

HW 5 due right now.

Remainder of the course:

(1) Least Squares Approximation ✓

(2) Diagonalization, i.e., finding the "correct" coordinate system for your problem. (Next)

Quiz 5: Tuesday Nov 10.



Today: HW 5 Discussion,
Odds & Ends.

Problem 1: Write $c = \cos \theta$, $s = \sin \theta$.

$$R_\theta = \begin{pmatrix} c & -s \\ s & c \end{pmatrix}, F_\theta = \begin{pmatrix} c & s \\ s & -c \end{pmatrix}, P_\theta = \begin{pmatrix} c^2 & cs \\ cs & s^2 \end{pmatrix}.$$

Determinants:

$$\det(R_\theta) = c^2 + s^2 = 1$$

$$\det(F_\theta) = -c^2 - s^2 = -1$$

$$\det(P_\theta) = c^2 s^2 - c^2 s^2 = 0$$

} θ doesn't
matter.

Recall: 2×2 matrix A is invertible

$$\Leftrightarrow A\vec{x} = \vec{0} \Rightarrow \vec{x} = \vec{0}$$

\Leftrightarrow columns of A not parallel

\Leftrightarrow rows of A not parallel

$$\Leftrightarrow \det(A) \neq 0.$$

In which case we can write an explicit formula for the inverse:

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}.$$

So in our case, R_θ & F_θ are invertible with

$$\bullet R_\theta^{-1} = \frac{1}{1} \begin{pmatrix} c & s \\ -s & c \end{pmatrix} = \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix}$$

Observe: $R_\theta^{-1} = R_{-\theta}$

$$(\text{rotate by } \theta)^{-1} = (\text{rotate by } -\theta)$$

$$\bullet F_{\theta}^{-1} = \frac{1}{-1} \begin{pmatrix} -c & -s \\ -s & c \end{pmatrix}$$

$$= \begin{pmatrix} c & s \\ s & -c \end{pmatrix} = F_{\theta} !$$

(reflect)⁻¹ = (same reflection)

$$F_{\theta}^{-1} = F_{\theta}$$

$$\cancel{F_{\theta}^{-1}} F_{\theta} = F_{\theta} F_{\theta}$$

$$I = F_{\theta}^2$$

(do nothing) = (reflect twice)

The matrix $P_{\theta} = \begin{pmatrix} c^2 & cs \\ cs & s^2 \end{pmatrix}$ is

not invertible because $\det(P_{\theta}) = 0$.

What does this matrix do?

Claim: P_{θ} is the projection onto the line $t(\cos\theta, \sin\theta)$, i.e., the line of angle θ .

Proof: Let $\vec{a} = (\cos \theta, \sin \theta)$ so

the projection matrix is

$$P = \vec{a} (\vec{a}^T \vec{a})^{-1} \vec{a}^T$$

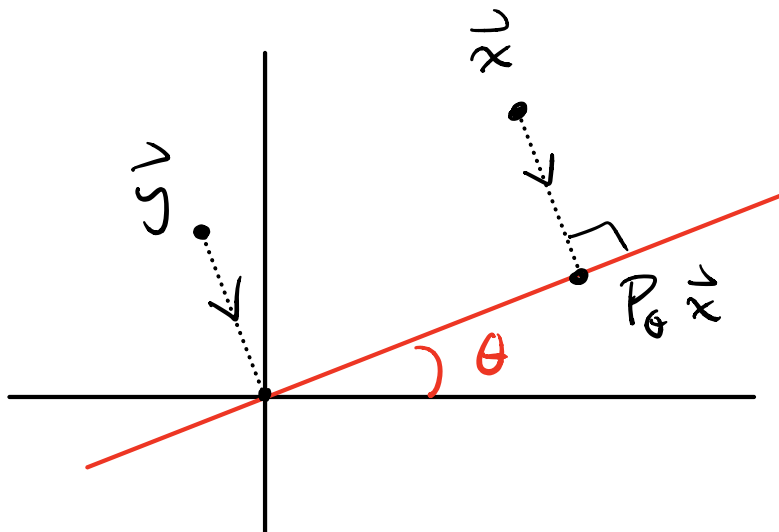
$$= \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix} \left[\begin{pmatrix} \cos \theta & \sin \theta \end{pmatrix} \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix} \right]^{-1} \begin{pmatrix} \cos \theta & \sin \theta \end{pmatrix}$$

$\cos^2 \theta + \sin^2 \theta$
1

$$= \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix} \begin{pmatrix} \cos \theta & \sin \theta \end{pmatrix}$$

$$= \begin{pmatrix} \cos^2 \theta & \cos \theta \sin \theta \\ \cos \theta \sin \theta & \sin^2 \theta \end{pmatrix} \quad \checkmark$$

Picture :



Another reason why P_G is not invertible: It sends some nonzero vectors to zero.



Problem 2: The algebra of projection matrices. Say P is a "projection matrix" if

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

(a) Let $Q = I - P$. Then Q is also a projection matrix:

$$\begin{aligned} \bullet \quad Q^T &= (I - P)^T \\ &= I^T - P^T = I - P = Q \quad \checkmark \end{aligned}$$

[Jargon: Matrices $A^T = A$ are called symmetric. The entries are symmetric across the main diagonal.]

$$\begin{aligned}
 \bullet \quad Q^2 &= (I-P)(I-P) \\
 &= I^2 - IP - PI + PP \\
 &= I - P - \cancel{P} + \cancel{P} \\
 &= I - P = Q \quad \checkmark
 \end{aligned}$$

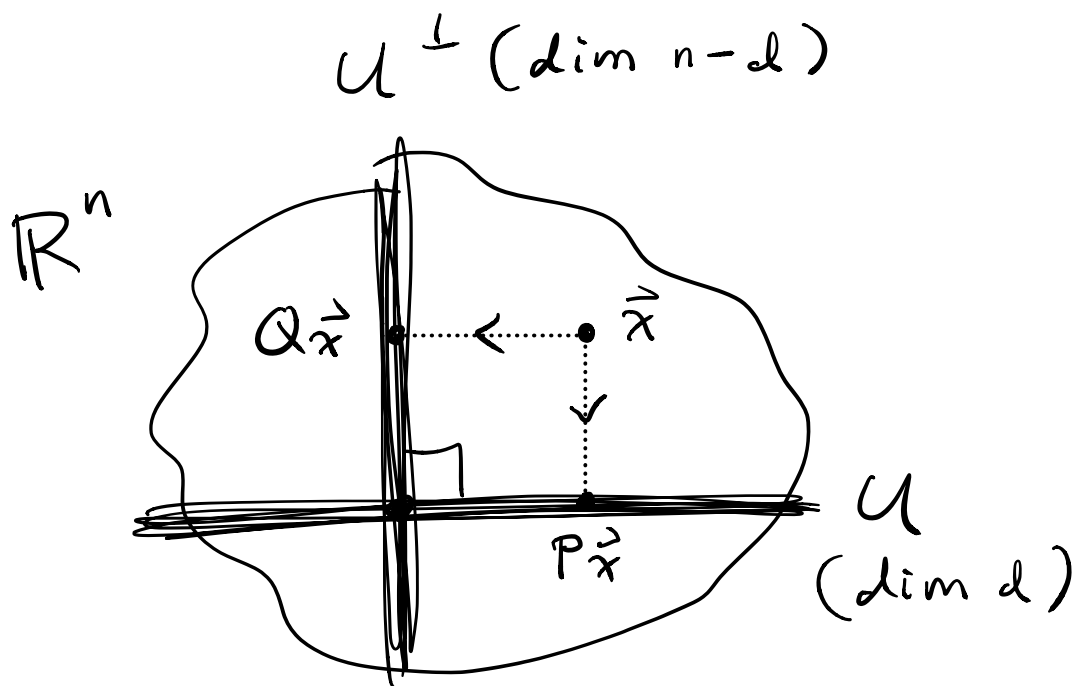
$$\begin{aligned}
 (b) \quad PQ &= P(I-P) \\
 &= P - P^2 \\
 &= P - P = 0.
 \end{aligned}$$

Summary of (a) & (b): Every projection P comes with a "complementary projection" Q satisfying:

$$P + Q = I \quad \& \quad PQ = QP = 0.$$

What is the picture?

P & Q project onto a pair of "complementary subspaces":



[Projections, like subspaces, come in complementary pairs.]

(c) It is "fun" to check that

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

$$P^T = P \text{ \& } P^2 = P.$$

[See the solutions.]

Geometrically, this is the matrix that projects onto the column space of matrix A .

(d) What if A is square & invertible?

Then we get

$$\begin{aligned} P &= A (A^T A)^{-1} A^T \\ &= A \cancel{(A)^{-1}} (\cancel{A^T})^{-1} A^T \\ &= I I = I \end{aligned}$$

"(project onto $C(A)$) = (do nothing)"

What?

If A is invertible then $C(A)$ is the whole space. Since every point is already in the whole space, there is no need to do anything!

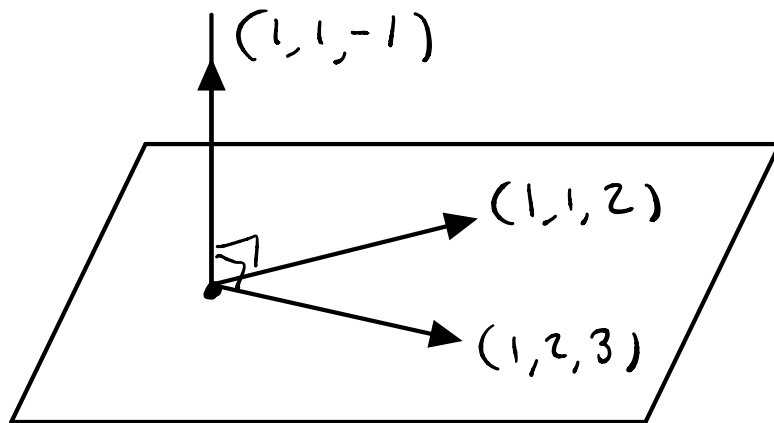


Example: Problem 3.

$$\text{Let } \vec{c} = (1, 1, -1)^T$$

$$A = \begin{pmatrix} 1 & 1 \\ 2 & 1 \\ 3 & 2 \end{pmatrix}.$$

Observe that line $C(\vec{a})$ & plane $C(A)$ are "orthogonal complements":



IF $P =$ project onto line,
 $Q =$ project onto plane,
then we will have

$$P + Q = I \quad \& \quad PQ = QP = 0.$$

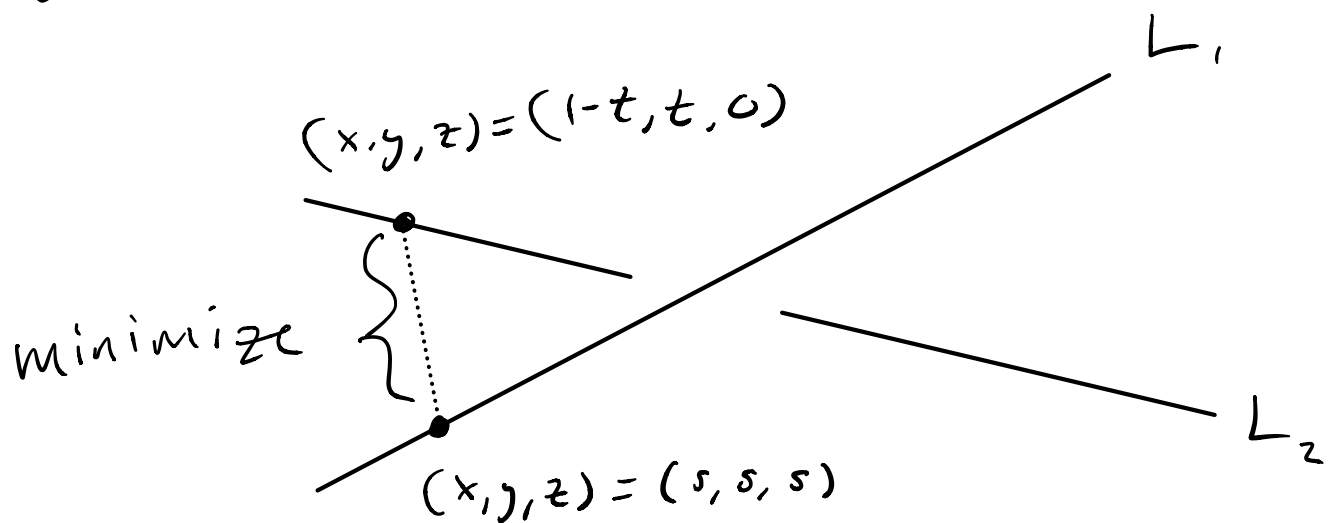
I asked you to compute the matrices
and check that this indeed the case.

[See solutions.]



Problem 4 : Geometric Application
of Least Squares.

We have two lines in \mathbb{R}^3 that do not intersect:



Find the points on L_1 & L_2 that minimize the distance.

Remark: We could use calculus. Let

$$F(s, t) = \text{distance between } (s, s, s) \text{ \& } (1-t, t, 0)$$

$$= \sqrt{(s-1+t)^2 + (s-t)^2 + s^2}$$

Then compute first & second partial derivatives, etc...

But we will use linear algebra!

Idea: Write down a silly equation.

The lines L_1 & L_2 intersect when

$$(s, s, s) = (1-t, t, 0)$$

$$\begin{cases} s = 1-t \\ s = t \\ s = 0 \end{cases} \rightsquigarrow \begin{cases} s+t = 1 \\ s-t = 0 \\ s+0 = 0 \end{cases}$$

Of course there is no solution,
so we solve the "normal equations"

instead:

$$\begin{pmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} s \\ t \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} \hat{s} \\ \hat{t} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & -1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} 3 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} \hat{s} \\ \hat{t} \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\implies \hat{s} = \frac{1}{3} \quad \& \quad \hat{t} = \frac{1}{2}.$$

Much easier than calculus!

Solution: Distance between L_1 & L_2 is minimized for the points

$$(\hat{s}, \hat{s}, \hat{s}) = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right) \text{ on } L_1$$

$$(1-\hat{t}, \hat{t}, 0) = \left(\frac{1}{2}, \frac{1}{2}, 0\right) \text{ on } L_2$$

Minimum distance between L_1 & L_2 :

$$\sqrt{\left(\frac{1}{2} - \frac{1}{3}\right)^2 + \left(\frac{1}{2} - \frac{1}{3}\right)^2 + \left(-\frac{1}{3}\right)^2}$$

$$= \sqrt{\left(\frac{1}{36} + \frac{1}{36} + \frac{1}{9}\right)} = \frac{1}{\sqrt{6}}$$



Problem 5: The usual application of least squares: Fitting shapes to collections of data points.

[See solutions.]

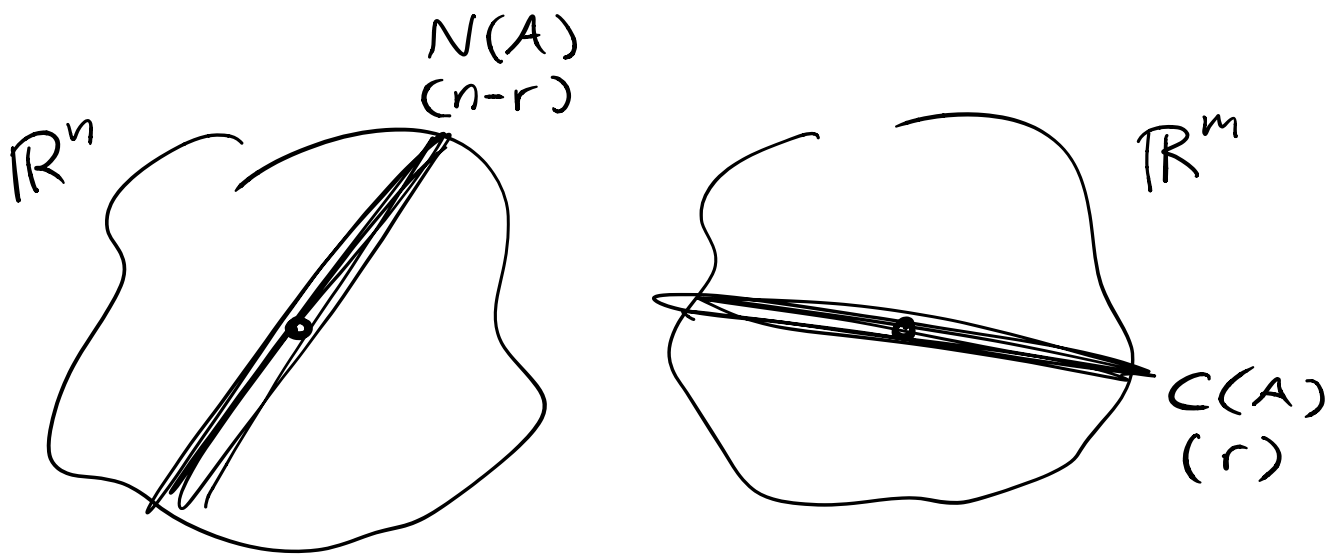


Odds & Ends : The 4 fundamental subspaces & the fundamental theorem.

Given $m \times n$ matrix A we define

$$\begin{aligned} C(A) &= \text{column space} \\ &= \{ A\vec{x} : \vec{x} \in \mathbb{R}^n \} \subseteq \mathbb{R}^m \end{aligned}$$

$$\begin{aligned} N(A) &= \text{null space} \\ &= \{ \vec{x} \in \mathbb{R}^n : A\vec{x} = \vec{0} \} \subseteq \mathbb{R}^n. \end{aligned}$$



$$\begin{aligned} \text{Let } r &= \text{rank}(A) \\ &= \# \text{ pivots in RREF}(A) \end{aligned}$$

$$\text{Then } \dim C(A) = r$$

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

$$= \# \text{ non-pivot columns} \\ \text{in RREF}(A)$$

Two more fundamental subspaces

$$R(A) = \text{row space of } A$$

$$= \text{column space of } A^T$$

$$= C(A^T)$$

$$N(A^T) = \left\{ \vec{x} \in \mathbb{R}^m : A^T \vec{x} = \vec{0} \right\}$$

Recall from least squares:

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

Since these are subspaces of \mathbb{R}^m

we know from HW3.5 that

$$\dim N(A^T) + \dim C(A) = m$$

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

$$= m - r.$$

And by plugging $B = A^T$ into the previous formula we get

$$N(B) = C(B^T)^\perp$$

$$N(B) = R(B)^\perp$$

For any B . In particular,

$$N(A) = R(A)^\perp$$

Since these are subspaces of \mathbb{R}^n we know from HW 3.5 that

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

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

$$= n - (n - r)$$

$$= r.$$

Surprise!

Let me state this as an official theorem.

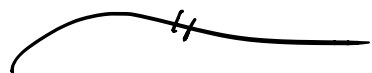
The Fundamental Theorem of Linear Algebra:

For any matrix A we have

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

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

$$\# \text{ pivots in RREF}(A) = \# \text{ pivots in RREF}(A^T)$$



This is a very simple statement, but as you see above, it was not easy to prove. Example:

$$\text{Let } A = \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 & 1 \\ 1 & 3 & 0 \end{pmatrix} \text{ \& } A^T = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & 3 \\ 2 & 1 & 0 \end{pmatrix}$$

$$\text{RREF}(A) = \begin{pmatrix} 1 & 0 & 3 \\ 0 & 1 & -1 \\ 0 & 0 & 0 \end{pmatrix}$$

$$\text{RREF}(A^T) = \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{pmatrix}$$

So $\text{rank}(A) = \text{rank}(A^T) = 2$.

We compute the 4 fundamental subspaces of A :

Columns 1 & 2 of A are pivots, so

$$C(A) = \text{plane } s \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} + t \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}.$$

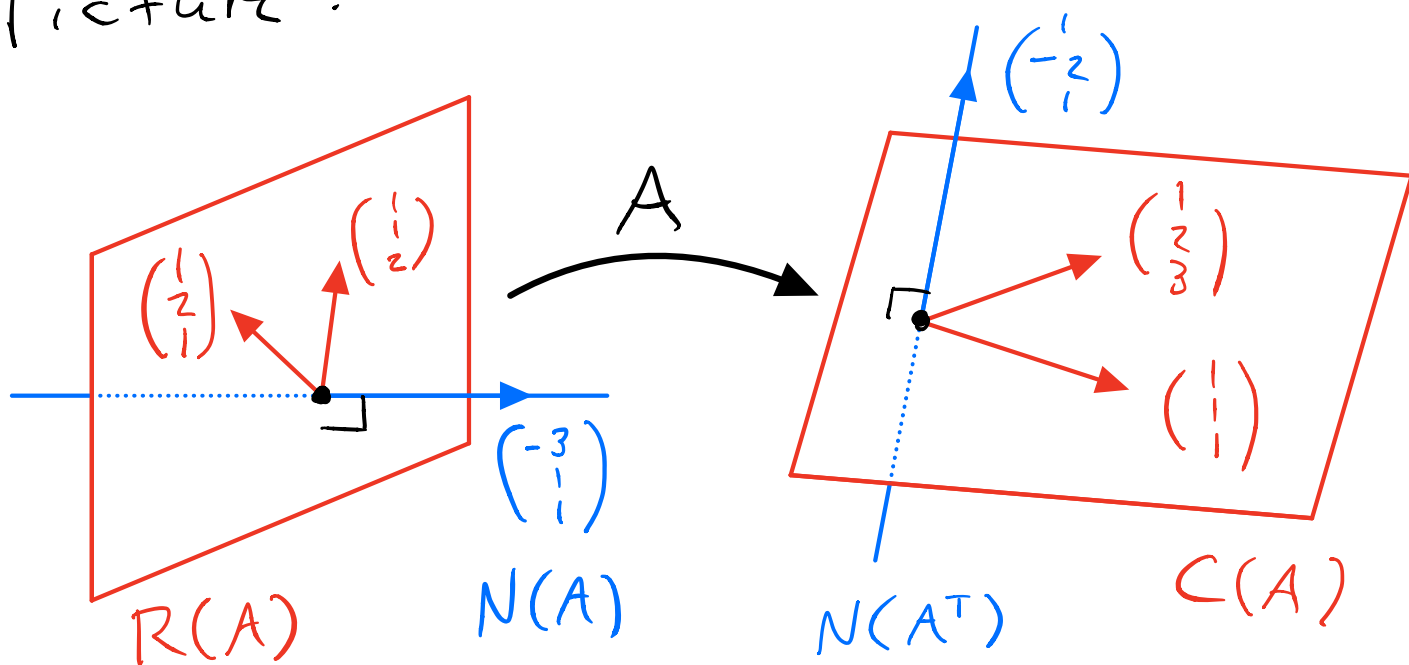
$$N(A^T) = C(A)^\perp = \text{line } t \begin{pmatrix} -1 \\ -2 \\ 1 \end{pmatrix}$$

Columns 1 & 2 of A^T are pivots, so

$$R(A) = C(A^T) = \text{plane } s \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix} + t \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}.$$

$$N(A) = R(A)^\perp = \text{line } t \begin{pmatrix} -3 \\ 1 \\ 1 \end{pmatrix}.$$

Picture:



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Don't worry too much about the
Fundamental theorem; I just
wanted you to see it.

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Quiz 5 is on Tuesday at
the beginning of class. As usual
there will be two problems:

- one problem about projection
- one problem about least squares