (in the standard basis) of
the projection on R parallel to N is:

$$P = A(B^T A)^{-1} B^T$$

where, $A = [u_1 \dots u_r]$ and $B = [v_1 \dots v_s]$

$R = \text{span}(\{u_i\})$ and $N^\perp = \text{span}(\{v_i\})$

& $V = R \oplus N$ where $R = \text{Range}(P)$
 $N = \text{Ker}(P)$

Proof

W.

For

Px

(I-1)

\Rightarrow
 $O = V$

$\sum_{j=1}^r$

where

Proof

Let $\alpha \in V$.

We search for $P\alpha \in R$.

For some scalars y_1, \dots, y_r ,

$$P\alpha = \sum_{j=1}^r y_j u_j = [u_1 \dots u_r] \begin{bmatrix} y_1 \\ \vdots \\ y_r \end{bmatrix} = Ay$$

$$(I - P)\alpha = \alpha - P\alpha \in N = (N^\perp)^\perp \Rightarrow \alpha - P\alpha \perp N^\perp$$

$$\therefore (v_k, \alpha - P\alpha) = v_k^T (\alpha - P\alpha) = 0 \quad \text{for all } k = 0, 1, \dots, r.$$

$$\Rightarrow 0 = v_k^T (\alpha - P\alpha) = v_k^T \alpha - v_k^T P\alpha = v_k^T \alpha - v_k^T \sum_{j=1}^r y_j u_j$$

$$0 = v_k^T \alpha - \sum_{j=1}^r y_j (v_k^T u_j), \quad k = 1, 2, \dots, r$$

$$\sum_{j=1}^r y_j (v_k^T u_j) = v_k^T \alpha$$

$$\Rightarrow v_k^T \alpha = \sum_{j=1}^r (v_k^T u_j) y_j$$

$$\sum_{j=1}^r (v_k^T u_j) y_j = (v_k^T u_1) y_1 + (v_k^T u_2) y_2 + \dots + (v_k^T u_r) y_r$$

$$= [v_k^T u_1 \dots v_k^T u_r] \begin{bmatrix} y_1 \\ \vdots \\ y_r \end{bmatrix} = (B^T A y)_k$$

where $v_k^T u_j = (B^T A)_{kj}$

$$V_k^T x = (B^T x)_k$$

$$\Rightarrow B^T A y = B^T x$$

$$R \oplus N = V = \mathbb{R}^n \quad \& \quad R = \text{Range}(P) = C(P) \quad | \quad N = \text{Ker}(P) = N(P)$$

$$\text{Range}(P) = R = \text{span}(\{u_i\}) \quad \& \quad \text{Ker}(P) = N = \text{span}(\{v_i\}) = \text{Range}(P^T)$$

$$A = [u_1 \dots u_r] \quad \& \quad B_{r \times r} = [v_1 \dots v_r]$$

*Start
7/9/2021*

If $B^T A$ is invertible iff $N(B^T A) = \{0\}$ (iff)
 $B^T A x = 0$ has only the solution $x = 0$

$$B^T A x = 0 \Rightarrow x \in N(B^T A)$$



$$Ax \in N(B^T)$$

$$Ax = [u_1 \dots u_r] \begin{bmatrix} x_1 \\ \vdots \\ x_r \end{bmatrix} = \vec{u}_1 x_1 + \dots + \vec{u}_r x_r$$

A has independent columns $\left. \right\} Ax = 0 \text{ iff } x = 0$

If $x \neq 0$, $Ax \neq 0$ & $Ax \in C(A)$

C(

R

dim

RHS

$$A\alpha \in N(B^T) \quad \& \quad A\alpha \in C(A)$$

$$\in C(B)^{\perp}$$

$$\implies A\alpha \in C(A) \cap C(B)^{\perp}$$

$$C(A) = \text{Range}(P) = \mathbb{R} \quad \& \quad C(B)^{\perp} = \text{Ker}(P) = N$$

$$\mathbb{R} \oplus N = C(A) \oplus C(B)^{\perp} = V = \mathbb{R}^n$$

$$\dim [C(A) + C(B)^{\perp}] = \dim [C(A)] + \dim [C(B)^{\perp}] - \dim [C(A) \cap C(B)^{\perp}]$$

$$\text{RHS} \leq r + (n-r) - 1 \xrightarrow{\text{since } A\alpha \neq 0} n-1 \neq n = \text{LHS}$$

$\implies \alpha = 0$ is the only solution to $B^T A \alpha = 0$

$$\text{i.e., } \mathbb{N}(B^T A) = \{0\}.$$

$\therefore B^T A$ is invertible

$$B^T A y = B^T \alpha \implies y = (B^T A)^{-1} B^T \alpha$$

$$\therefore P\alpha = Ay = A(B^T A)^{-1} B^T \alpha$$

$$P = (B^T A)^{-1} B^T \alpha$$

$$P = V = (B^T A)^{-1} B^T \alpha$$

$$\begin{bmatrix} t(a) \\ t(b) \end{bmatrix}_{\text{mid}} + \begin{bmatrix} t(a) \\ t(b) \end{bmatrix}_{\text{mid}} = \begin{bmatrix} t(a) + t(b) \\ t(b) \end{bmatrix}_{\text{mid}}$$

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

$$0 = x A^T S \quad \leftarrow \text{auswählen der Zeile } i \quad 0 = x_i$$

$$\{0\} = (A^T e_1) b_1$$

$$\text{eliminieren } \{0\} = A^T e_1$$

□ Orthogonal Projection

ILA ⑩
Pseudo Inverse

- * An orthogonal projection is a projection P for which $\text{Range}(P)$ and $\text{Ker}(P)$ are orthogonal subspaces.

$$\text{Range}(P) \perp \text{Ker}(P)$$

$$P \text{ is a projection} \rightarrow P^2 = P$$

$$\text{Orthogonal projection} \rightarrow C(P) \perp N(P)$$

$$\begin{aligned} Px &\in C(P) \\ (I-P)x &= y - Py \in N(P) \end{aligned}$$

$$Px \perp y - Py$$

$$\begin{aligned} 0 &= (Px)^T (y - Py) = x^T P^T (y - Py) \\ &= x^T P^T (I - P)y \end{aligned}$$

$$= x^T (P^T - P^T P)y \quad \forall x, y \in \mathbb{R}^n$$

$$\begin{array}{l} \forall x, y \in \mathbb{R}^n \\ xy \neq 0. \end{array}$$

$$\implies P^T = P^T P \quad \text{longito}$$

$$\therefore P = (P^T)^T = (P^T P)^T = P^T P = P^T$$

\Rightarrow Let V be a finite dimensional inner product space. A linear transformation $P: V \rightarrow V$ is an orthogonal projection if and only if $P^2 = P$ and $P = P^T$.

* A
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satis

Proof

P^2

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$$\begin{aligned}
 & \text{Let } x \in V \\
 & \text{Then } x = Px + (I-P)x \\
 & \text{Since } P = P^T \text{ and } P^2 = P \\
 & \text{we have } (I-P)x = Ix - Px = x - Px \\
 & \text{Also } x \perp (I-P)x \\
 & \text{Therefore } x^T(I-P)x = 0 \\
 & \text{Hence } x^T(I-P)^T(I-P)x = 0 \\
 & \text{But } (I-P)^T = I-P \\
 & \text{So } x^T(I-P)(I-P)x = 0
 \end{aligned}$$

* A projection P on a Hilbert space V is called an orthogonal projection if it satisfies : $\langle P\alpha, y \rangle = \langle \alpha, Py \rangle \quad \forall \alpha, y \in V$.

Proof

$$P^2 = P = P^T \quad \& \quad V = \text{Range}(P) \oplus \text{Ker}(P)$$

$$\text{Range}(P) \perp \text{Ker}(P)$$

For any $\alpha, y \in V$,

$$P\alpha \in \text{Range}(P) \quad \& \quad y - Py \in \text{Ker}(P)$$

$$\begin{aligned} \langle P\alpha, y - Py \rangle &= 0 = \langle P^2\alpha, y - Py \rangle = \langle P\alpha, P(I-P)y \rangle \\ &= \langle P\alpha, (P - P^2)y \rangle \end{aligned}$$

$$\hookrightarrow \langle P\alpha, y \rangle = \langle P\alpha, Py \rangle = \langle Py, P\alpha \rangle = \langle Py, \alpha \rangle = \langle \alpha, Py \rangle$$

Projection onto a line comes from a rank one matrix. Projection onto a plane comes from a rank - 2 matrix:

Projection matrix onto the z-axis : $P_z = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

Projection matrix onto xy-plane : $P_{xy} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$$P_1 = P_1 b = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$$

$$P_2 = P_2 b = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ z \\ 0 \end{bmatrix}$$

The line ($z=0$) and plane (xy -plane) are orthogonal complements.

dimensions $1+2=3$.

\therefore Every vector b in the whole space is the sum of its parts in the 2 subspaces. The projections P_1 and P_2 are exactly those 2 parts of b :

The vectors give $P_1 + P_2 = b$

The matrices give $P_1 + P_2 = I$

Every subspace of \mathbb{R}^m has its own $m \times m$ projection matrix. To compute P , we absolutely need a good description of the subspace that it projects onto. The best description of a subspace is a basis. We put the basis vectors into the columns of X . Now, we are projecting onto the $C(A)$.

Our problem is,

to project any b onto the column space of any $m \times n$ matrix.

Projection matrices

- $P^T = P$ & $P^2 = P$
(symmetric) (idempotent)

- $\lambda = 0$ (or) 1

Proof:

$$PV = \lambda V, P^2V = \lambda^2 V = \lambda V$$

$$V \neq 0 \Rightarrow \lambda = 0 \text{ (or)} 1$$

- $\text{trace}(P) = \text{rank}(P)$

Proof:

$$\text{trace}(P) = \sum \lambda_i = \text{total \# of non-zero eigenvalues that are } 1.$$

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

$N(A)$ is all vectors of the form, $AV = 0 = 0V$

$N(A)$ is the eigenspace corr. to eigenvalue 0.

$$\text{rank}(A) = \dim(C(A)) = \text{total \# of non-zero eigenvalues that are } 1 = \text{trace}(P)$$

if A is diagonalizable

$$P^T = P \text{ and } P^2 = P$$

$$\Rightarrow a_{ii} = |a_i|^2$$

Proof

$$P^T P = P^2 = P$$

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \begin{bmatrix} a_1 & a_2 & \dots & a_n \end{bmatrix} = \begin{bmatrix} |a_1|^2 & & & \\ & |a_2|^2 & & \\ & & \ddots & \\ & & & |a_n|^2 \end{bmatrix} = \begin{bmatrix} a_{11} & & & \\ & a_{22} & & \\ & & \ddots & \\ & & & a_{nn} \end{bmatrix}$$

$|a_1| = \sqrt{a_1^2} = \sqrt{q_1}$
 $|a_2| = \sqrt{a_2^2} = \sqrt{q_2}$
 \vdots
 $|a_n| = \sqrt{a_n^2} = \sqrt{q_n}$

- $P_c A P_R = A$

4.2(30)

indicates norm of A & total = $\|A\|_{\text{sum}} = \sqrt{\sum (a_{ij})^2}$

$$A = (a_{ij}) \Rightarrow \|A\|_{\text{sum}} = (\sum (a_{ij})^2)^{1/2}$$

No. of rows \times no. of columns $\Rightarrow \|A\|_{\text{sum}}$

\Rightarrow indicates it agrees completely with $\|A\|_{\text{sum}}$

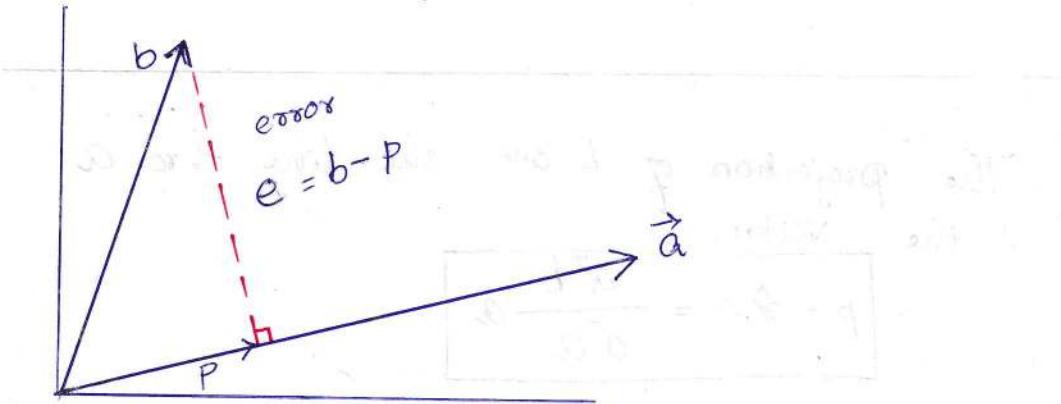
indicates norm of A & total = $(\sum (a_{ij})^2)^{1/2} = \|A\|_{\text{sum}}$

(a_{ij}) work \Rightarrow no. of cols.

absolute imports of A is

□ Projection Onto a Line

A line goes thro' the origin in the direction of $a = (a_1, \dots, a_m)$. Along that line we want a point p closest to $b = (b_1, \dots, b_m)$. The key to projection is orthogonality: The line from b to p is \perp to the vector a . This is $e = b - p$ for the error on the left side of figure. We now compute p by algebra.



The projection p will be some multiple of a , say $p = \hat{x}a$

find \hat{x} , then find the vector p , then find the matrix P .

Projecting b onto a with error, $e = b - p = b - \hat{x}a$

$$a \cdot e = a \cdot (b - \hat{x}a) = a \cdot b - \hat{x}a \cdot a = 0$$

$$\rightarrow \hat{x} = \frac{a \cdot b}{a \cdot a} = \frac{a^T b}{a^T a}$$

The projection of b onto the line thro' a
is the vector,

$$p = \hat{x}a = \frac{a^T b}{a^T a} a$$

The projection matrix,

$$P = \hat{a}\hat{a}^T = a \frac{a^T b}{a^T a} = Pb \implies P = \boxed{\frac{aa^T}{a^T a}}$$

$$P = \frac{aa^T}{a^T a} = \frac{a \otimes a}{a \cdot a} = \frac{1}{\|a\|^2} \begin{bmatrix} & \\ & \end{bmatrix} \Rightarrow \text{rank} = 1$$

- The projection matrix P is $m \times m$, but its rank is one. , $P = \hat{a}\hat{a}^T$
- We are projecting onto a 1D subspace, the line thro' 'a'. That line is the $C(P)$, column space of P .

- If the vector 'a' is doubled, the matrix P stays the same. It still projects onto the same line

Ex:1

- If the matrix is squared,

$$P^2 = P$$

Projecting a 2nd time doesn't change anything.

Ans:

- When P projects onto one subspace, I-P projects onto the L subspace

- For P,

$$\sum a_{ii} = 1$$

Ex: 1 Project $b = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$ onto $a = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$ to find $P = \hat{x}a$

$$\text{Ans: } \hat{x} = \frac{a^T b}{a^T a}$$

$$a^T b = \begin{bmatrix} 1 & 2 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = 5$$

$$a^T a = 9.$$

So, the projection, $P = \frac{5}{9} a = \left(\frac{5}{9}, \frac{10}{9}, \frac{10}{9} \right)$

The error vector b/w b and p is,

$$e = b - p = \left(\frac{4}{9}, -\frac{1}{9}, -\frac{1}{9} \right)$$

Ex: 2. Find the projection matrix $P = \frac{aa^T}{a^Ta}$ onto the line thru, $a = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$

$$\text{Ans: } P = \frac{aa^T}{a^Ta} = \frac{1}{9} \begin{bmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{bmatrix} \quad \frac{1}{9} \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & 2 & 2 \end{bmatrix}$$

$$= \frac{1}{9} \begin{bmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{bmatrix}$$

$$P = Pb = \frac{1}{9} \begin{bmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} 5 \\ 10 \\ 10 \end{bmatrix}$$

$$\left(\frac{1}{9} \cdot \frac{1}{9} \cdot \frac{1}{9} \right) = 9 \cdot 9 = 81$$

Projection onto a subspace

Start with 'n' vectors a_1, a_2, \dots, a_n in \mathbb{R}^m .

Assume that these a 's are linearly independent.

Problem: Find the combination $p = \hat{\alpha}_1 a_1 + \dots + \hat{\alpha}_n a_n$ closest to a given vector b .

We are projecting each b in \mathbb{R}^m onto the subspace spanned by the a 's., i.e., $C(A)$

$A_{m \times n}$

The combinations in \mathbb{R}^m are the vectors Ax in the column space.

The matrix A has n columns a_1, \dots, a_n .

(We are looking for \Rightarrow the particular combination $p = A\hat{x}$ (the projection) that is closest to b)

$$(A)\hat{x} = e$$

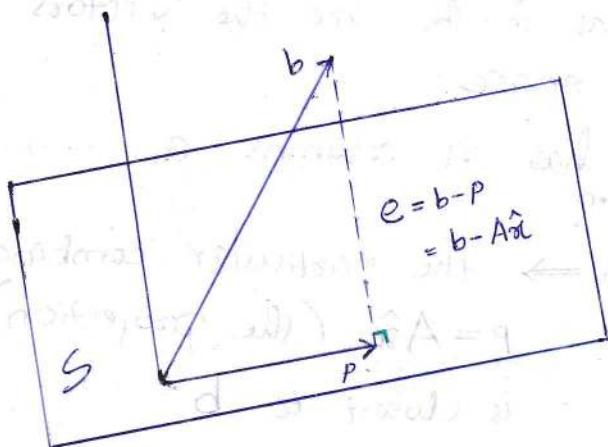
\hat{x} over \hat{x} indicates the best choice \hat{x} , to give the closest vector in the column space.

$$\text{When } n=1, \hat{x} = \frac{\mathbf{a}^T \mathbf{b}}{\mathbf{a}^T \mathbf{a}}$$

For $n > 1$,

$$\hat{x} = (\hat{x}_1, \dots, \hat{x}_n) \quad ?$$

Projections onto n -D subspaces : Find the vector \hat{x} , find the projection $p = A\hat{x}$, find the projection matrix P .



The projection p of b onto $S = C(A)$

The error vector $e = b - A\hat{x}$ is \perp to the subspace S .

$$e = b - A\hat{x} \perp S = C(A) = \alpha_1 a_1 + \dots + \alpha_n a_n$$

→ $e = b - A\hat{x}$ makes a right angle with all the vectors a_1, \dots, a_n in the base.

The 'n' right angles give the 'n' equations for \hat{x} :

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

⋮

(or)

$$a_n^T (b - A\hat{x}) = 0$$

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

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

$$A^T (b - A\hat{x}) = 0 \implies A^T A \hat{x} = A^T b$$

(3)

The combination $p = \hat{a}_1 a_1 + \dots + \hat{a}_n a_n = A \hat{x}$
 that is closest to b comes from \hat{x} :

① Find $\hat{x}_{n \times 1}$

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

$A_{m \times n}$

3.3(19)

$\text{rank}(A^T A) = \text{rank}(A)$

The symmetric matrix $A^T A$ is $n \times n$.
 $A^T A$ is invertible if the a 's are independent.

The solution is,

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

② Find $P_{m \times 1}$

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

③ Find $P_{m \times m}$, the projection matrix that is multiplying b , to project it onto the subspace spanned by the column vectors of A . (or) onto $C(A)$

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

- Our subspace is $C(A)$
- The error vector, $e = b - A\hat{x}$ $\perp C(A)$
- $\Downarrow e = b - A\hat{x}$ is in the null space of A^T (left nullspace of A) $\Rightarrow A^T(b - A\hat{x}) = 0$
 $C(A) \perp N(A^T)$

The vector b is being split into the projection p and the error $e = b - p$.

$$\rightarrow b = p + e$$

- P projects onto $C(A)$, whereas $I - P$ projects onto $N(A^T)$.

$$P^2 = A(A^T A)^{-1} A^T \cdot A(A^T A)^{-1} A^T$$

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

$$= A(A^T A)^{-1} A^T = P.$$

Warr

A

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ion

* A^T
column

Proof

Let
i.e.,

Warning :

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

$$(A^T A)^{-1} \neq A^{-1}(A^T)^{-1} \text{ since}$$

The matrix A is rectangular. It has no inverse matrix.

- * $A^T A$ is invertible iff A has linearly independent columns.

Proof

Let A be any matrix. If x is in its nullspace.
i.e., $x \in N(A)$. Then $Ax = 0$

$$\implies A^T A x = 0 \implies x \in N(A^T A)$$

If $\alpha \in N(A^T A)$,

$$A^T A \alpha = 0$$

We can't multiply by $(A^T)^{-1}$, which generally doesn't exist.

$$\alpha^T A^T A \alpha = (A\alpha)^T A\alpha = (A\alpha) \cdot (A\alpha) = \|A\alpha\|^2 = 0$$

$$\implies A\alpha = 0 \implies \alpha \in N(A)$$

$$\rightarrow N(A^T A) = N(A)$$

If $A^T A$ has dependent columns, so has A .

If $A^T A$ has independent columns, so has A .

When A has independent columns,

$$N(A) = \mathbb{Z} \implies N(A^T A) = \mathbb{Z}$$

$\implies A^T A$ has independent columns.,

$A^T A$ is square, symmetric, & invertible

\rightarrow (OR) $\nexists A^T A \alpha = 0,$

$A\alpha \in N(A^T)$ & $A\alpha \in C(A)$

$C(A) \perp N(A^T) \implies \underline{\nexists A\alpha = 0}$

4.2(A) Project the vector $b = (3, 4, 4)$ onto the line
thru' $a = (2, 2, 1)$ and then onto the plane that
also contains $a^* = (1, 0, 0)$.

Check the error vector $e = b - p \perp a$? &
the 2nd vector $e^* = b - p^*$ is also $\perp a^*$?

Find the 3×3 projection matrix P onto that plane
of a and a^* .

Find a vector whose projection onto the plane is
the zero vector. Why is it exactly the error e^* ?

Ans: $p = Pb = \frac{aa^T}{a^Ta}b = \frac{18}{9} \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} = 2(2, 2, 1) = 2a$

$e = b - p = (3, 4, 4) - (4, 4, 2) = (-1, 0, 2)$

$a^T e = 0 \Rightarrow e \perp a$

$$A = \begin{bmatrix} 2 & 1 \\ 2 & 0 \\ 1 & 0 \end{bmatrix} \Rightarrow A^T A = \begin{bmatrix} 2 & 2 & 1 \\ 1 & 0 & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 2 & 0 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 9 & 2 \\ 2 & 1 \end{bmatrix}$$

$$(A^T A)^{-1} = \frac{1}{5} \begin{bmatrix} 1 & -2 \\ -2 & 9 \end{bmatrix}$$

$$P = A(A^T A)^{-1} A^T = \frac{1}{5} \begin{bmatrix} 2 & 1 \\ 2 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & -2 \\ -2 & 9 \end{bmatrix} \begin{bmatrix} 2 & 2 & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

$$= \frac{1}{5} \begin{bmatrix} 2 & 1 \\ 2 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & 2 & 1 \\ 5 & -4 & -2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.8 & 0.4 \\ 0 & 0.4 & 0.2 \end{bmatrix}$$

$$P^* = Pb = \begin{pmatrix} 3 \\ 4.8 \\ 2.4 \end{pmatrix}$$

$$e^* = b - P^*b = (0, -0.8, 1.6). \perp \text{ to } a \text{ & } a^*$$

e^* is in the

$$Pe^* = Pb - P^2b = Pb - Pb = 0$$

$\implies e^* \in N(P)$ & its projection is zero.

$$P^2 = P = P^T$$

4.2(B)

Suppose your pulse is measured at $\alpha = 70$ beats/minutely,

then at $\alpha = 80$, then at $\alpha = 120$. Those 3 equations
of $A\alpha = b$ in one unknown have $A^T = [1 \ 1 \ 1]$ and
 $b = (70, 80, 120)$. The best $\hat{\alpha}$ is the _____

of $70, 80, 120$. Use calculus & projection:

① Minimize $E = (\alpha - 70)^2 + (\alpha - 80)^2 + (\alpha - 120)^2$ by

solving $\frac{dE}{d\alpha} = 0$.

② Project $b = (70, 80, 120)$ onto $a = (1, 1, 1)$ to

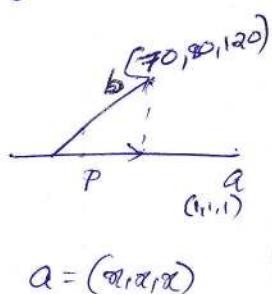
find $\hat{\alpha} = \frac{a^T b}{a^T a}$

~~Ques:~~ The closest horizontal line to the heights

~~70, 80, 120~~ is the average $\hat{x} = 90$.

$$b = (70, 80, 120); C(A) = \text{span}(1, 1, 1)$$

④ $E = \frac{\Delta}{(70, 80, 120) \rightarrow (x, y, z)} = (x - 70)^2 + (x - 80)^2 + (x - 120)^2$



$$a = (x, y, z)$$

$$\frac{\partial E}{\partial x} = 2(x - 70) + 2(x - 80) + 2(x - 120) = 0$$

$$\Rightarrow 3x - 270 = 0 \Rightarrow \underline{\underline{\hat{x} = 90}}$$

⑤ $\hat{x} = \frac{a^T b}{a^T a} = \frac{\begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 70 \\ 80 \\ 120 \end{bmatrix}}{\begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}} = \frac{70 + 80 + 120}{3} = 90 //$

* In recursive least squares,

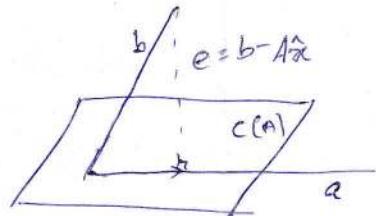
a 4th measurement 130 changes the average

$$\hat{x}_{\text{old}} = 90 \text{ to } \hat{x}_{\text{new}} = 100$$

$$\hat{x}_{\text{new}} = \hat{x}_{\text{old}} + \frac{1}{4}(130 - \hat{x}_{\text{old}})$$

□ Least Square Approximations

It often happens that $Ax=b$ has no solution. The usual reason is: There are more equations than unknowns. The matrix A has more rows than columns ($m > n$). The n -columns span a small part of m -D space. Unless all measurements are perfect, b is outside that column space of A . Elimination reaches an impossible equation and stops. But, we can't stop just because measurements include noise!



We can't always get the error $e = b - Ax$ down to zero.

When $e=0$,
 x is an exact solution to $Ax=b$

When the length of e is as small as possible,
 \hat{x} is a least square solution

* When $Ax=b$ has no solution, multiply by A^T and solve $\underline{A^T A \hat{x} = A^T b}$

Ans:

provided A is non-singular
number of $A^T \cdot A$ (second column with zero)
and $A^T \cdot b$ are linearly independent
obtained by multiplying the second column of A with b
columns $A^T \cdot b$ are linearly independent if
the second and fourth columns of A are linearly
independent since they have same
linear combination



as it satisfies condition of perpendicularity

so $A^T \cdot b$ is linearly independent

rank of matrix $A^T \cdot b$ is 3

condition is same as if b is not in the
column space of A^T

Ex:1 A crucial application of least squares is fitting a straight line to ~~on~~ points. Start with 3 points. Find the closest line to the points $(0,6), (1,0), (2,0)$

Ans: ~~$y = mx + c$~~

No straight line $\underline{y = mx + c}$ goes thro' these 3 points.

What are the 2 numbers m, c that satisfy these 3 points.

$$\begin{aligned} 6 &= m \cdot 0 + c \\ 0 &= m \cdot 1 + c \\ 0 &= m \cdot 2 + c \end{aligned} \Rightarrow \left[\begin{array}{cc|c} 0 & 1 & m \\ 1 & 1 & c \\ 2 & 1 & \\ \hline A & x = b & \end{array} \right] = \left[\begin{array}{c} 6 \\ 0 \\ 0 \end{array} \right]$$

This 3×2 system has no solution.

$Ax = b$ is not solvable.

~~$Ax = b$~~ $A^T A = \left[\begin{array}{ccc} 0 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \end{array} \right] \left[\begin{array}{cc} 0 & 1 \\ 1 & 1 \\ 2 & 1 \end{array} \right] = \left[\begin{array}{cc} 5 & 3 \\ 3 & 3 \end{array} \right]$

$$(A^T A)^{-1} = \frac{1}{6} \begin{bmatrix} 3 & -3 \\ -3 & 5 \end{bmatrix}$$

$$\begin{aligned} \hat{x} &= (A^T A)^{-1} A^T b = \frac{1}{6} \begin{bmatrix} 3 & -3 \\ -3 & 5 \end{bmatrix} \left[\begin{array}{ccc} 0 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \end{array} \right] \left[\begin{array}{c} 6 \\ 0 \\ 0 \end{array} \right] \\ &= \frac{1}{6} \begin{bmatrix} -3 & 0 & 3 \\ 5 & 2 & -1 \end{bmatrix} \left[\begin{array}{c} 6 \\ 0 \\ 0 \end{array} \right] = \boxed{\begin{bmatrix} -3 \\ 5 \end{bmatrix}} \end{aligned}$$

$$\hat{m} = (m, c) = (-3, 5)$$

These numbers are the best m & c , so
 $y = -3x + 5$ will be the best line for the 3 points.

$$\begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} m \\ m \\ m \end{bmatrix} = \begin{bmatrix} 2-m \\ 2-m \\ 2-m \end{bmatrix}$$
$$2-m = 0$$
$$2+6-2m = 0$$

Notice no and slope are left.

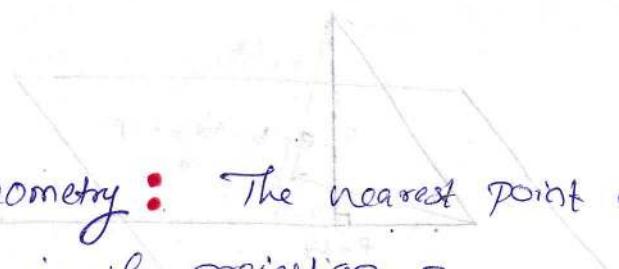
$$\begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} m \\ m \\ m \end{bmatrix} = \begin{bmatrix} 2-m \\ 2-m \\ 2-m \end{bmatrix}$$

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

$$\begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = 0 \cdot A \cdot (A^T A)^{-1} \cdot 0$$

$$\begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = 0 \cdot A \cdot (A^T A)^{-1} \cdot 0$$

□ Minimizing the error



By geometry : The nearest point ~~closest~~ to b is the projection p .

- The best choice for \hat{a} is $p \in c(A)$.
The smallest possible error is, $e = b - p$,
- perpendicular to the columns.

$$b = p + e$$

By algebra : Every vector b splits into 2 parts. The part in $c(A)$ is p . The perpendicular part (part in $N(A)$) is e .

$$A\hat{a} = b = p + e \rightarrow \text{is impossible to solve}$$

$$\hat{A}\hat{a} = p$$

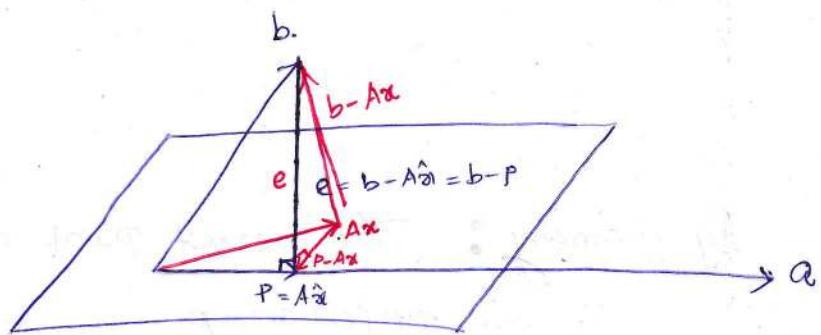
is solvable

$$\text{where } p = Pb$$

$$A^T A \hat{a} = A^T P$$

$$\hat{a} = \underline{(A^T A)^{-1} A^T P}$$

→ The solution to $A\hat{x} = p$ leaves the least possible error. (which is e) .



squared length for any \hat{x} ,

$$|A\hat{x} - b|^2 = |A\hat{x} - p|^2 + |e|^2$$

* The least squares solution \hat{x} makes $E = \|Ax - b\|^2$ as small as possible.

By calculus : The error function E to be minimized is a sum of squares $e_1^2 + e_2^2 + e_3^2$ (the square of the error in each equation):

$$E = |Ax - b|^2 = e_1^2 + e_2^2 + e_3^2$$

Ex:-

$$E = |Ax - b|^2 = (m \cdot 0 + c - 6)^2 + (m \cdot 1 + c)^2 + (m \cdot 2 + c)^2$$

The unknowns are m & c . With 2 unknowns there are 2 derivatives - both zero at the minimum. They are "partial derivatives" because $\frac{\partial E}{\partial c}$ treats m as constant and $\frac{\partial E}{\partial m}$ treats c as constant:

$$\frac{\partial E}{\partial c} = \sqrt{2} (\cancel{A} \cancel{x})$$

$$\frac{\partial E}{\partial c} = 2(m \cdot 0 + c - 6) + 2(m \cdot 1 + c) + 2(m \cdot 2 + c) = 0$$

$$\frac{\partial E}{\partial m} = 2(m \cdot 0 + c - 6)(0) + 2(m \cdot 1 + c)(1) + 2(m \cdot 2 + c)(2) = 0$$

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

~~$$\frac{\partial E}{\partial c} = 0 \Rightarrow 3m + 3c = 6$$~~

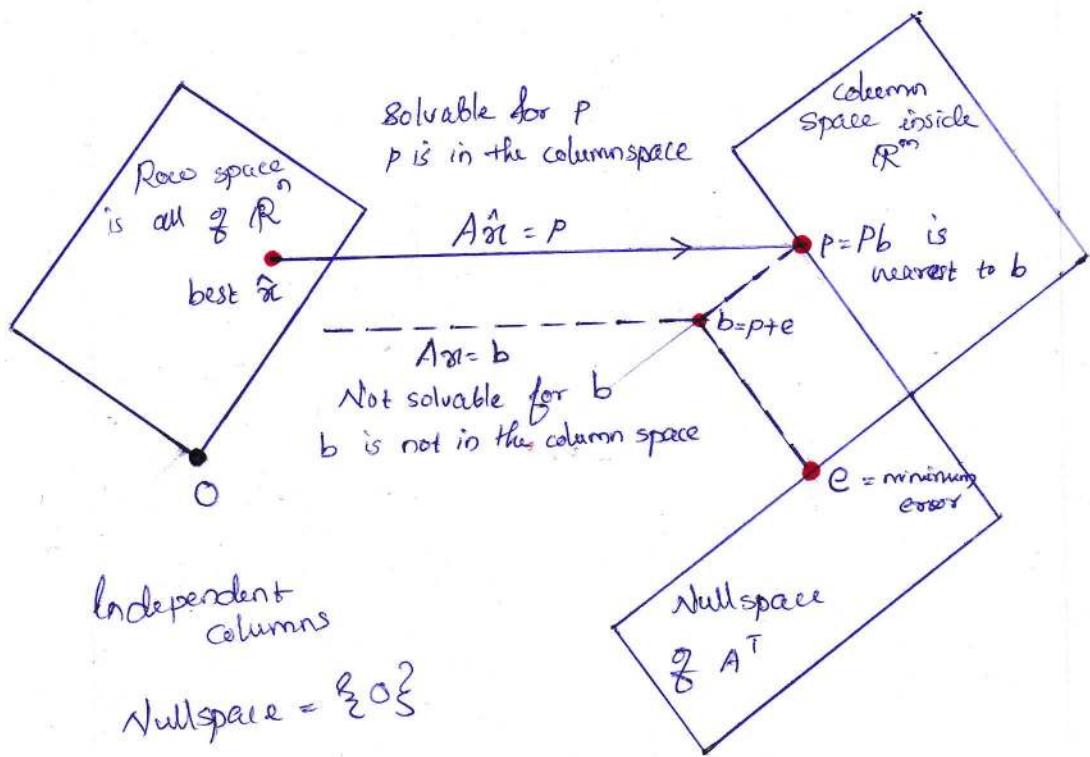
$$\Leftrightarrow \underline{\underline{A^T A \hat{x} = A^T b}}$$

$$\frac{\partial E}{\partial m} = 0 \Rightarrow 5m + 3c = 0$$

$$A^T A = \begin{bmatrix} 3 & 3 \\ 5 & 3 \end{bmatrix}$$

The best m & c are the components of \hat{x} .

- * The partial derivatives of $E = \|Ax - b\|^2$ are zero when $A^T A \hat{x} = A^T b$.



- The projection $p = A\hat{x}$ is closest to b , so \hat{x} minimizes $E = \|b - A\hat{x}\|^2$

□ Fitting a straight Line

- Application of least squares

If starts with $m > 2$ points, hopefully near a straight line.

At times t_1, \dots, t_m those m points are at heights b_1, \dots, b_m . The best line $C + Dt$ misses the points by vertical distances e_1, \dots, e_m . No line is perfect, and the least square line minimizes, $E = e_1^2 + \dots + e_m^2$.

To fit the m points, we are trying to solve ' m ' equations (and we only have 2 unknowns).

$A\vec{x} = b$ is

$$\left. \begin{array}{l} C + Dt_1 = b_1 \\ C + Dt_2 = b_2 \\ \vdots \\ C + Dt_m = b_m \end{array} \right\} \quad \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix}$$

$C(A)$ is so thin that almost certainly b is outside of it.

When b happens to lie in the $C(A)$, the points happen to lie on a line. In that case, $b = p$. Then $A\vec{x} = b$ is solvable and the errors are $e = (0, \dots, 0)$.

In
The

* The closest line $C + Dt$ has heights p_1, \dots, p_m with errors e_1, \dots, e_m .

* Solve $A^T A \hat{x} = A^T b$ for $\hat{x} = (C, D)$. The errors are $e_i = b_i - C - D t_i$

$$\begin{bmatrix} d \\ d \\ \vdots \\ d \end{bmatrix} = \begin{bmatrix} 1 & t_1 & \dots & t_m \\ t_1 & t_2 & \dots & t_m \\ \vdots & \vdots & \ddots & \vdots \\ t_1 & t_2 & \dots & t_m \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} \Leftrightarrow d^T A = b^T A$$

The 2 columns of A are independent (unless all times t_i are the same). So we turn to least squares and solve $A^T A \hat{x} = A^T b$.

$$A^T A = \begin{bmatrix} 1 & 1 & \dots & 1 \\ t_1 & t_2 & \dots & t_m \end{bmatrix} \begin{bmatrix} 1 & t_1 & t_2 & \dots & t_m \\ 1 & t_1 & t_2 & \dots & t_m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & t_1 & t_2 & \dots & t_m \end{bmatrix} = \begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix}$$

$$A^T b = \begin{bmatrix} 1 & 1 & \dots & 1 \\ t_1 & t_2 & \dots & t_m \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

In a specific problem these numbers are given.
The best $\hat{x} = (C, D)$ is $(A^T A)^{-1} A^T b$.

The line $C+Dt$ minimizes $e_1^2 + \dots + e_m^2 = |A\hat{x} - b|^2$
when $A^T A \hat{x} = A^T b$:

$$A^T A \hat{x} = A^T b \Leftrightarrow \begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

The vertical errors at the 'm' points on the line are the components of $e = b - p$. This error vector $b - A\hat{x}$ is \perp to the columns of A , (geometry). The error is in the nullspace of A^T (linear algebra). The best $\hat{x} = (C, D)$ minimizes the total error E , the sum of squares (calculus):

$$E(\hat{x}) = |A\hat{x} - b|^2 = (C+Dt_1 - b_1)^2 + \dots + (C+Dt_m - b_m)^2$$

Calculus sets the derivatives $\frac{\partial E}{\partial C}$ and $\frac{\partial E}{\partial D}$ to zero, and produces $A^T A \hat{x} = A^T b$.

In general,

- we are fitting m data points by n parameters $\alpha_1, \dots, \alpha_n$. The matrix A has n columns and $m < n$. The derivatives of $|A\alpha - b|^2$ give the n equations $A^T A \hat{\alpha} = A^T b$
- The derivative of a square is linear. This is why the method of least squares is so popular.
- $mC + D \sum t_i = \sum b_i \rightarrow C + D\hat{t} = \hat{b}$
→ The best line goes thro' the center point (\hat{t}, \hat{b})

- note
w-3(u).

Ex: 2

A has orthogonal columns when the measurement times t_i add to zero.

Gram-Schmidt

Suppose,

$b = (1, 2, 4)$ at times $t = -2, 0, 2$. These times add to zero.

The columns of A has zero dot product:

$$C + D(-2) = 1$$

$$C + D(0) = 2 \quad (\text{or})$$

$$C + D(2) = 4$$

$$A = \begin{bmatrix} 1 & -2 \\ 1 & 0 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 4 \end{bmatrix}$$

When the Columns of A are orthogonal, $A^T A$ will be a diagonal matrix

$$A^T A = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} = \begin{bmatrix} |a_1|^2 & 0 & \cdots & 0 \\ 0 & |a_2|^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & |a_n|^2 \end{bmatrix}$$

$$A^T A \hat{x} = A^T b \implies \begin{bmatrix} 3 & 0 \\ 0 & 8 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 7 \\ 6 \end{bmatrix} \quad \textcircled{①}$$

$$\implies C = \frac{7}{3}, D = \frac{3}{4}$$

* Orthogonal columns are so helpful that it is worth shifting the times by subtracting the average time, $\hat{t} = \frac{t_1 + t_2 + \dots + t_m}{m}$.

If the original times were 1, 3, 5, then $\hat{t} = 3$.

The shifted times $T = t - \hat{t} = t - 3$ adds up

to zero.

- The sum of the deviations taken from the mean is zero.

$$\left. \begin{array}{l} T_1 = 1 - 3 = -2 \\ T_2 = 3 - 3 = 0 \\ T_3 = 5 - 3 = 2 \end{array} \right\} A_{\text{new}} = \begin{bmatrix} 1 & T_1 \\ 1 & T_2 \\ 1 & T_3 \end{bmatrix}, A^T A_{\text{new}} = \begin{bmatrix} 3 & 0 \\ 0 & 8 \end{bmatrix}$$

Now, C & D comes from the easy equation ⑨
 The best straight line cases $C + DT$ which is
 $C + D(t - \hat{t}) = C + D(t - 3)$

→ Nothing wrong with shifting the data points left or right.

2(30)

$$T = t - \hat{t} : C = \frac{b_1 + \dots + b_m}{m} \quad \text{and} \quad D = \frac{b_1 T_1 + \dots + b_m T_m}{T_1^2 + \dots + T_m^2}$$

→ Make the columns orthogonal in advance.

Then $A^T A_{\text{new}}$ is diagonal and \hat{x}_{new} is easy.

* The Best line is $C + DT$ or $C + D(t - \hat{t})$

The time shift that makes $A^T A$ diagonal is an example of the Gram-Schmidt process: orthogonalize the columns of A in advance.

□ Dependent columns in A : What is \hat{x} ?

variables: t, b
 $C+Dt = b$

Which \hat{x} is best if A has dependent columns?

$$Lx + \alpha t = b$$

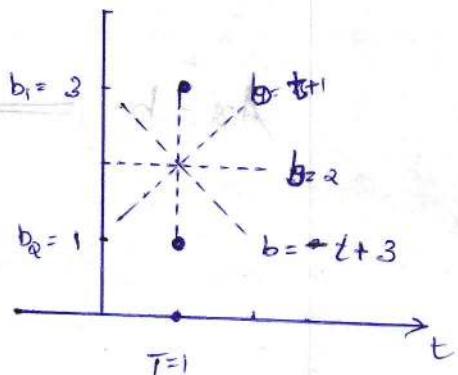
Ex:- points: $(1, 3), (1, 1)$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix} = b$$

$$Ax = b$$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} = p$$

$$A\hat{x} = p \leftarrow$$



around each variable or other things and
approximate from plotting it's outputs and

The measurements $b_1 = 3$ and $b_2 = 1$ are at the same time $T = 1$.

Q straight line $C+Dt$ can not go through both points

$$(3, 3) - (1, 1) = (1, 2) = q-d = 2$$

Projecting $b = (3, 1)$ onto the column space of A
 $C(A) = C(1, 1)$, hence $a = (1, 1)$

~~Perp to \hat{a} & $b - \hat{a}$~~

$$p = Pb = \frac{aa^T}{a^T a} b = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

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

$\rightarrow \underline{p = (2, 2)}$

$$Ax = b \quad \xrightarrow{\text{d} = d} \quad A\hat{x} = p$$

An equation with no solution has become an equation with infinitely many solutions.

The problem is that A has dependent columns and $(1, 1)$ is in its nullspace

$$e = b - p = (1, 1) - (2, 2)$$

A
What solution \hat{x} should we choose?

$$\hat{x}_1 + \hat{x}_2 = 2 \Rightarrow \begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \end{bmatrix} = \hat{\alpha}_2 \begin{bmatrix} -1 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \\ 0 \end{bmatrix}$$

$$(\hat{x}_1, \hat{x}_2) = (2, 0), (1, 1), (3, -1), \dots$$

$$b = a \quad b = t+1 \quad \rightarrow b = -t + 3$$

All these lines (drawn as dashed lines in fig) have the same 2 errors 1 and -1 at time T. These errors $e = b - p = (1, -1)$ are as small as possible. But, this doesn't tell us which dash line is best.

In section 7.4,

the "pseudo inverse" of A will choose the shortest solution to $A\hat{x} = p$. Also, the shortest solution will be $\hat{x}^+ = (1, 1)$.

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

$$(1-2)(1, 1) = (0, 0)$$

Revise

7.4

short (fit in least perfect w/ noise) \Rightarrow good fit

\Rightarrow unit to 1-band in error in sense of
adding less terms to $\sin(2\pi t)$ error in least

error \Rightarrow less noise w/ more terms in fit
 \Rightarrow good

□ Fitting by a Parabola

If we throw a ball, it would be crazy to fit the path by a straight line.

A parabola $b = C + Dt + Et^2$ allows the ball to go up and come down again (b is the height at time t). The actual path is not a perfect parabola, but the whole theory of projectiles starts with that approximation.

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

Solution: With $m > 3$, the m equations for an exact fit are generally unsolvable:

$$C + Dt_1 + Et_1^2 = b_1$$

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

$$\left\{ \begin{array}{l} \left[\begin{array}{c|c|c|c} 1 & D & E & \\ \hline t_1 & t_1^2 & & \\ \hline 1 & t_m & t_m^2 & \end{array} \right] \left[\begin{array}{c} C \\ D \\ E \end{array} \right] = \left[\begin{array}{c} b_1 \\ \vdots \\ b_m \end{array} \right] \end{array} \right.$$

where,

$$A\vec{a} = b \text{ with } A =$$

$$\begin{bmatrix} 1 & t_1 & t_1^2 \\ \vdots & \vdots & \vdots \\ 1 & t_m & t_m^2 \end{bmatrix}$$

(i) If n of points of bivariate data (t_i, y_i) are given then

(ii) If n of points of bivariate data (t_i, y_i) are given then

Least squares: The closest parabola $C + Dt + Et^2$ chooses

$\hat{\vec{a}} = (C, D, E)$ to satisfy the (3) normal equations $A^T A \hat{\vec{a}} = A^T b$.

(i) (A) has dimensions $3 \times n$ in \mathbb{R}^m .

The projection of b is $p = A \hat{\vec{a}}$, which combines the 3 columns using the coefficient C, D, E .

The error at the 1st data point is

$$e_1 = b_1 - [C + Dt_1 + Et_1^2]$$

The total squared error is, $E = e_1^2 + e_2^2 + \dots + e_m^2$

$$= [C + Dt_1 + Et_1^2]^2 + [C + Dt_2 + Et_2^2]^2 + \dots + [C + Dt_m + Et_m^2]^2$$

If you prefer to minimize by calculus,
take the partial derivatives of E w.r.t C, D, E .
These 3 derivatives will be zero when $\hat{\alpha} = (C, D, E)$
solves the 3×3 system of equations $A^T A \hat{\alpha} = A^T b$.

* The closest parabola $C + Dt + Et^2$ has heights
 p_1, p_2, \dots, p_m with errors e_1, \dots, e_m .

* Solve $A^T A \hat{\alpha} = A^T b$ for $\hat{\alpha} = (C, D, E)$. The
errors are $e_i = b_i - C - Dt_i - Et_i^2$.

Section 10.5,

Fourier Series - approximating functions instead of vectors.

The function to be minimized changes from a sum of squared errors $e_1^2 + \dots + e_m^2$ to an integral of the squared error.

Integrated cost function: minimizing $\int_{\Omega} |u(x) - f(x)|^2 dx$

est. $(\hat{u}(x)) = \hat{\alpha}$ of $d^T A = \hat{A}^T A$ under $\hat{A}^T \hat{A} = I_d \Rightarrow \hat{A} = d^{-1/2} \cdot \hat{A}^T$, $\hat{d} = d^{-1/2} \cdot d$ errors

Ex:3. For a parabola $b = C + Dt + Et^2$ to go through the 3 heights $b = 6, 0, 0$ with $t = 0, 1, 2$, the eq's for C, D, E are:

$$\left. \begin{array}{l} C + D \cdot 0 + E \cdot 0^2 = 6 \\ C + D \cdot 1 + E \cdot 1^2 = 0 \\ C + D \cdot 2 + E \cdot 2^2 = 0 \end{array} \right\} \begin{array}{l} \text{Ax=b} \\ \text{determinant} \end{array}$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 2 & 4 \end{bmatrix} \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix}$$

$$|A| = 4 - 2 = 2 \Rightarrow \begin{bmatrix} C \\ D \\ E \end{bmatrix} = A^{-1} \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{array}{ll} C = 6, & \begin{array}{l} \Leftrightarrow 6 + D + E = 0 \\ 6 + 2D + 4E = 0 \end{array} \end{array} \left. \begin{array}{l} 2D + 4E = -6 \\ 2E + 4E = -12 \end{array} \right\} \begin{array}{l} 2E = -12 \Rightarrow E = 3 \\ D = -9 \end{array}$$

$$(C, D, E) = (6, -9, 3)$$

The parabola thro' the 3 points is $b = 6 - 9t + 3t^2$

The $C(A) = \mathbb{R}^3$

Projection matrix, $P = I$, The projection of b is b .

The error is zero.

We didn't need $A^T A \hat{x} = A^T b$ because we solved $Ax = b$

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

$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}^T \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}^T \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \iff 1 \cdot 1 + 0 \cdot 1 + 0 \cdot 1 = 1 \neq 0$$

$$\frac{\begin{array}{l} 1 = 1 + 0 + 0 \\ 0 = 1 + 1 + 1 \end{array}}{1 = 1 + 1 + 1} \iff \begin{array}{l} 1 = 1 + 0 + 0 \\ 0 = 1 + 1 + 1 \end{array} \iff \begin{array}{l} 1 = 1 \\ 0 = 1 \end{array}$$

$$P = I \iff (I, I^T) = (I, I)$$

MAPLE did the same thing as MATLAB

4.3(a)

Start with 9 measurements b_1 to b_9 , all zero, at times $t=1, \dots, 9$. The 10th measurement $b_{10}=40$ is an outlier. Find the best horizontal line $y=c$ to fit the 10 points $(1, 0), (2, 0), \dots, (9, 0), (10, 40)$ using 3 options for the error E .

① Least squares, $E_Q = e_1^2 + \dots + e_{10}^2$

Ans:

$$C + Dt = b$$

MANNA

$$C + D = 0$$

$$C + 2D = 0$$

$$\vdots$$

$$C + 9D = 0$$

$$C + 10D = 40$$

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 40 \end{bmatrix}$$

$$Ax = b.$$

$$A^T A = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ 1 & 3 & 9 & 27 & 81 & 243 & 729 & 2187 & 6561 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ 1 & 3 & 9 & 27 & 81 & 243 & 729 & 2187 & 6561 \end{bmatrix}^T = \begin{bmatrix} 10 & 55 \\ 55 & 385 \end{bmatrix}$$

$$A^T b = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix} = \begin{bmatrix} 40 \\ 400 \end{bmatrix}$$

$$\frac{n(n+1)(n+2)}{6} = \frac{5(5+1)(5+2)}{6} = \frac{5 \times 11 \times 21}{6} = \frac{55}{2}$$

$$A^T A x = A^T b \Rightarrow C = -8, D = \frac{24}{11}$$

Half : with outlier included

With help of d. minimization to derive the linear regression line. (a)

Minimise the $\sum_{i=1}^n$ product error to, i.e.
 Least square fit will reduce the sum of squares of residuals
2 terms after ref worked 8 times (method)

$$y = c$$

$$\begin{bmatrix} 0 \\ 10 \\ 20 \\ \vdots \\ 40 \end{bmatrix} \quad \left\{ \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix} \right\} \begin{bmatrix} c \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 40 \end{bmatrix}$$

$c = 0$

$c = 40$

$$A^T A = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 0 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = 10$$

$d = 10 A$

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

$$\begin{bmatrix} 23 & 0 \\ 288 & 23 \end{bmatrix} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 0 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 40 \end{bmatrix}$$

$$\therefore c = \frac{1}{10} \times 40 = 4$$

- The least square fit to $0, 10, \dots, 40$ by a horizontal line is $C = 4$

Best horizontal Line: $y = 4$

⑤ Least max. error, $E_{\infty} = |e_{\max}|$ and how? ⑤

Ques:

9. Order order formula is measure of only
maximum error

$$C = \underline{0}$$

contd

(c) Least sum of errors, $E_1 = |e_1| + \dots + |e_{10}|$

Ans: $|e_1| + \dots + |e_{10}| = 9/c + |c - 40|$

- Sum of deviation is minimized when taken from the median

$c=0$

4.3(B) Find the parabola $C + Dt + Et^2$ that comes closest
 (least squares error) to the values $b = (0, 0, 1, 0, 0)$
 at the times $t = -2, -1, 0, 1, 2$.

$$\begin{aligned} C + D(-2) + E(-2)^2 &= 0 \\ \text{Ans: } C + D(-1) + E(-1)^2 &= 0 \\ C + D(0) + E(0)^2 &= 1 \\ C + D(1) + E(1)^2 &= 0 \\ C + D(2) + E(2)^2 &= 0 \end{aligned} \quad \left\{ \begin{array}{l} \\ \\ \\ \\ \end{array} \right. \quad \left[\begin{array}{ccc|c} 1 & -2 & 4 & 0 \\ 1 & -1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 2 & 4 & 0 \end{array} \right] \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$A \mathbf{x} = \mathbf{b}$

$$A^T A = \begin{bmatrix} 5 & 0 & 10 \\ 0 & 10 & 0 \\ 10 & 0 & 34 \end{bmatrix} \rightarrow \text{col}(2) \text{ of } A \text{ is orthogonal to col}(1) \text{ & col}(3).$$

A : orctangular Vandermonde matrix.

$$A^T A \hat{x} = A^T b \Rightarrow \begin{bmatrix} 5 & 0 & 10 \\ 0 & 10 & 0 \\ 10 & 0 & 34 \end{bmatrix} \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$C = \frac{34}{70}, \quad D = 0, \quad E = -\frac{10}{70}.$$

$$\begin{bmatrix} 0 \\ 0 \\ 1 \\ 3 \\ 0 \end{bmatrix} = \begin{bmatrix} 5 & 0 & 10 \\ 0 & 10 & 0 \\ 10 & 0 & 34 \end{bmatrix} \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} 5C + 10E \\ 10D \\ 10C + 34E \end{bmatrix}$$

d.e.s

basecase is $g(0) = 0$
 $(e) \text{ base } (0) = 0 \Rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = 0$

other dimensions will depend on λ

