

$A = \text{Age}$

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_n \end{bmatrix}$$

$x_i \in \mathbb{R}$

A : random variable

sample space

$$A: \Omega \rightarrow \mathbb{R}$$

$\{x_1, x_2, \dots, x_n\}$: random sample

Set of
Random Variables

IID with A

Independent

Identically
distributed

"Unknown" probability distribution

Continuous var
PDF

discrete
PMF

prob. density function

prob mass
function

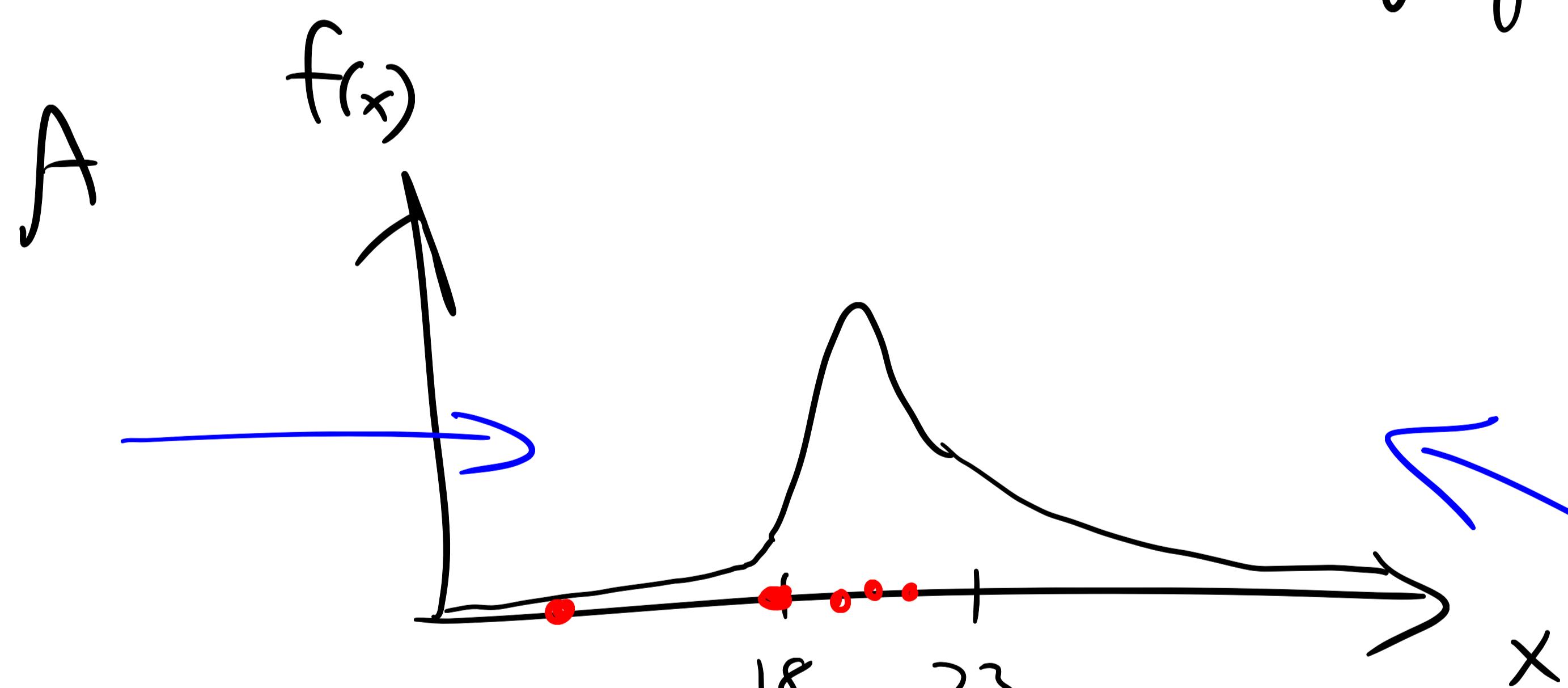
Prob mass

$$\rightarrow P(A = 50) = 0$$

$$\underline{P(A = 50) = 0.2}$$

$$P(A \in [a, b]) = \int_a^b f(x) dx$$

density function

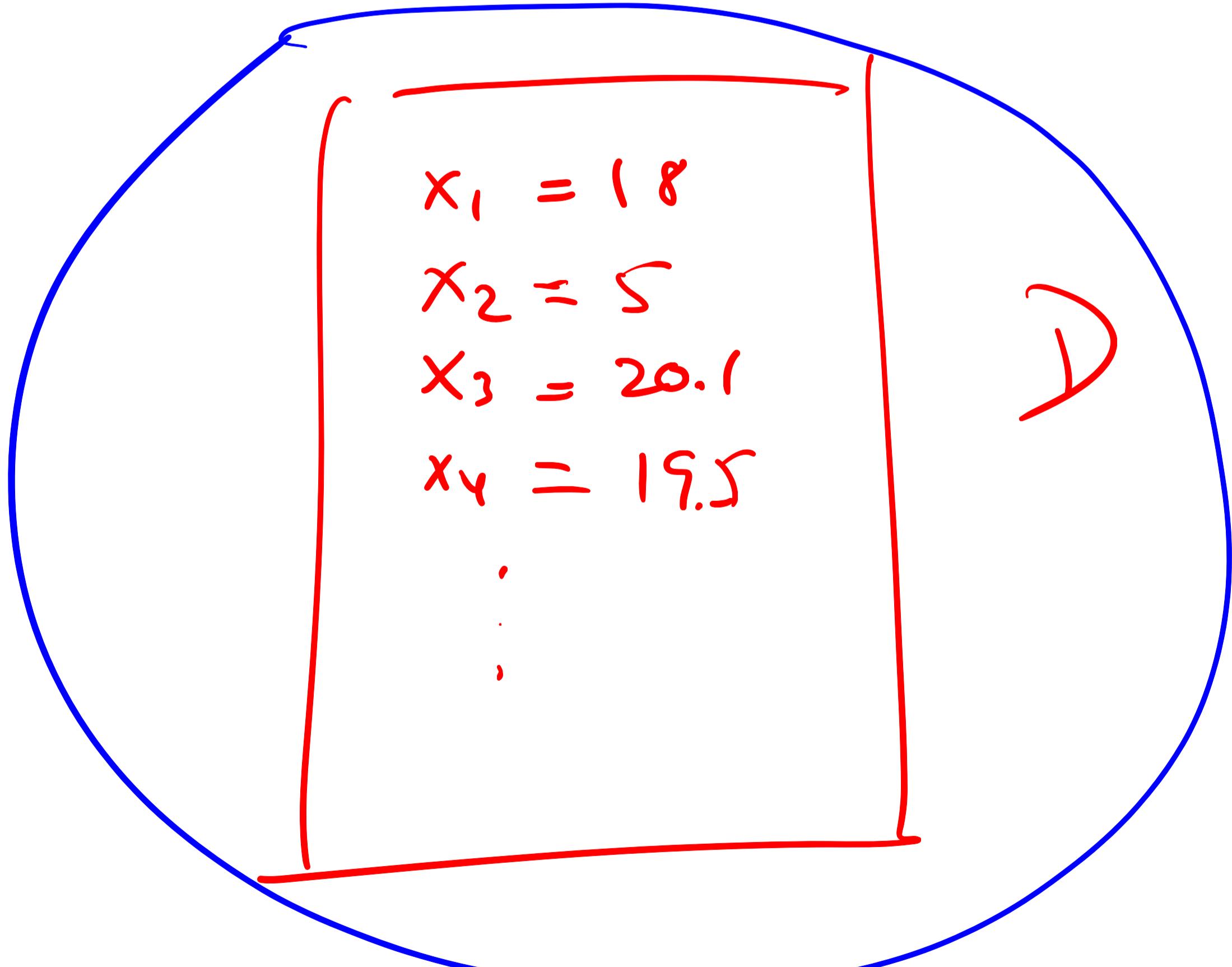


Unknown

Population Parameters

Sample
mean $\hat{\mu}$
Variance $\hat{\sigma}^2$
std $\hat{\sigma}$

statistics



μ mean \rightarrow location ?
 σ^2 Variance \rightarrow spread ?
 σ Standard deviation ?
(std)

Salary: { 100k, 200k, 400k, 1.000, 750 million }
median \leftarrow robust

Statistic : $\hat{\theta} : \{x_1, x_2, \dots, x_n\} \Rightarrow \mathbb{R}$

\downarrow
true but
unknown
parameters

mean : Expected value of the random variable (rv)

$$\mu = E[A] \rightarrow \int_x x \cdot f(x) dx \quad \text{Continuous}$$

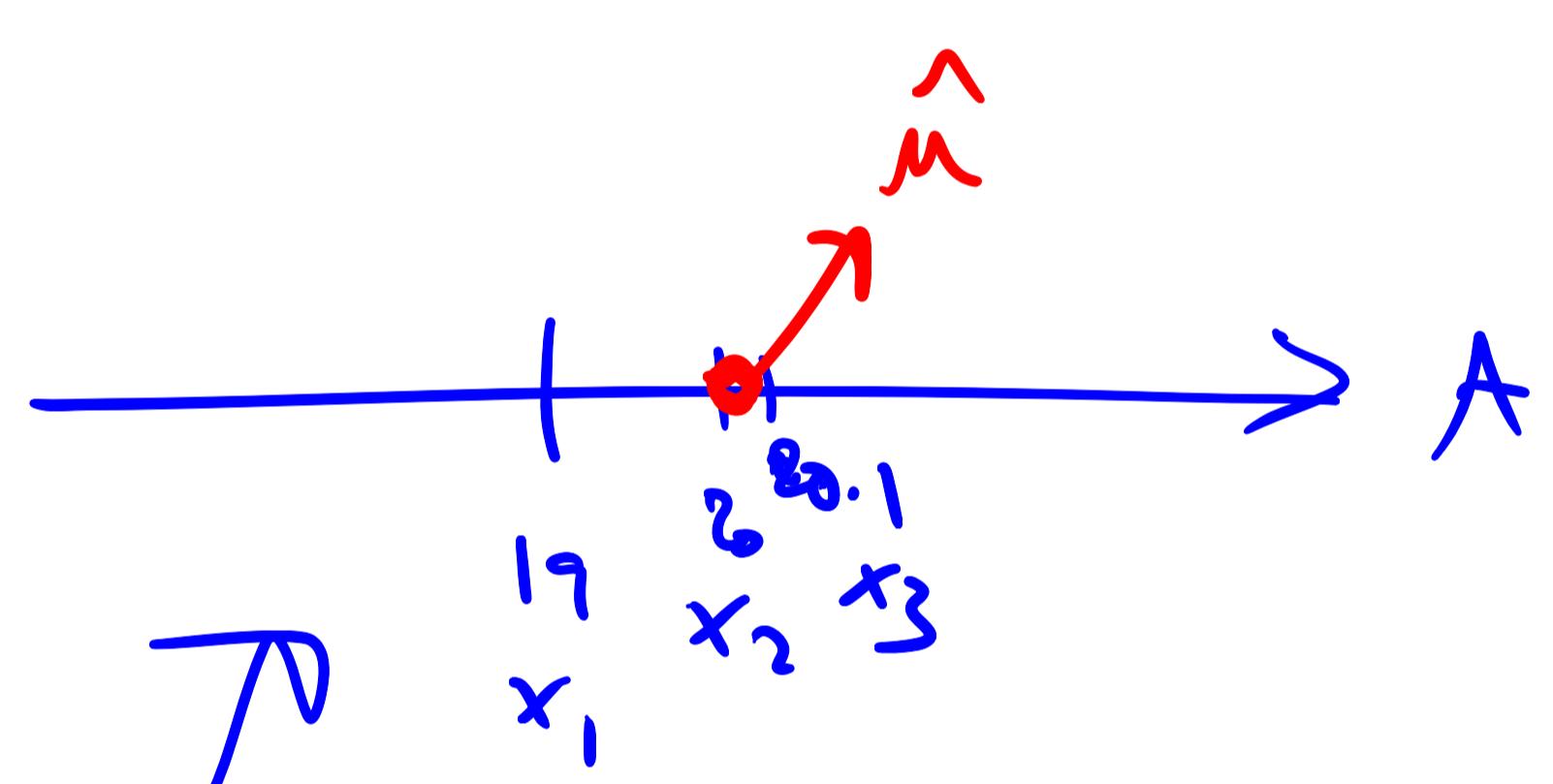
$$\sum_x x \cdot P(A=x) \quad \text{discrete}$$

Sample mean

A
x_1
x_2
\vdots
x_n

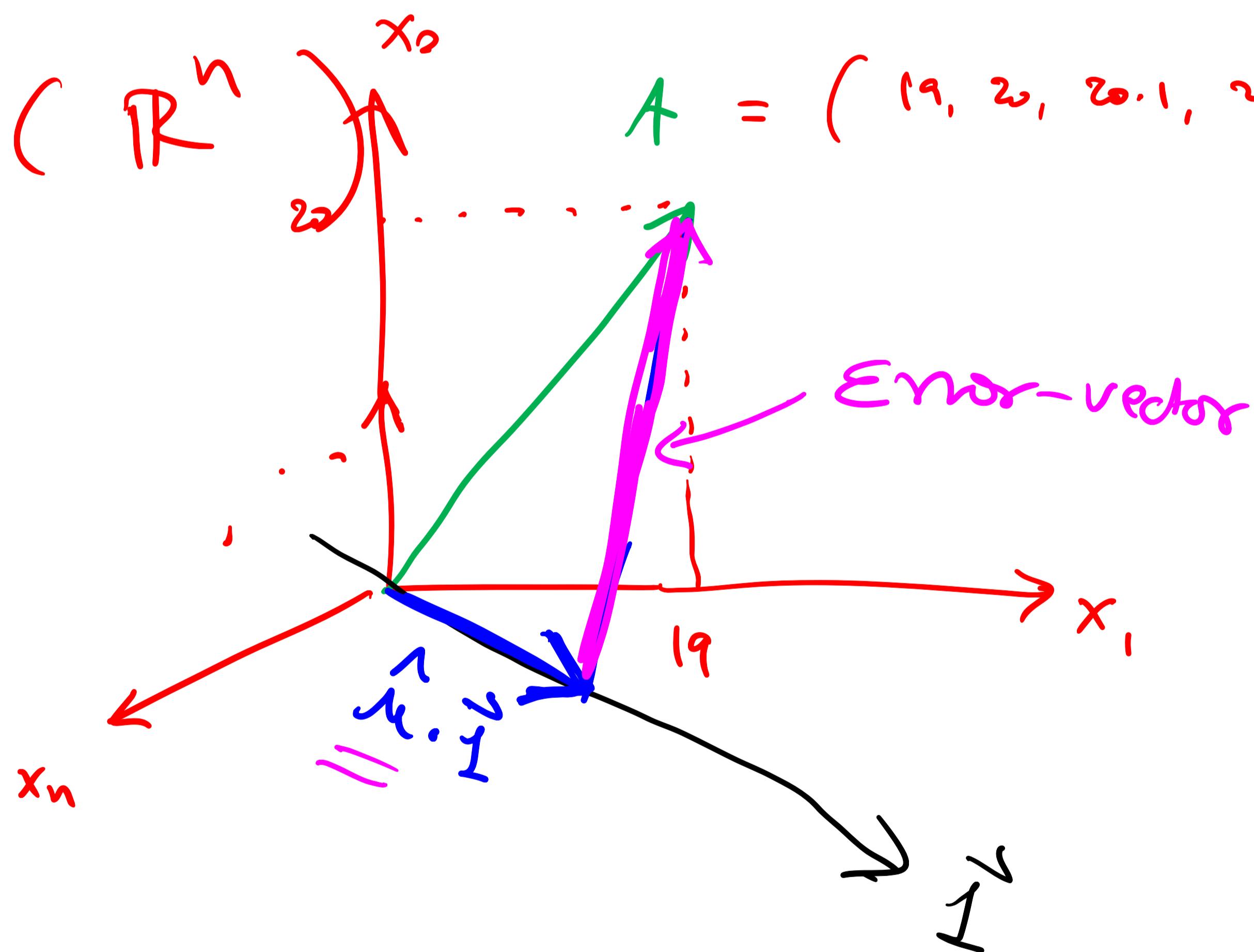
Age

n : sample size



$$\rightarrow \hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i \quad (\text{Row-view})$$

$$\text{Column-view} \quad (\mathbb{R}^n) \quad A = (19, 20, 20.1, 22, 18.5, \dots)^T$$



Ones-vector

$$\begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} = \vec{1} \in \mathbb{R}^n$$

Dot-product

$$\vec{a} = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} \quad \vec{b} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix} \quad \mathbb{R}^n$$

$$\vec{a} \cdot \vec{b} = \vec{a}^T \vec{b} = a_1 b_1 + a_2 b_2 + \dots + a_n b_n$$

dot product

$$\langle \vec{a}, \vec{b} \rangle$$

inner - product

↓

leads to the notion of length (norm)

$$\vec{a}^T \vec{a} = \sum_{i=1}^n a_i^2 = a_1^2 + a_2^2 + \dots + a_n^2 = \|\vec{a}\|^2$$

$$\|\vec{a}\|_2 = \sqrt{\|\vec{a}\|^2} = \sqrt{a_1^2 + a_2^2 + \dots + a_n^2}$$

\downarrow

ℓ_2 norm

$$\ell_p\text{-norm} = \left(\sum_{i=1}^n |a_i|^p \right)^{1/p}$$

as $p \rightarrow \infty$

$$\ell_\infty = \max_{i=1}^n \{|a_i|\}$$

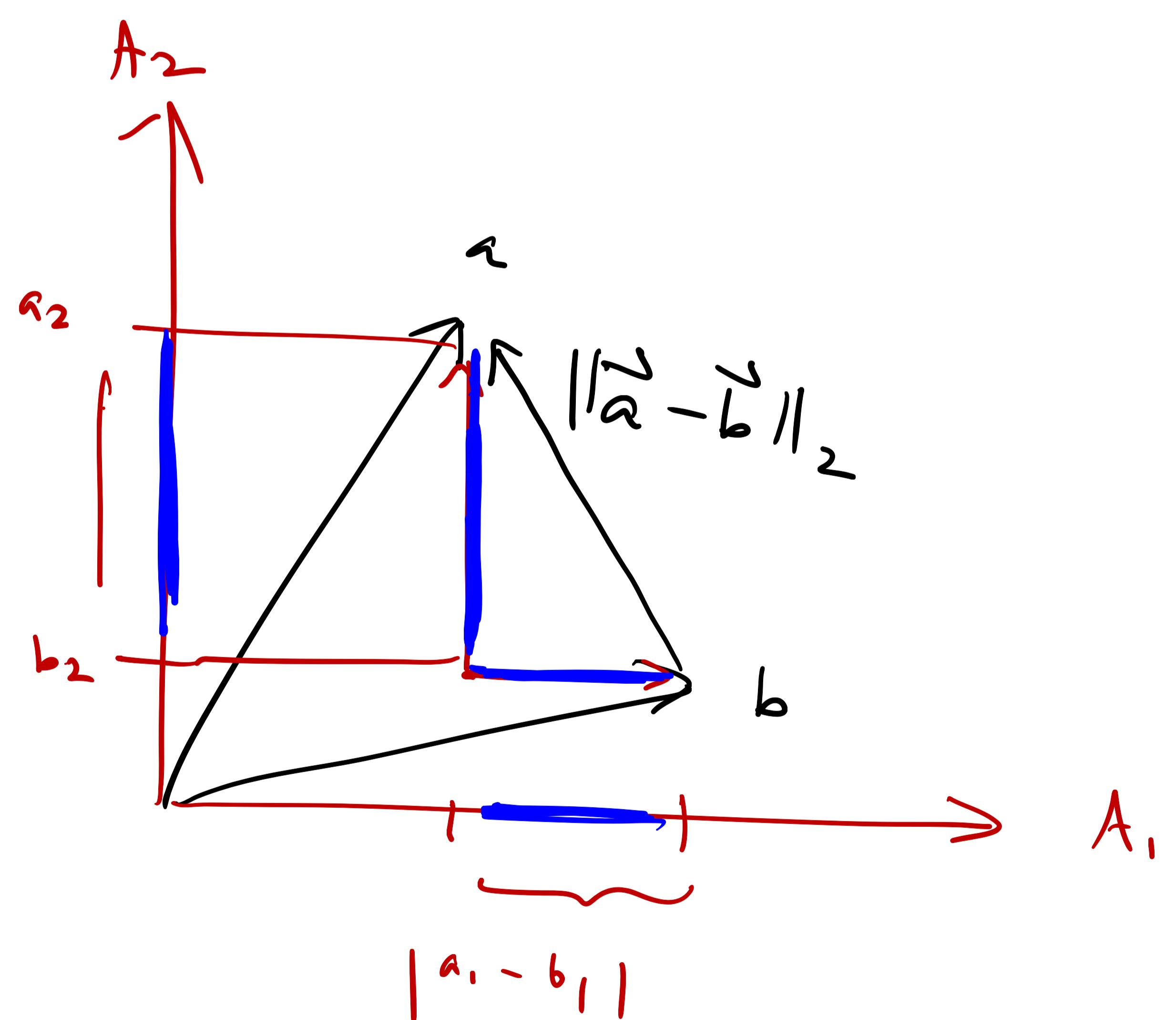
$$\ell_2 = \left(\sum_{i=1}^n a_i^2 \right)^{1/2} \quad \leftarrow \text{Euclidean length}$$

$$\ell_1 = \sum_{i=1}^n |a_i| = |a_1| + |a_2| + \dots + |a_n|$$

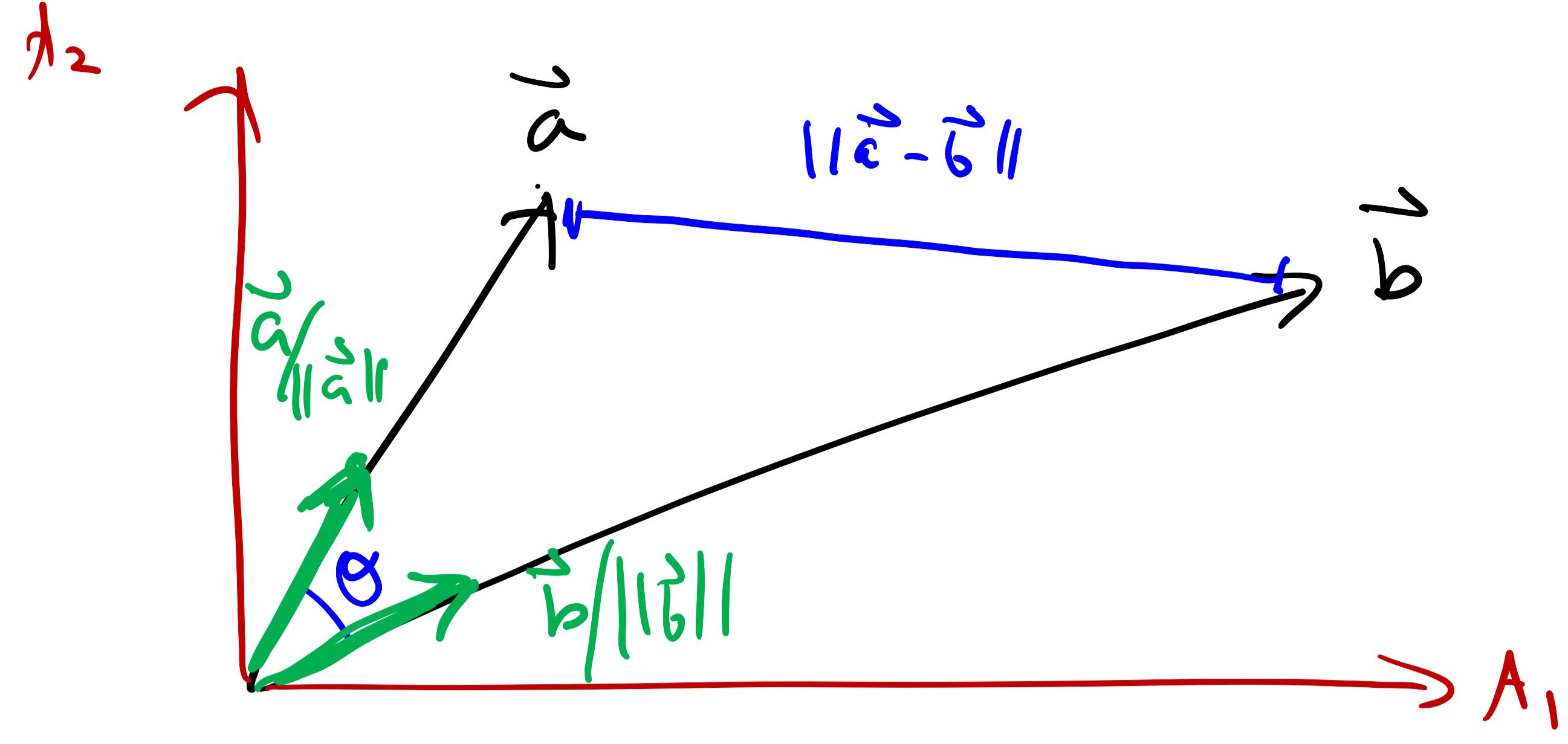
norm \Rightarrow distance

$$\vec{a}, \vec{b} \in \mathbb{R}^n$$

$$\|\vec{a} - \vec{b}\|_2 = \sqrt{\sum_{i=1}^n (a_i - b_i)^2}$$

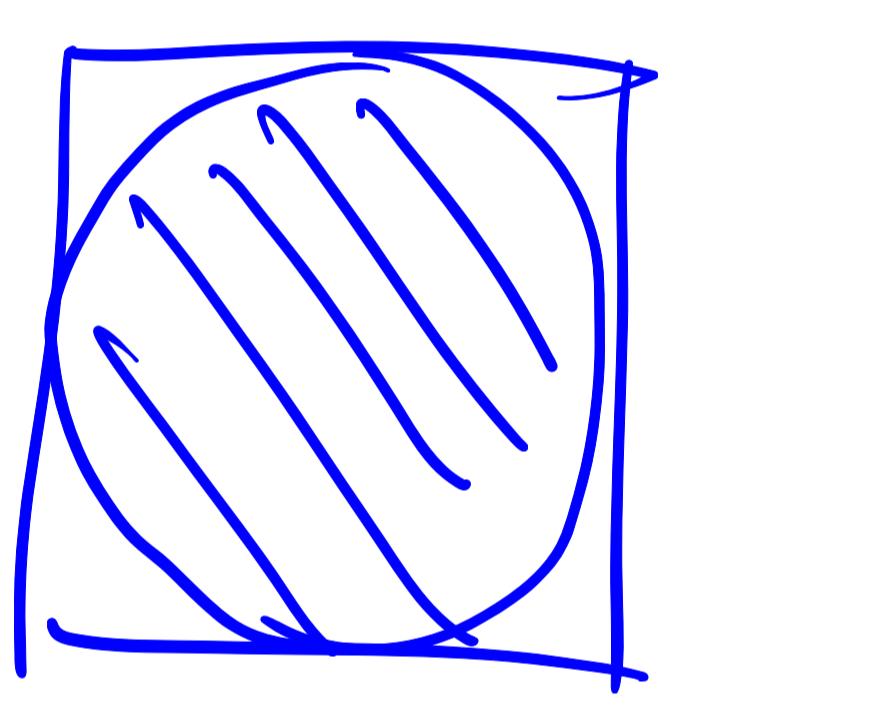
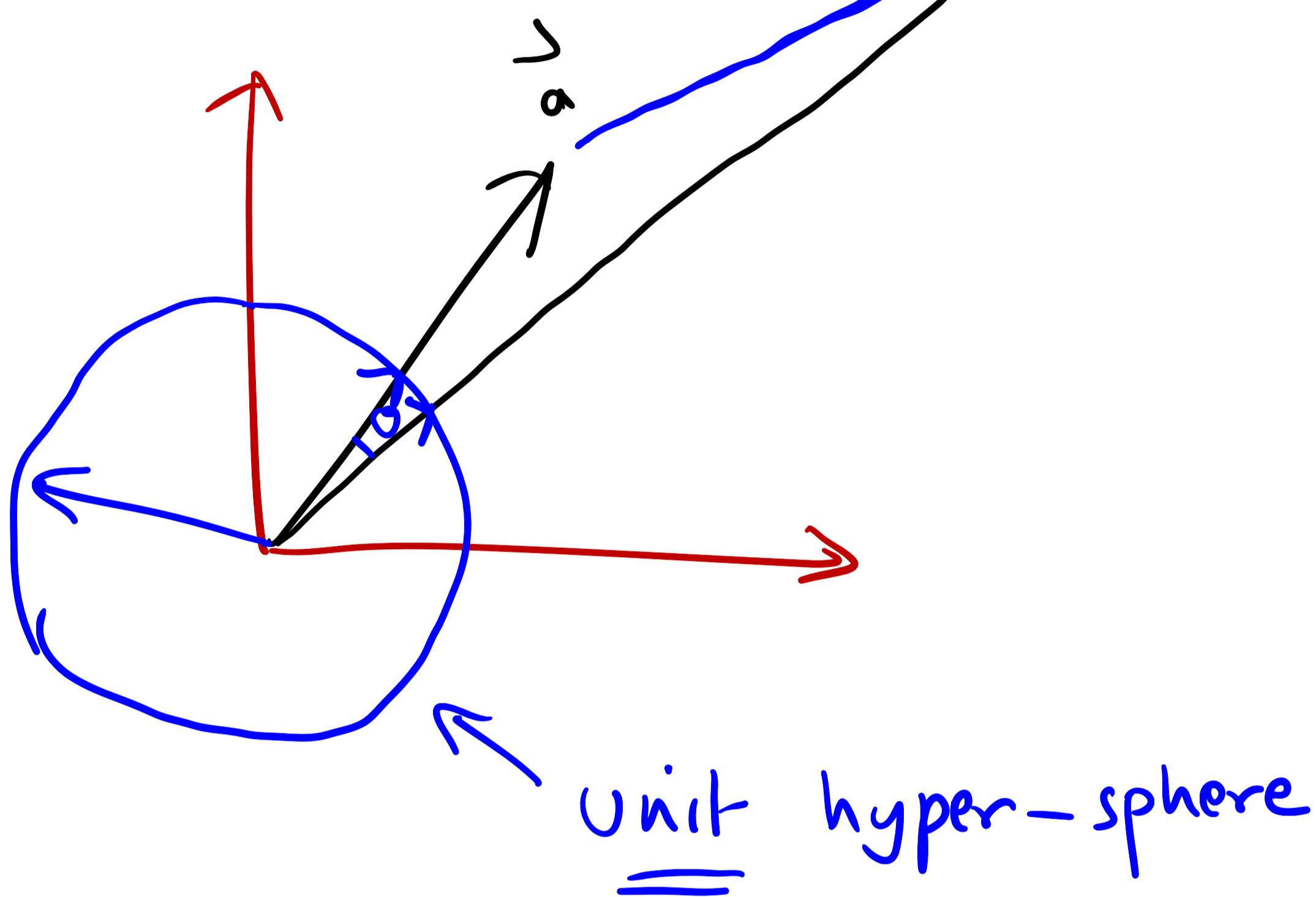


$$\|\vec{a} - \vec{b}\|_1 = |a_1 - b_1| + |a_2 - b_2|$$

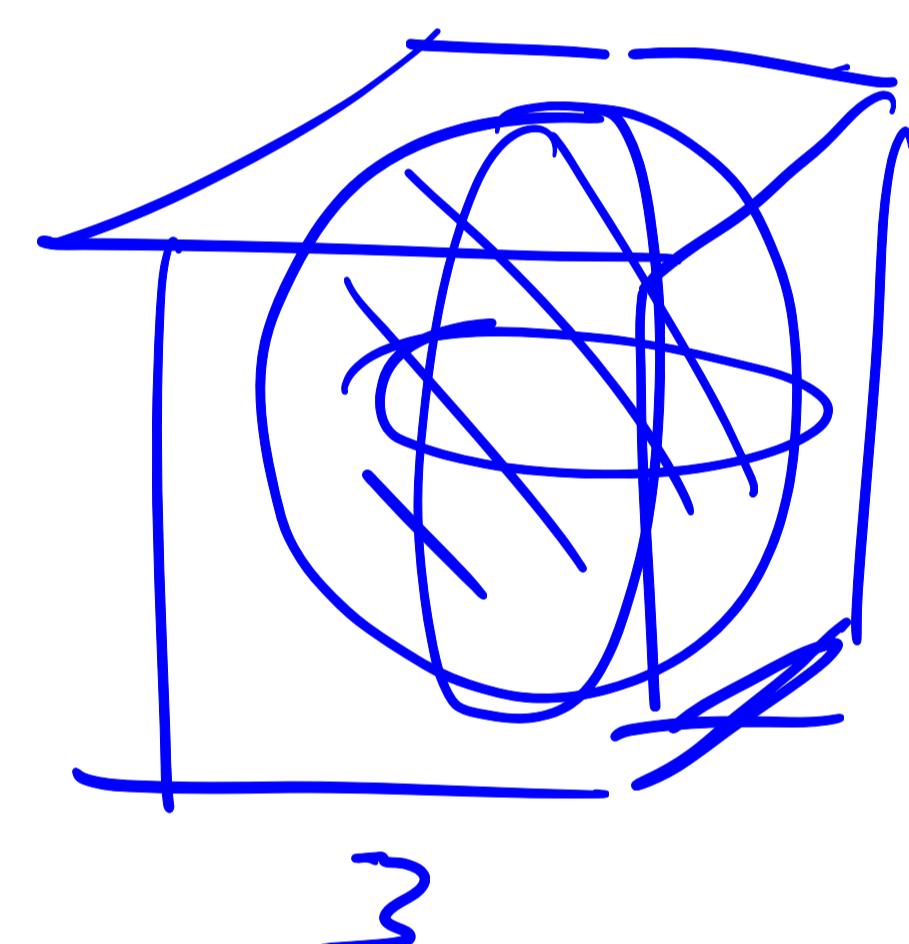


$$\cos \theta = \frac{\vec{a}^T \vec{b}}{\|\vec{a}\| \|\vec{b}\|} = \left(\frac{\vec{a}}{\|\vec{a}\|} \right)^T \left(\frac{\vec{b}}{\|\vec{b}\|} \right)$$

dot product
between unit vectors



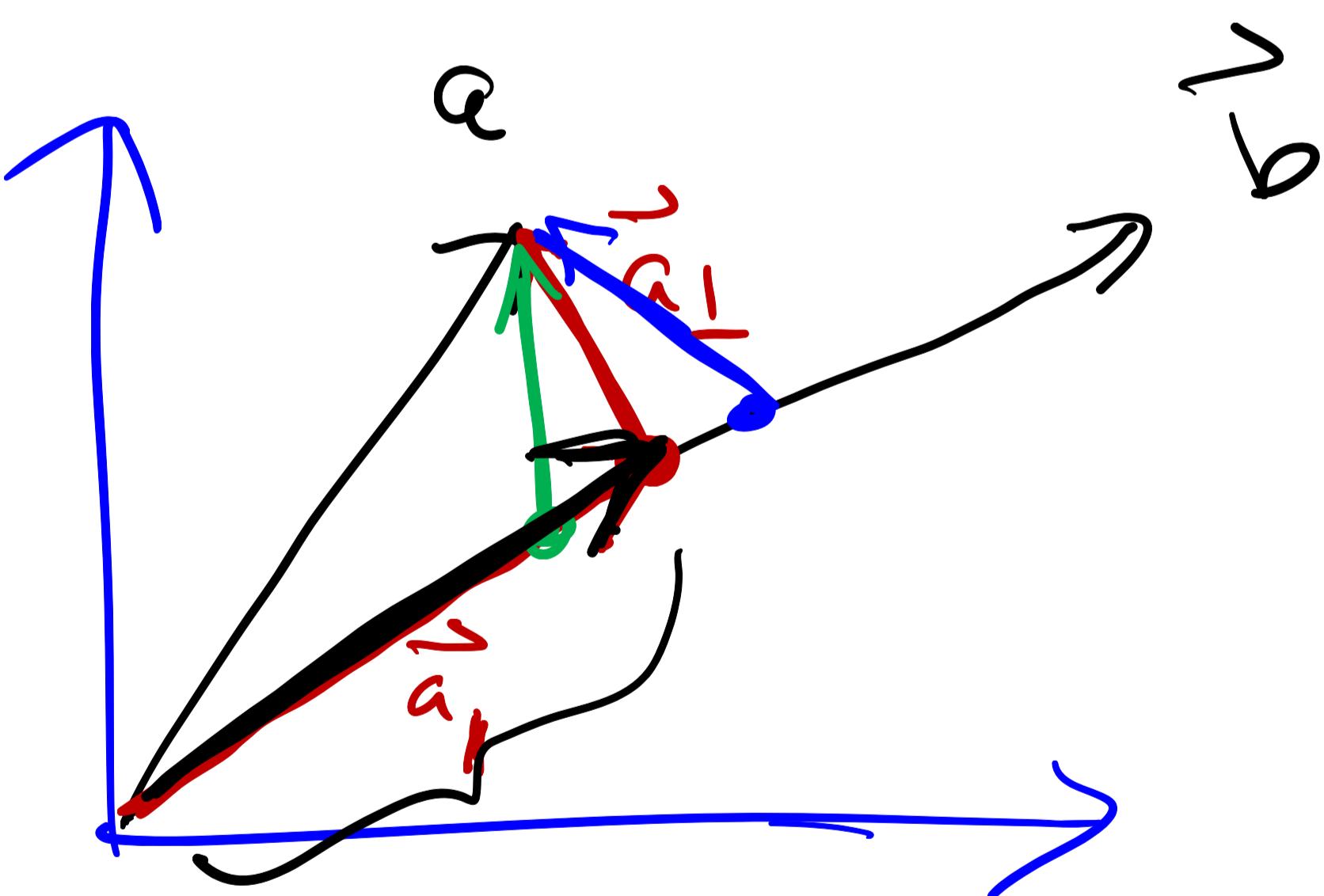
2



3

4 . . .

Projection of \vec{a} onto \vec{b}



$\vec{a}_\parallel \leftarrow$ approximation to \vec{a} in the \vec{b} direction

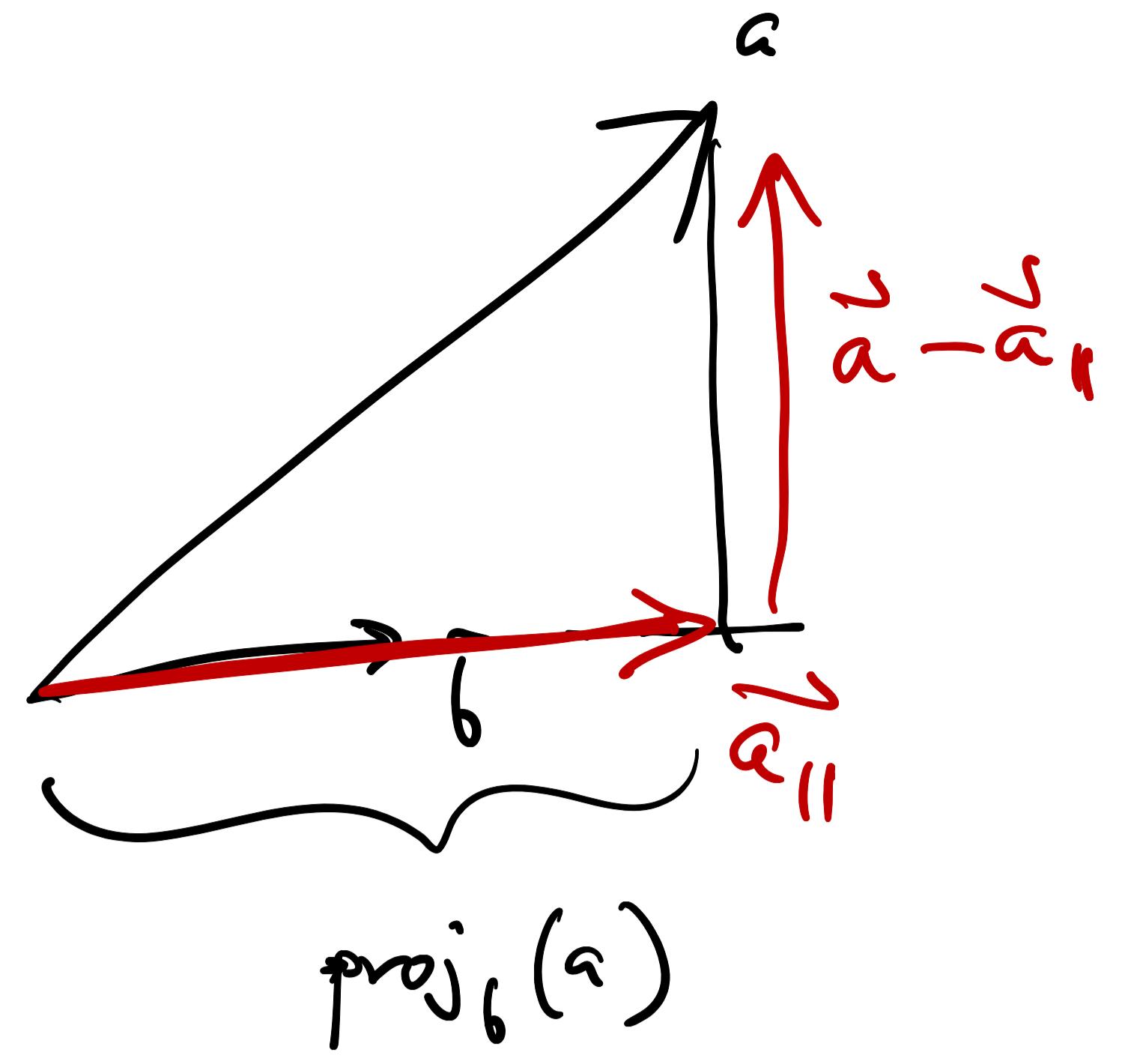
$\|\vec{a}_\perp\|^2 \leftarrow$ error

$$\vec{a}_\parallel = \underbrace{\text{proj}_{\vec{b}}(\vec{a})}_{\text{Scalar offset}} \cdot \underbrace{\vec{b}}_{\text{Vector direction}}$$

$$a_{\parallel} = \left(\frac{a^T b}{b^T b} \right) \vec{b}$$

Proj_b(a)
Scalar

direction

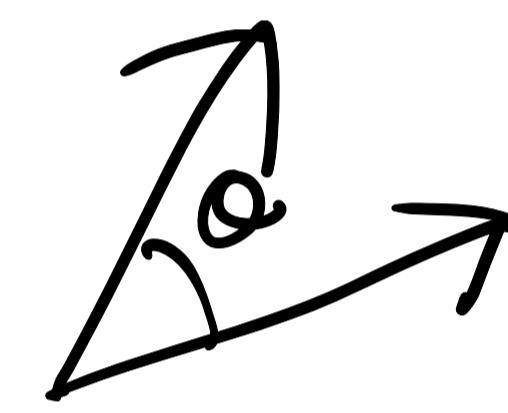
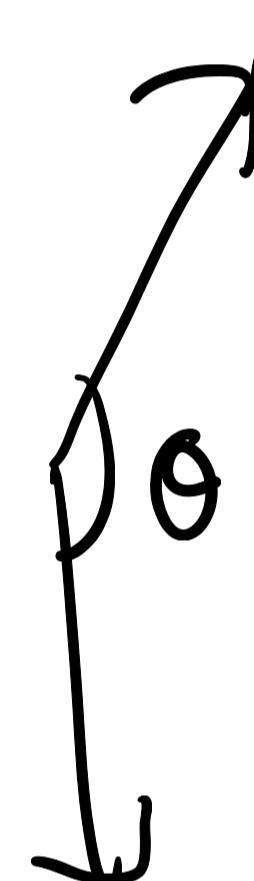
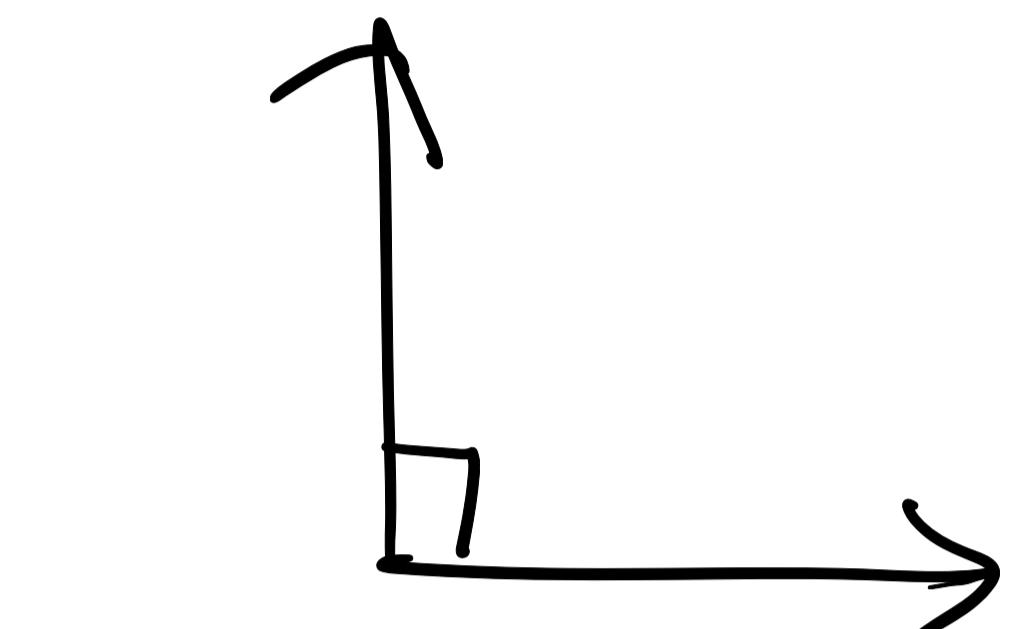


$$\text{error} = \vec{a} - \vec{a}_{\parallel}$$

Orthogonal means

$$g_{ab}^T = 0$$

or $G, \theta = 90^\circ$



A

x_1
 x_2
·
·
·
·
 x_n

feature vector

$$\frac{d}{A} \in \mathbb{R}^n$$

A hand-drawn diagram illustrating orthogonal projection in a 2D coordinate system. The horizontal axis is labeled x_1 and the vertical axis is labeled x_2 . A red vector labeled 'A' is shown originating from the origin. A blue vector labeled 'v' is also shown. The projection of vector 'A' onto the direction of vector 'v' is highlighted in green and labeled 'proj_v(A)'. The formula for the projection is written as $\hat{A} = A - \frac{v \cdot A}{v \cdot v} v = A - \frac{v}{v^2} v$.

$$\text{Proj}_{\mathbb{1}}(A) = A^T \mathbb{1}$$

$$\hat{\mu} = \frac{x_1 + x_2 + \dots + x_n}{1 + 1 + \dots + 1} = \frac{\sum x_i}{n}$$

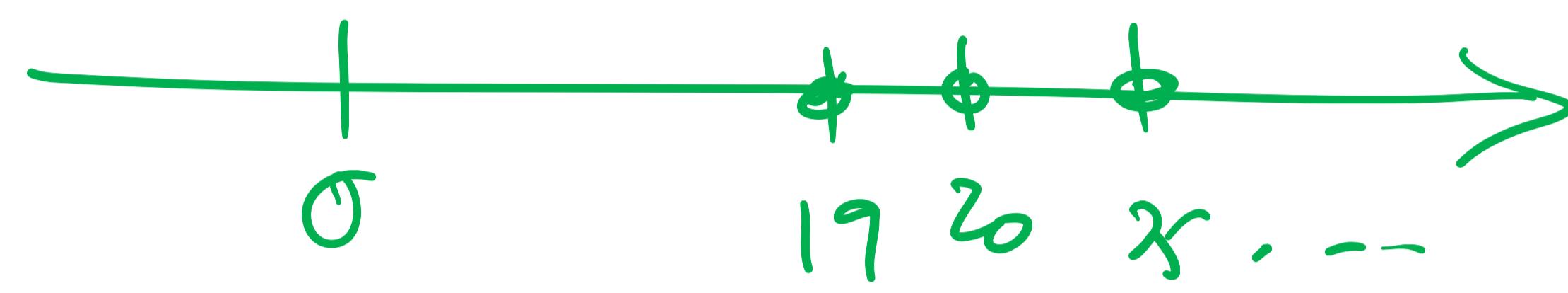
$$\vec{A}^j = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \quad \vec{l}^j = \begin{pmatrix} - \\ \dots \\ i \end{pmatrix}$$

$$\text{error: } \vec{A} - (\hat{\mu}) \cdot \vec{1}$$

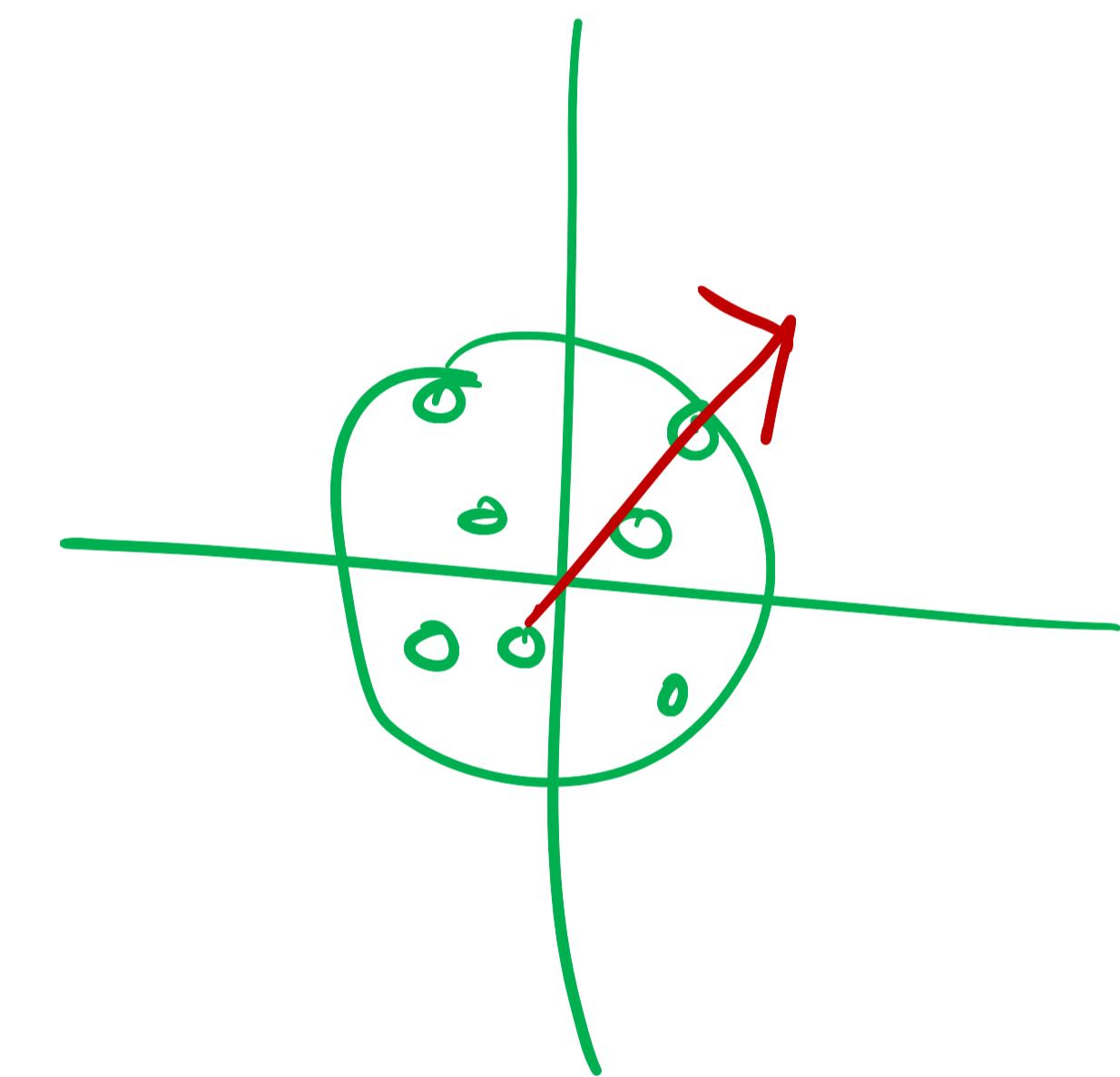
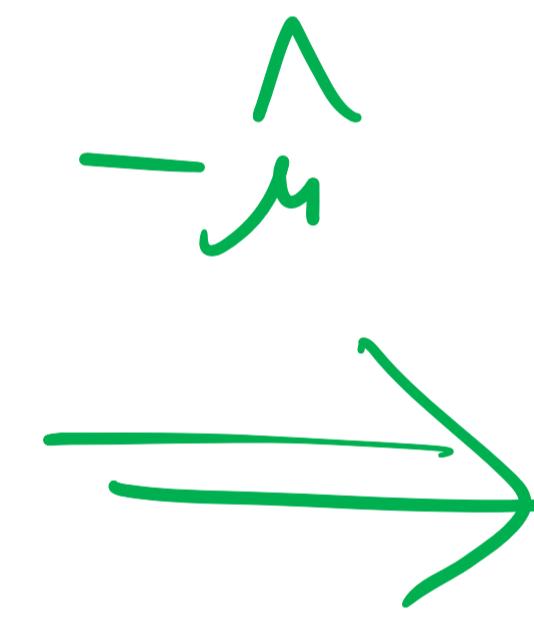
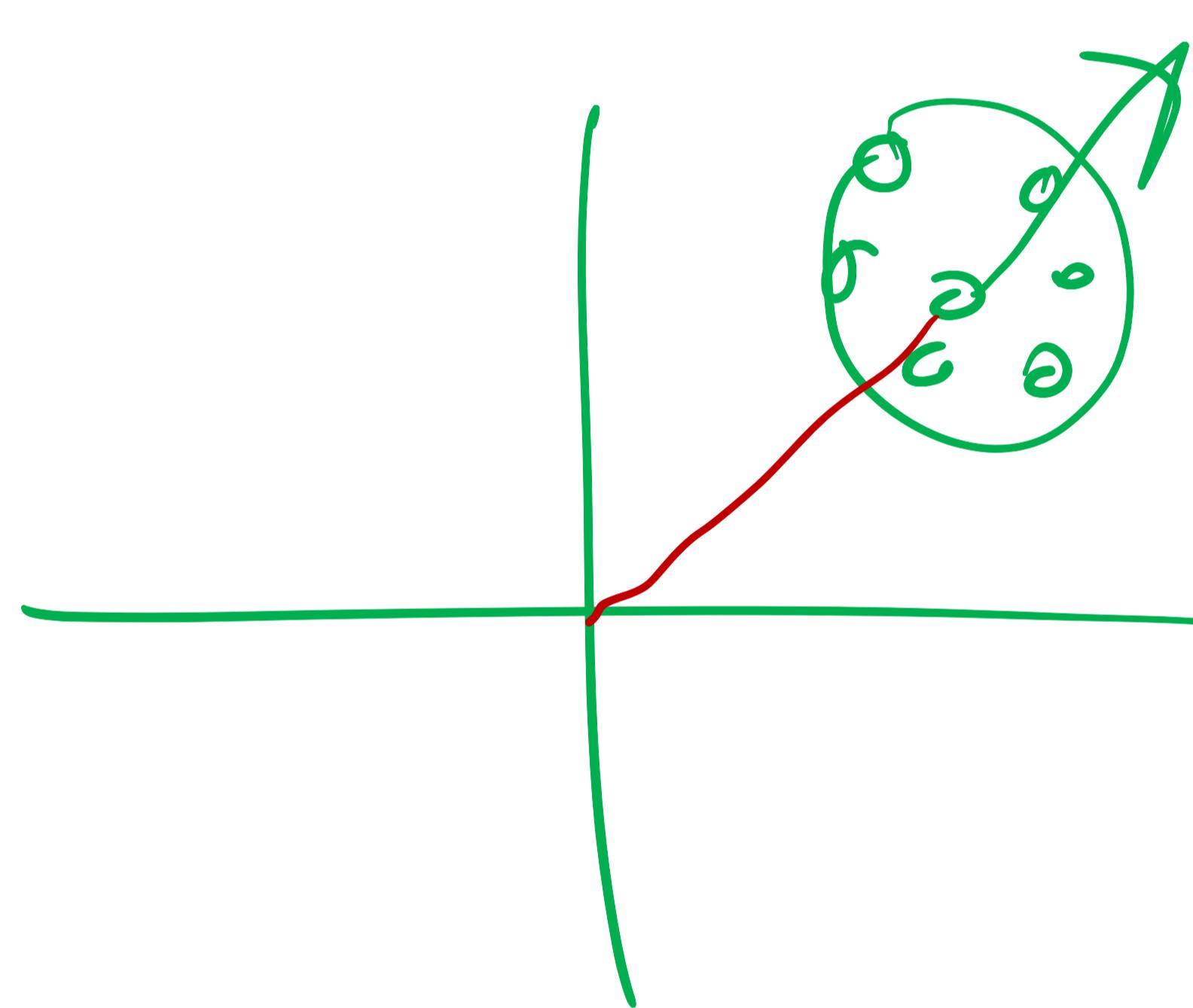
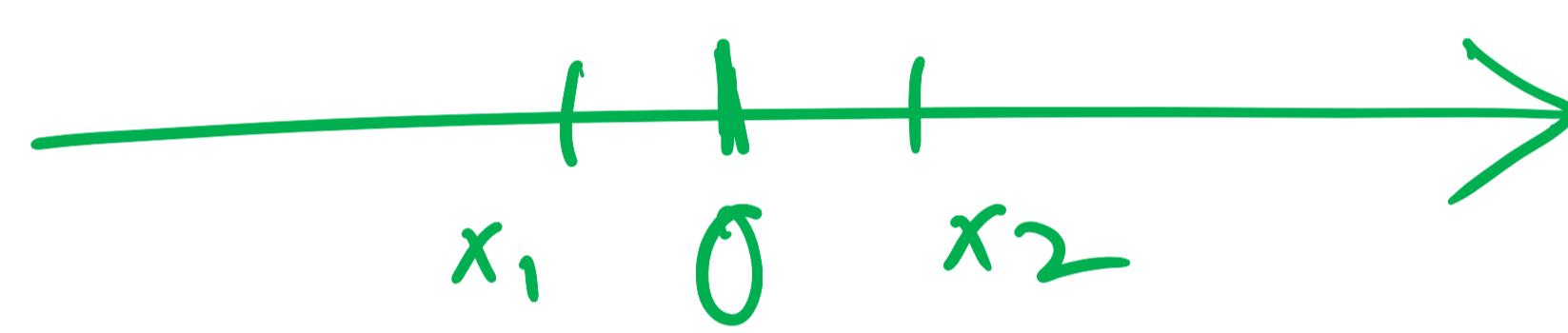
$$= \begin{pmatrix} x_1 - \hat{\mu} \\ x_2 - \hat{\mu} \\ \vdots \\ x_n - \hat{\mu} \end{pmatrix}$$

$$= \vec{\tilde{A}} \leftarrow \text{centered vector}$$

Data centering!



\downarrow $-\hat{\mu}$ translation



$$\vec{A} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_n \end{bmatrix}$$

$$\text{Variance} = E \left[\underbrace{(\vec{A} - \mu)^2}_{\vec{x}^T \vec{x}} \right]$$

$$\int_{x_1}^{x_n} \vec{x}^T \vec{x}$$