

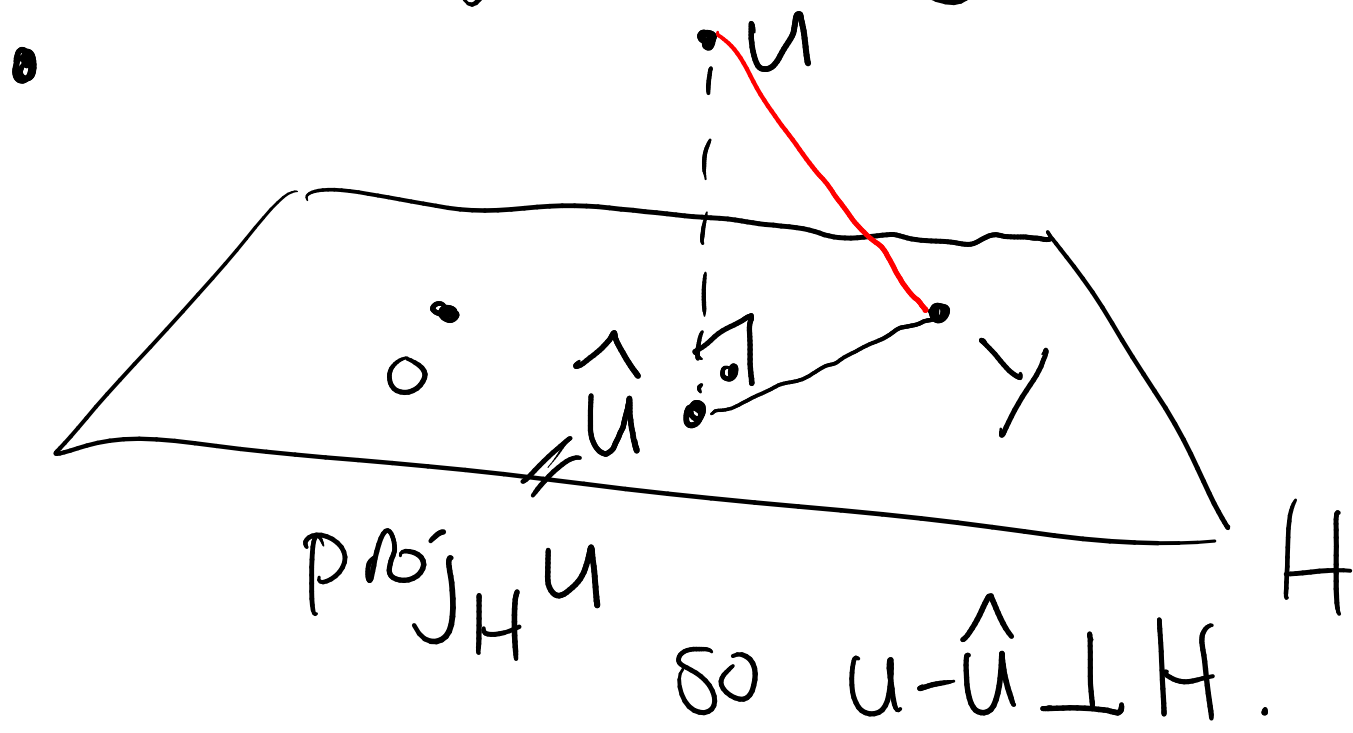
- Given $H \subset \mathbb{R}^n$ a subspace; ($k \leq n$)
 $A_{n \times k}$ with $\text{col}(A) = H$ & columns linearly independent.

$P = A(A^T A)^{-1} A^T$ projects orthogonally
 $n \times n$ vectors in \mathbb{R}^n to H .

- $P^2 = P$ & $P^T = P$; i.e. P is a projection matrix.
- So $\text{col}(P) = \text{col}(A)$.

& $\text{rank}(P) = \text{rank}(A) = k$.

- $\dim \text{null}(P) = n - k$.
- If $Pu = \hat{u}$ then for any $n \in \text{null} P$,
 $u + n$ projects orthog to \hat{u} too.



Therefore for any $y \in H$, the distance from u to y \geq the distance from u to \hat{u} .

thm1. $\text{proj}_H u$ is the closest point in H to u (in the Euclidean distance)

thm2. Any projection matrix $Q_{n \times n}$ orthogonally projects to a subspace of \mathbb{R}^n .

proof. For any x , $Qx \in H = \text{col}(Q)$

We claim that $Qx = \text{proj}_H x$.

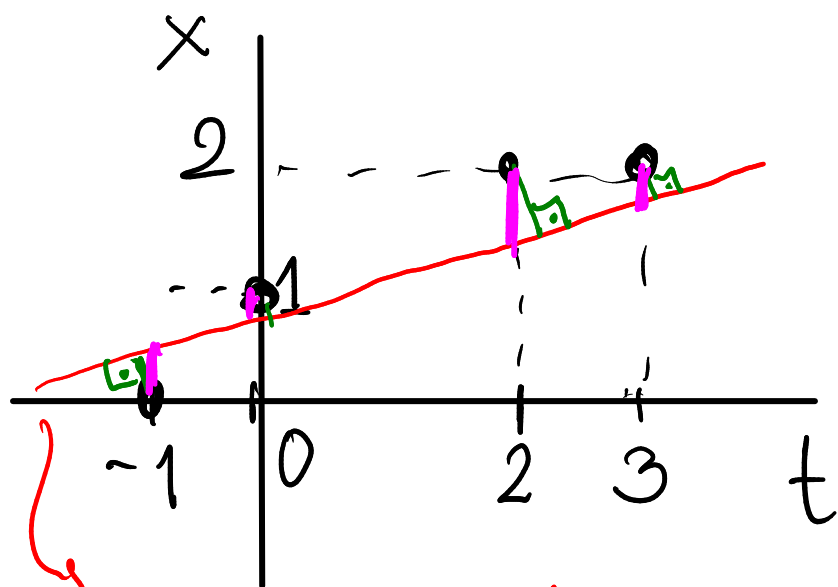
$Qx \in H$ already. We must prove:

$x - Qx \perp H$ i.e. $x - Qx \perp$ every column of Q

$$\Leftrightarrow Q^T(x - Qx) = 0$$

$$Q^T x - Q^T Q x \stackrel{Q^T = Q}{=} Qx - Q^2 x \stackrel{Q^2 = Q}{=} Qx - Qx$$

LEAST SQUARES APPROXIMATION



t	x
-1	0
0	1
2	2
3	2

L is the "best fitting" line.

$L: x = a + bt$; a, b unknown.

Find them, so that the sum of the square of the **vertical** distances of the data points to L is made minimum.

(minimizing the orthog. distance to the line is another problem.)

We fancy a line

$$\underbrace{L: A}_{\text{matrix}} \underbrace{\begin{pmatrix} a \\ b \end{pmatrix}}_{\text{vector}} = \underbrace{\begin{pmatrix} 0 \\ 1 \\ 2 \\ 2 \end{pmatrix}}_{\text{vector}}$$

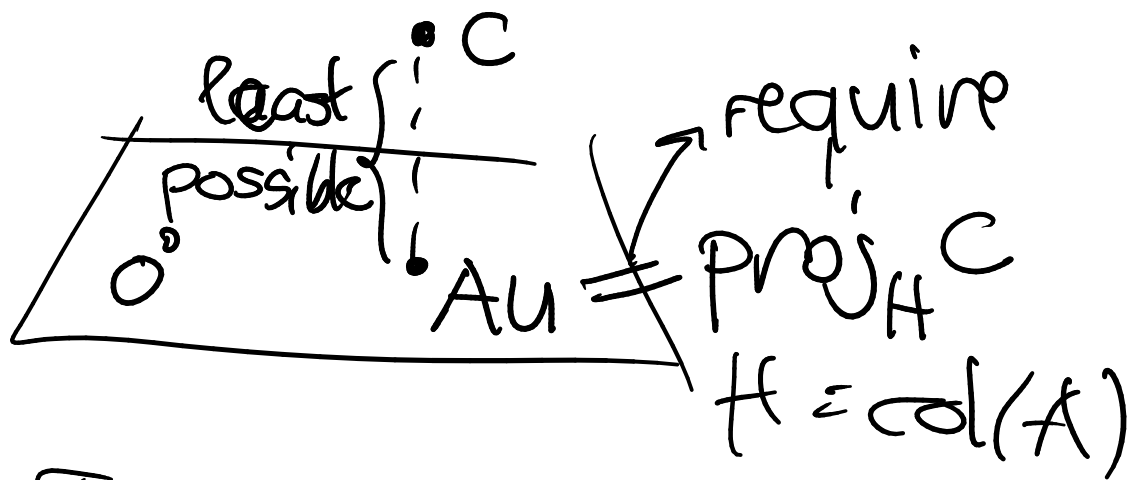
$$a + (-1)b = 0$$

$$a + 0 \cdot b = 1 \Leftrightarrow$$

$$a + 2b = 2$$

$$a + 3b = 2$$

There is no soln for u because apparently the data points are not collinear. Instead we are content to solve u such that Au is closest to c ,



This solves the minimizing the sum of the square of vertical distances problem.

Let's solve.

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

$$= A \cdot \begin{pmatrix} 4 & 4 \\ 4 & 14 \end{pmatrix}^{-1} \cdot A^T = A \cdot \frac{1}{40} \begin{pmatrix} 14 & -4 \\ -4 & 4 \end{pmatrix} A^T$$

$$= A \cdot \frac{1}{40} \cdot \begin{pmatrix} 18 & 14 & 6 & 2 \\ -8 & -4 & 4 & 8 \end{pmatrix}$$

Thus solve $Au = Pc \in \text{col}(A)$
 The soln for u is ^{4×2} unique because $A_{4 \times 2}$ has rank 2.

$$Au = Pc = A \underbrace{(A^T A)^{-1} A^T}_{\text{projection matrix}} c$$

So the unique soln^u for u is

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

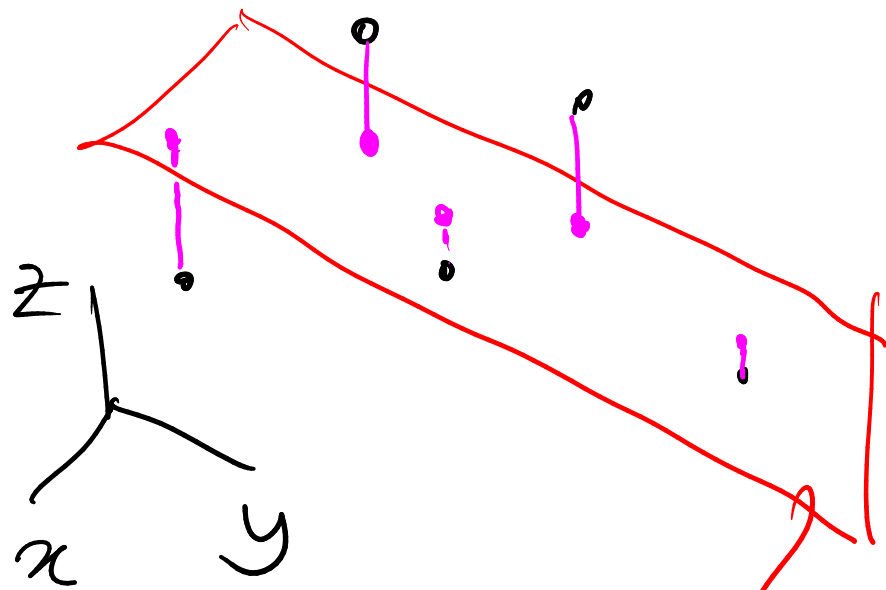
$$= \frac{1}{20} \begin{pmatrix} 9 & 7 & 3 & 1 \\ -4 & -2 & 2 & 4 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 2 \\ 2 \end{pmatrix} = \frac{1}{20} \begin{pmatrix} 15 \\ 10 \end{pmatrix}$$

so that $a = \frac{3}{4}$, $b = \frac{1}{2}$.

ex: Measurement:

x	y	z
x_1	y_1	z_1
\vdots	\vdots	\vdots
x_k	y_k	z_k

Here $z = z(x, y)$



best fitting plane

$$z = a + bx + cy$$

We solve

$$\underbrace{\begin{pmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ \vdots & \vdots & \vdots \\ 1 & x_k & y_k \end{pmatrix}}_A \cdot \underbrace{\begin{pmatrix} a \\ b \\ c \end{pmatrix}}_u = \begin{pmatrix} z_1 \\ \vdots \\ z_k \end{pmatrix} = Z$$

Instead solve $Au = \text{proj}_{\text{col}(A)} Z$:

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

ORTHONORMALITY & ORTHOGONAL MATRICES

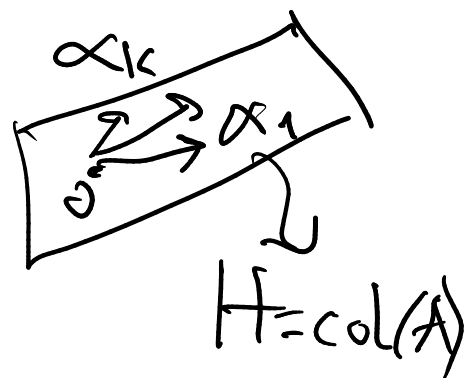
Back to projection matrices.

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

with $A = (\alpha_1 : \dots : \alpha_k)$

& $\{\alpha_1, \dots, \alpha_k\}$ a basis

for H . Observe:



$$A^T A = \begin{pmatrix} \alpha_1^T \\ \vdots \\ \alpha_k^T \end{pmatrix} (\alpha_1 : \dots : \alpha_k)$$

$$= \begin{pmatrix} \alpha_1^T \alpha_1 & \alpha_1^T \alpha_2 & \dots \\ \alpha_2^T \alpha_1 & \ddots & \ddots \\ \vdots & \ddots & \ddots \end{pmatrix} = I$$

↑ we'd have

Assume $\alpha_1, \dots, \alpha_k$ is an orthogonal collection with lengths 1
i.e. $\alpha_i^T \alpha_j = \delta_{ij} = \begin{cases} 1, & i=j \\ 0, & i \neq j \end{cases}$
Kronecker delta

In that case $P = AA^T$.

defn: An orthogonal collection with all lengths 1 is called an orthonormal collection.

thm 3. Let $\alpha_1, \dots, \alpha_k$ be orthonormal basis for \mathbb{R}^k . Then for $u \in \mathbb{R}^k$,
 $u = \text{proj}_{\alpha_1} u + \dots + \text{proj}_{\alpha_k} u$.

proof: Let $u = c_1 \alpha_1 + \dots + c_k \alpha_k$.

$$\begin{aligned} \text{Then } \alpha_1^T u &= c_1 \alpha_1^T \alpha_1 + \dots + c_k \alpha_1^T \alpha_k \\ &= c_1 \end{aligned}$$

Similarly $c_j = \alpha_j^T u$ so that

$$\begin{aligned} u &= (\alpha_1^T u) \alpha_1 + \dots + (\alpha_k^T u) \alpha_k \\ &= \text{proj}_{\alpha_1} u + \dots + \text{proj}_{\alpha_k} u. \end{aligned}$$