

- Group formation
- Survey

Today

- Least squares + trilateration
- When does least squares fail?
- $\text{Null}(A^T A) = \text{Null}(A)$
- Model fitting, test data, validation data, training data.

LINEAR in \vec{x}

① $\|\vec{x} - \vec{a}\|^2 = d_1^2$

② $\|\vec{x} - \vec{b}\|^2 = d_2^2$

③ $\|\vec{x} - \vec{c}\|^2 = d_3^2$

④ $\|\vec{x} - \vec{e}\|^2 = d_4^2$

$$-2\langle \vec{x}, \vec{a} \rangle + 2\langle \vec{x}, \vec{c} \rangle$$

$$= d_1^2 - d_3^2 - \|\vec{a}\|^2 + \|\vec{c}\|^2$$

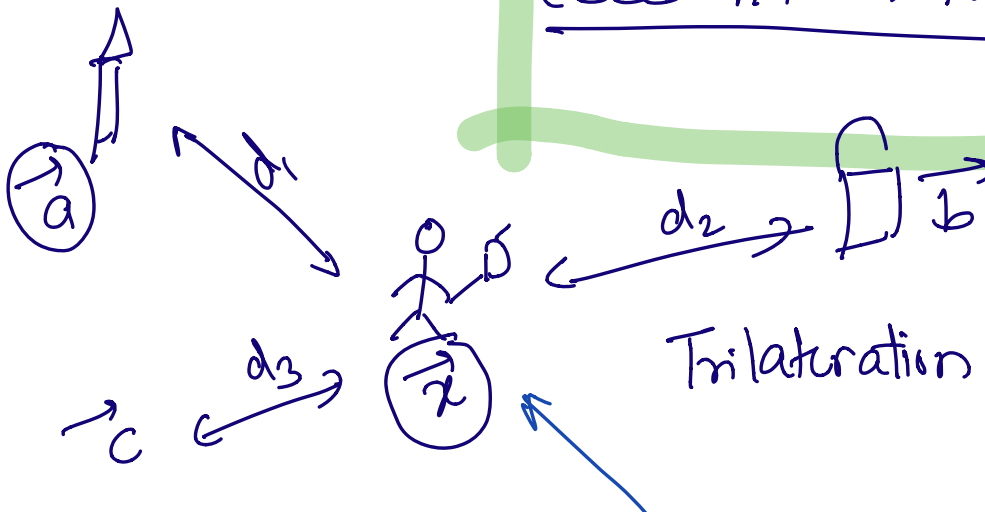
$$-2\langle \vec{x}, \vec{a} \rangle + 2\langle \vec{x}, \vec{b} \rangle$$

$$= d_1^2 - d_2^2 - \|\vec{a}\|^2 + \|\vec{b}\|^2$$

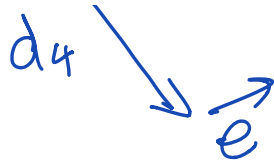
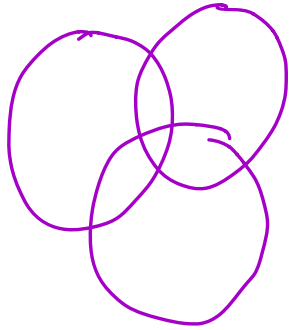
$$-2\langle \vec{x}, \vec{a} \rangle + 2\langle \vec{x}, \vec{e} \rangle$$

$$= d_1^2 - d_4^2 - \|\vec{a}\|^2 + \|\vec{e}\|^2$$

(See note on Nov 17th)



Trilateration algorithm



$$\langle \vec{x}, \vec{y} \rangle = \vec{x}^T \vec{y} = \vec{y}^T \vec{x}$$

$$\rightarrow -2\vec{a}^T \vec{x} + 2\vec{c}^T \vec{x} = d_1^2 - d_3^2 - \|\vec{a}\|^2 + \|\vec{c}\|^2$$

$$\Rightarrow (-2\vec{a}^T + 2\vec{c}^T) (\vec{x}) = \text{--- " ---}$$

$$\underbrace{\begin{bmatrix} -2\vec{a}^T + 2\vec{c}^T \\ -2\vec{a}^T + 2\vec{b}^T \\ -2\vec{a}^T + 2\vec{e}^T \end{bmatrix}}_A \underbrace{\begin{bmatrix} \vec{x} \end{bmatrix}}_{\vec{x}} = \underbrace{\begin{bmatrix} d_1^2 - d_3^2 - \|\vec{a}\|^2 + \|\vec{c}\|^2 \\ d_1^2 - d_2^2 - \|\vec{a}\|^2 + \|\vec{b}\|^2 \\ d_1^2 - d_4^2 - \|\vec{a}\|^2 + \|\vec{e}\|^2 \end{bmatrix}}_b$$

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

$$\vec{a} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \quad \vec{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

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

$$-2\vec{a}^T + 2\vec{c}^T =$$

$$= -2 \begin{bmatrix} a_1 & a_2 \end{bmatrix} + 2 \begin{bmatrix} c_1 & c_2 \end{bmatrix}$$

$$= \begin{bmatrix} -2a_1 + 2c_1 & -2a_2 + 2c_2 \end{bmatrix}$$

$$\begin{bmatrix} -2a_1 + 2c_1 & -2a_2 + 2c_2 \\ -2a_1 + 2b_1 & -2a_2 + 2b_2 \\ -2a_1 + 2e_1 & -2a_2 + 2e_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \\ \\ \end{bmatrix}$$

How do we know if $(A^T A)^{-1}$ exists?

What if it does not???

Invertibility \longleftrightarrow Nullspaces

Square
Matrix A is invertible if and only if

$\text{Null}(A) = \{\vec{0}\}$. (Nullspace is trivial).

Idea: Explore $\text{Null}(A^T A)$ to understand invertibility of $A^T A$.

• Thm: $\text{Null}(A^T A) = \text{Null}(A)$

Some reminders before the proof:

① Property of transposes.

$$(AB)^T = B^T A^T$$

$$A: n \times m$$

$$B: m \times k$$

$$AB: n \times k$$

$$\underline{(AB)^T: k \times n}$$

$$A^T: m \times n$$

$$B^T: k \times m$$

Is $A^T B^T$ a valid multiplication?

Is $B^T A^T$ a valid multiplication?

$$\underline{B^T A^T: k \times n}$$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

② Thm: If $\|\vec{x}\| = 0$, then $\vec{x} = \vec{0}$

Proof:

$$\|\vec{x}\| = 0$$

$$\|\vec{x}\|^2 = 0$$

$$x_1^2 + x_2^2 + \dots + x_n^2 = \langle \vec{x}, \vec{x} \rangle = 0$$

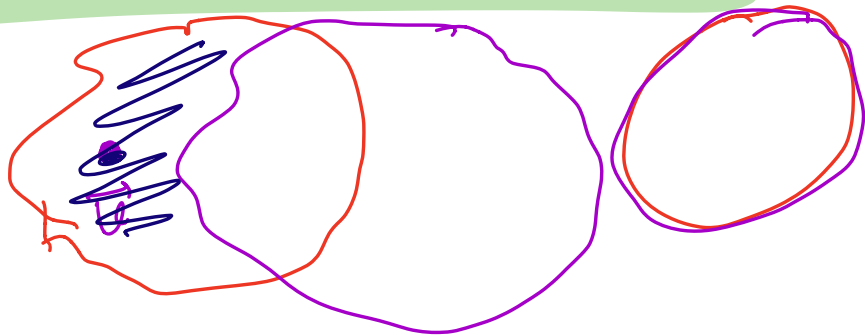
$$\underbrace{x_1^2}_{\geq 0} + \underbrace{x_2^2}_{\geq 0} + \dots + \underbrace{x_n^2}_{\geq 0} = 0$$

$x_1^2 = 5 \rightarrow$ not possible

The only way to satisfy the equation is to have all $x_1 = x_2 = \dots = x_n = 0$.

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow \vec{x} \text{ is the } 0 \text{ vector.}$$

Thm: $\text{Null}(A^T A) = \text{Null}(A)$



\rightarrow Say $\vec{v} \in \text{Null}(A^T A)$, then it had also better belong to $\text{Null}(A)$

Say $\vec{w} \in \text{Null}(A)$, then it had also better belong to $\text{Null}(A^T A)$

Formally:

(i) If $\vec{w} \in \text{Null}(A)$, then $\vec{w} \in \text{Null}(A^T A)$

(ii) If $\vec{w} \in \text{Null}(A^T A)$, then $\vec{w} \in \text{Null}(A)$.

(i) Known: $\vec{w} \in \text{Null}(A)$

$$A \cdot \vec{w} = \vec{0} \quad (1)$$

Want: $\vec{w} \in \text{Null}(A^T A)$
 $(A^T A) \vec{w} = \vec{0}$

Multiply by A^T .

$$A^T (A \vec{w}) = A^T \cdot \vec{0} = \vec{0}$$

$$A^T A \cdot \vec{w} = \vec{0}$$

$$(A^T A) \vec{w} = \vec{0} \Rightarrow \vec{w} \in \text{Null}(A^T A)$$

$$(ii) \text{ Known: } \vec{v} \in \mathbb{N} \quad (ATA) \quad \left| \quad \begin{array}{l} \text{Want: } \vec{v} \in \text{Null}(A) \\ \underline{A\vec{v} = \vec{0}} \end{array} \right.$$

$$ATA\vec{v} = \vec{0}$$

$$\begin{aligned} \text{Consider: } \|A\vec{v}\|^2 &= \langle A\vec{v}, A\vec{v} \rangle \\ &= (A\vec{v})^T (A\vec{v}) \\ &= \vec{v}^T A^T (A\vec{v}) \\ &= \vec{v}^T (ATA\vec{v}) \\ &= \vec{v}^T \vec{0} \\ &= 0 \end{aligned}$$

$$\Rightarrow \|A\vec{v}\|^2 = 0 \quad \Rightarrow \|A\vec{v}\| = 0$$

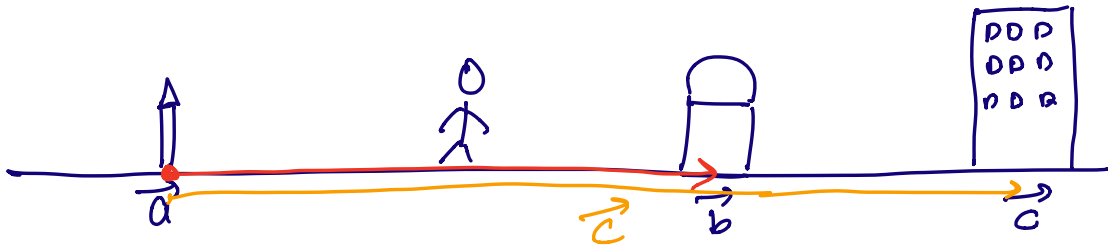
$$\Rightarrow A\vec{v} = \vec{0}$$

A: Columns of A are linearly dependant.

→ Null(A) ⇒ non-trivial.

Col's of A are lin. independant

Null(A) ⇒ trivial.



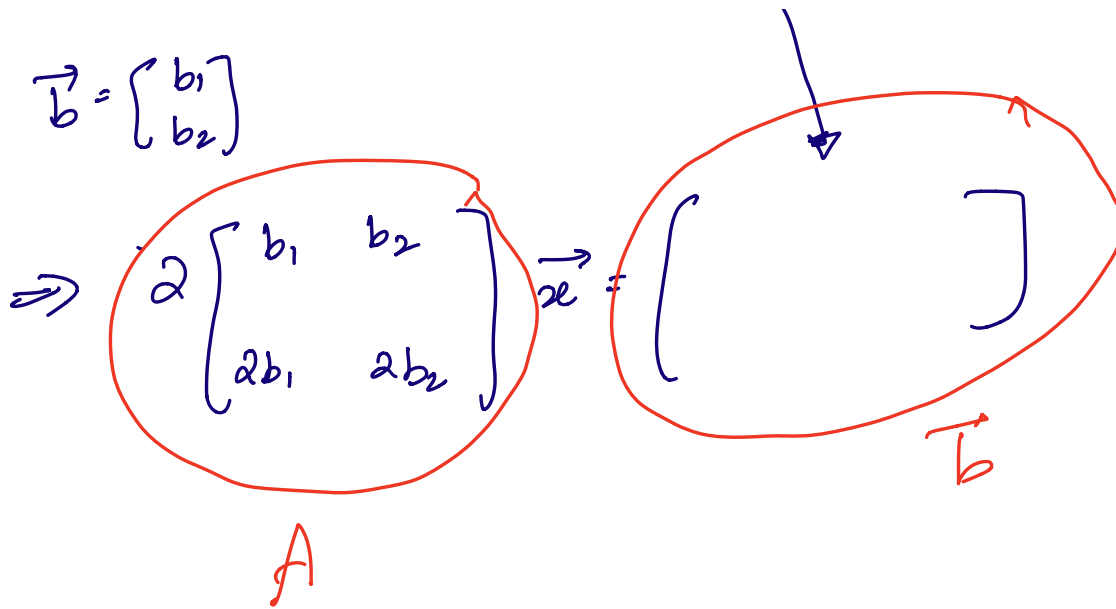
$$\vec{a} = \vec{0}$$

$$\vec{b} = \vec{b}$$

$$\vec{c} = 2\vec{b}$$

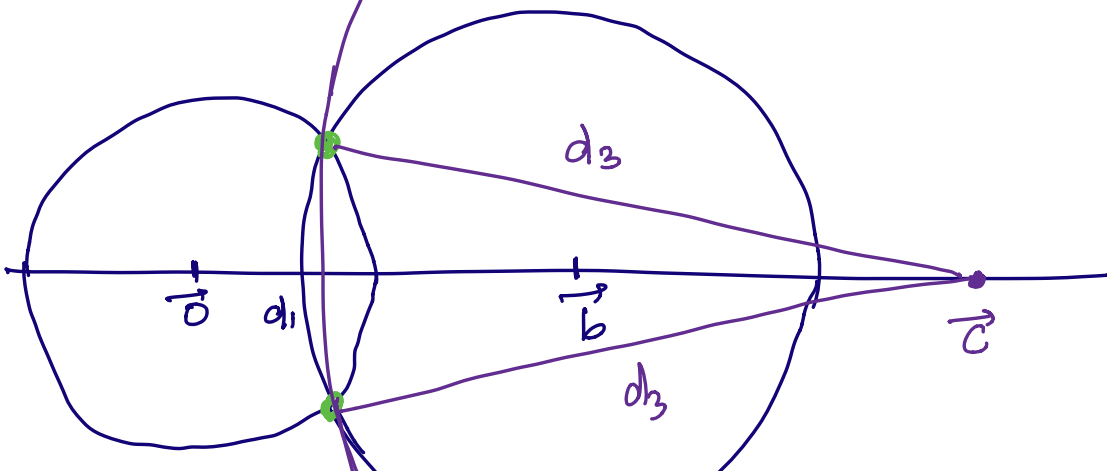
$$2 \begin{bmatrix} \vec{b}^T - \vec{a}^T \\ \vec{c}^T - \vec{a}^T \end{bmatrix} \vec{x} = \begin{bmatrix} d_1^2 - d_2^2 - \|\vec{a}\|^2 + \|\vec{b}\|^2 \\ d_1^2 - d_3^2 - \|\vec{a}\|^2 + \|\vec{c}\|^2 \end{bmatrix}$$

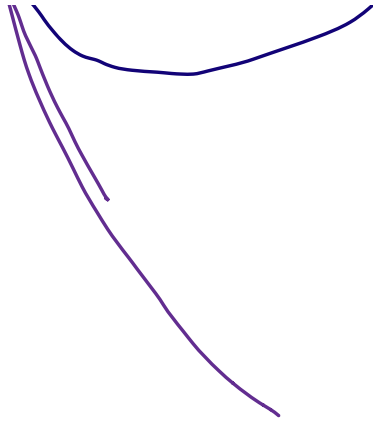
$$\Rightarrow 2 \begin{bmatrix} \vec{b}^T \\ 2\vec{b}^T \end{bmatrix} \vec{x} = \begin{bmatrix} d_1^2 - d_2^2 + \|\vec{b}\|^2 \\ d_1^2 - d_3^2 + 4\|\vec{b}\|^2 \end{bmatrix}$$



- $\Rightarrow A$ lin dep. columns
- $\Rightarrow A$ has non-trivial nullspace
- $\Rightarrow (A^T A) \rightarrow \parallel \text{---} \perp \text{---} \rightarrow$

$(A^T A)$ is NOT invertible!





Machine learning : Using data to understand the ~~rest of~~ real world.

↳ Making a model.

→ How do you know that your model is any good ?!!