

1. ① what is Machine learning? ✓
  - ② Data, Model & ML Tasks ✓
  - ③ Supervised learning: Regression
  - ④ \_\_\_\_\_ : Classification ✓
  - ⑤ Unsupervised learning: dimensionality Reduction ✓
  - ⑥ \_\_\_\_\_ : density Estimation
- 
- 
- 

three main parts:

- ↳ ① Linear Algebra }
- ↳ ② Probability
- ↳ ③ Optimization }

Traditional prog :- Input + Rules  $\rightarrow$  Output

2.

ML:- Input + Output  $\rightarrow$  Algorithm  
finds the  
rules.

Eg: Netflix / movie Recommendations:

Manual labour:-

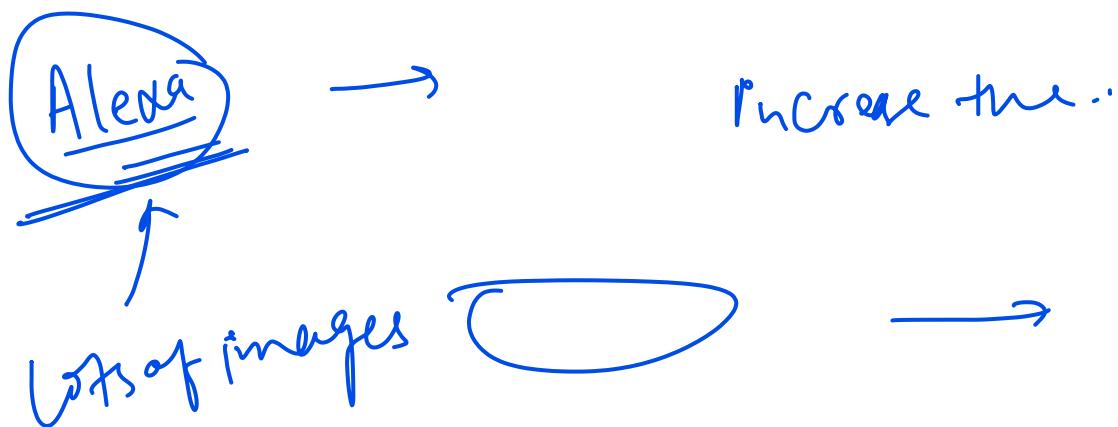
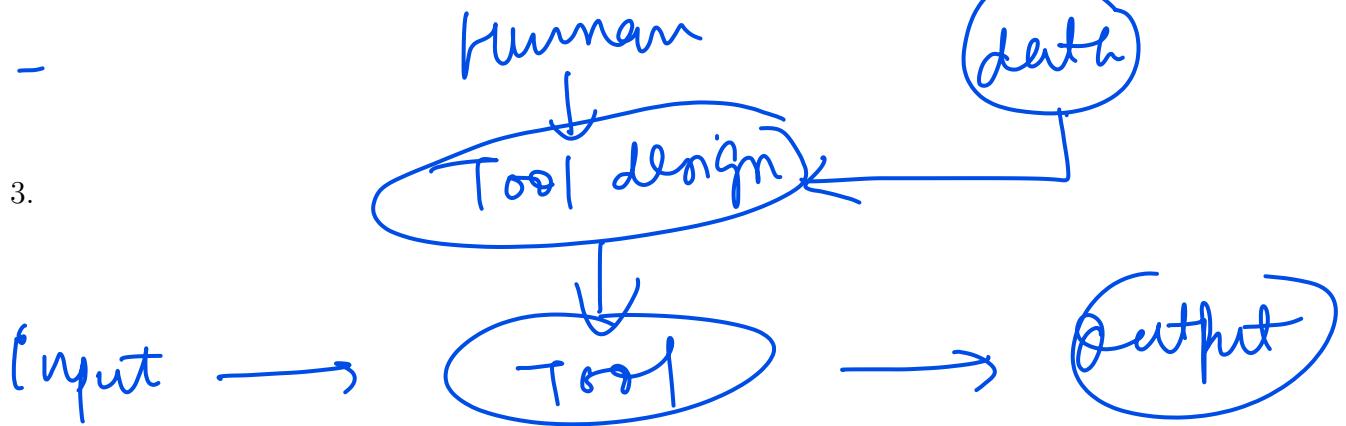
Input  $\rightarrow$  Human  $\rightarrow$  output

Prog :-

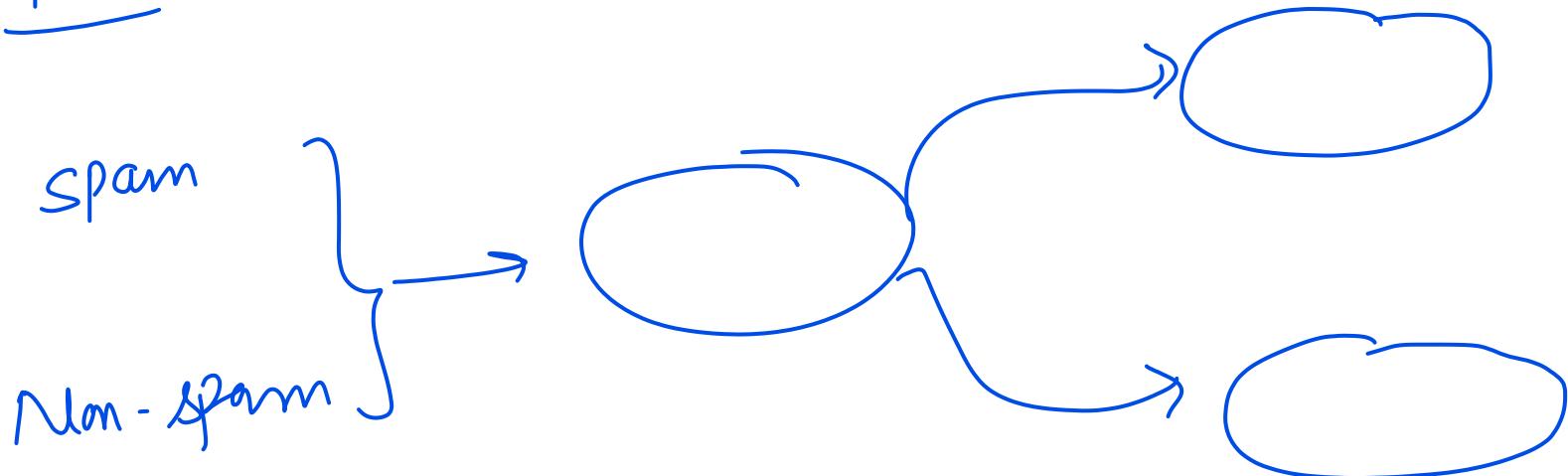
Human  
 $\downarrow$   
Input  $\rightarrow$  Tool  $\rightarrow$  output

ML:-

3.



ML:-



4.

$$\begin{array}{r} \cancel{102} + \cancel{205} = \\ \hline 126 + 400 = \end{array} \quad \begin{array}{c} 307 \\ \cancel{307} \rightarrow \\ \text{labeled} \end{array}$$

~~exam~~

Now addition works.  
he needs to have a mental  
model of addition.

learn a function from  
input (question) to the output (answer)

real numbers



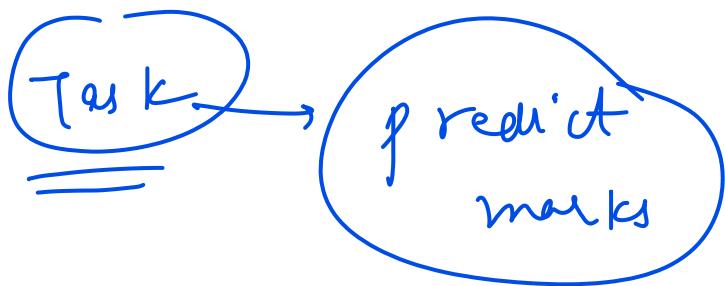
→ Suppose you want to predict a student's exam marks. What do you need?

5. : need a data (hours studied, attendance, part marks)

: You'll need a model

↓  
mathematical formula that relates  
hours studied → marks.

: Need to define a



what is data?

train ML models-

Model:- Mathematical simplification of reality.

- Predictive Model ✓

↳ Regression model ≈

6.

↳ Classification model. ≈

- Probabilistic Model

Data:	Collection of Vectors			S.0
	feature F1	F2	F3	
H1:-	3	9	1.9	
H2:-	2	7	2.1	3.2
H3:-	4	12	2.8	6.6
H4:-	5	16	0.9	9.8

$$x_1 = [3 \quad 2 \quad 4 \quad 5]^T = \begin{bmatrix} 3 \\ 2 \\ 4 \\ 5 \end{bmatrix}$$

$$x_2 = [9 \quad 7 \quad 12 \quad 16]^T$$

6

$$x_3 =$$

## Regression Model:-

7.  $\downarrow \rightarrow$  predicting a continuous numerical value.

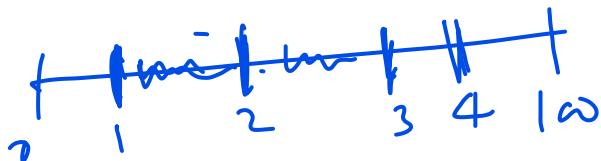
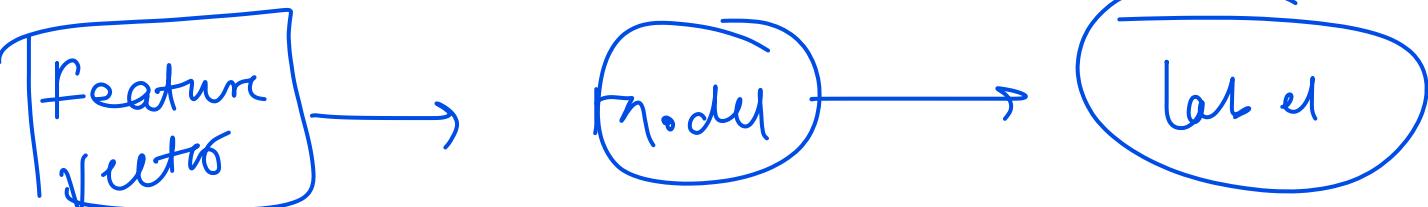
has to learn a mapping from input to output.

Once this mapping has been learnt, the model can be used to predict the unseen inputs.

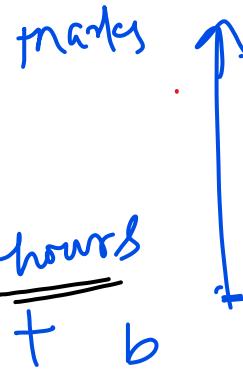
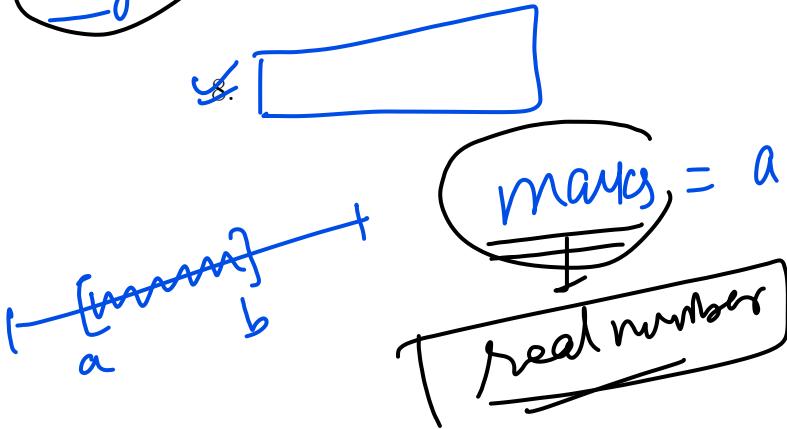
- Model:

$$f: \mathbb{R}^d \rightarrow \mathbb{R}$$

$$y = f(x)$$

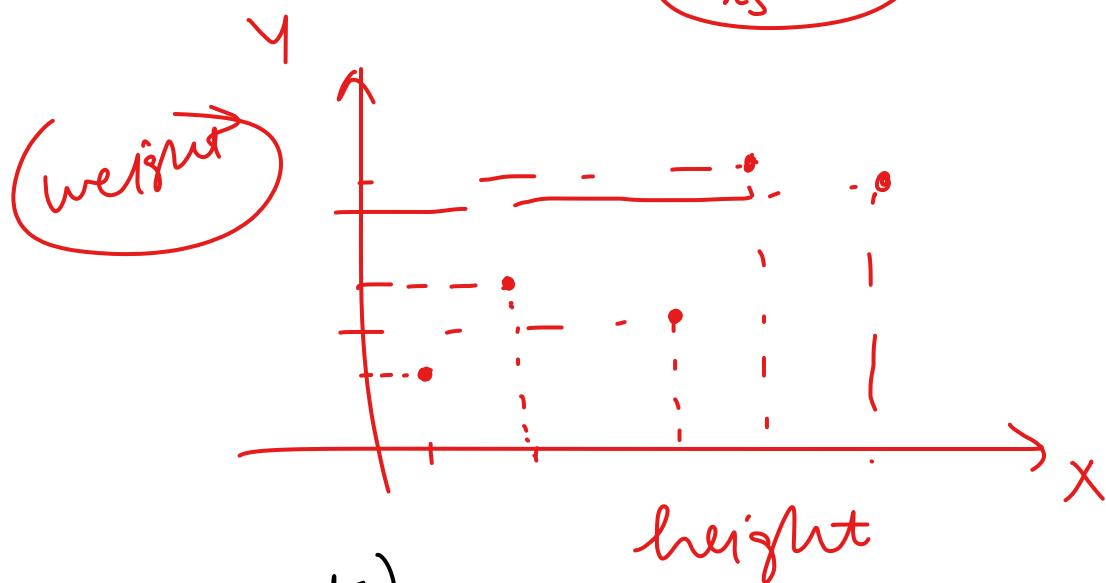


Eg:-



no. of hours  
studied

$$n_5 = 6$$



$$\text{weight} = a * (\text{height})$$

T  
Real numbers.

$$x_6 = 5 \text{ feet } 5 \text{ inches}$$

Regression model:

$$\text{Tip price} = 0.5 * \text{Area} - \text{distance}$$

T  
Tip price  
Real numbers

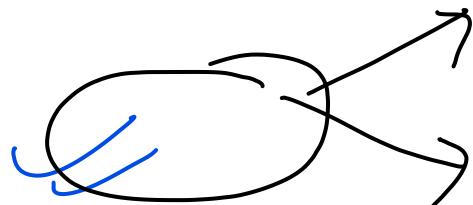
## Classification model:



→ Model whether a house is closer than 2km to a metro based on price area

$$\text{Answer} = \begin{cases} \text{Close;} & \text{if } 2^{\alpha} \text{ Roans - Price} < 1 \\ \text{Far;} & \text{otherwise.} \end{cases}$$

e.g.: - ① Spam or not Spam



② Medical diagnosis : disease = yes/no

Oranges →

Apple →

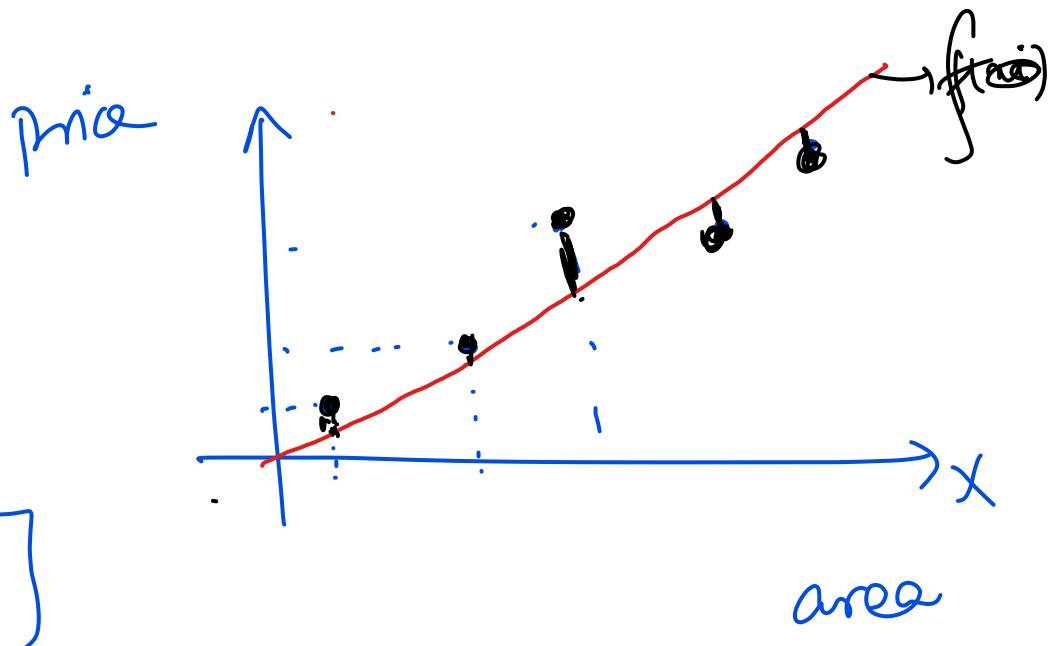
Banana →

$$\text{Price} = \underline{\underline{a}} * (\text{area}) + \underline{\underline{b}} * (\# \text{ rooms})$$

10.

$$+ \underline{\underline{c}} * (\text{distance to metro})$$

$a, b, c \rightarrow$  parameters.



$$\text{Price} = a * \text{area}$$



~~best~~

minimum error:

Student A: 90, 92, 95, 92

Student B: 70, 90, 50, 40

Why?

Variability is less

•  $\mathbb{R}$ : real numbers  $\begin{bmatrix} 1 \\ 2 \end{bmatrix} \in \mathbb{R}^2$

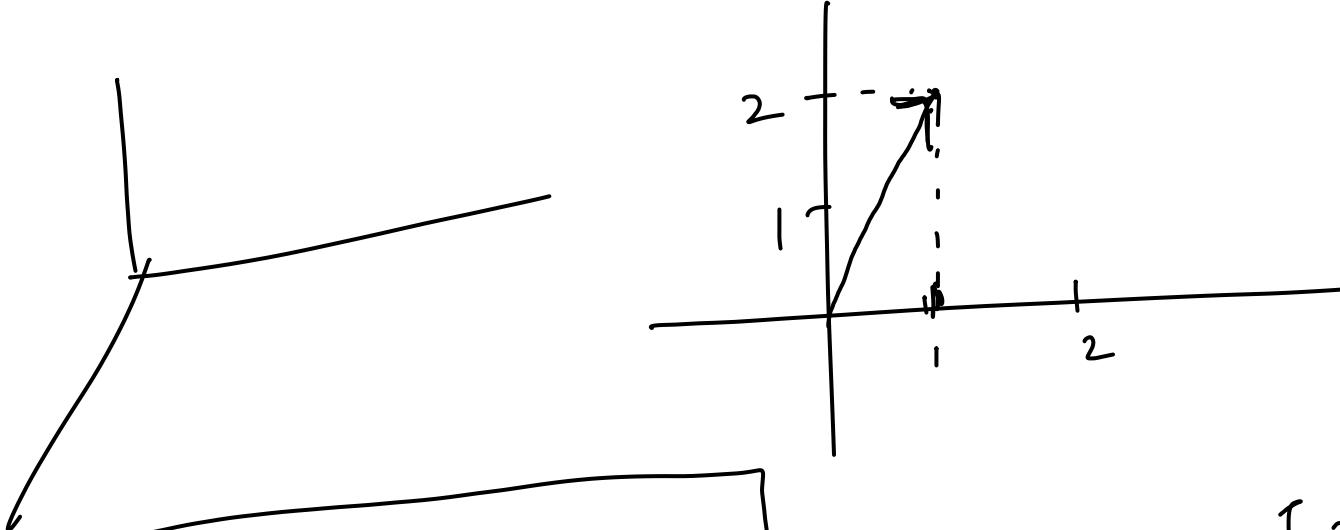
•  $\mathbb{R}_+$ : positive reals  $\rightarrow$

•  $\mathbb{R}^d$ : d-dimensional vector of reals.

•  $\mathbf{x}$ : vector.

$$\begin{pmatrix} 1 \\ 1.2 \\ -3 \end{pmatrix} \in \mathbb{R}^3$$

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



$x_j$ : jth coordinate:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$\|\mathbf{x}\|$ : length of vector  $\mathbf{x}$ .

$$\underbrace{\|\mathbf{x}\|^2}_{\text{length}} = x_1^2 + x_2^2 + x_3^2$$

$$\|\mathbf{x}\| = \sqrt{x_1^2 + x_2^2 + x_3^2}$$

$$I(2 \text{ is even}) = 1, \quad I(2 \text{ is odd}) = 0.$$

12.

$$\|x\|^2 = x^T x = [x_1 \ x_2 \ x_3] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$\|x\|^2 = x_1^2 + x_2^2 + x_3^2$$

$$\Rightarrow \|x\| = \sqrt{x_1^2 + x_2^2 + x_3^2}$$

$$x = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} : \|x\| = \sqrt{1+4+9} = \sqrt{14}$$

$x_j^i$  : jth coordinate of  $i^{th}$  vector.

$x^1, x^2, x^3, \dots, x^n$ : collection of  $n$  vectors.

$x_j^i$ :

$$\textcircled{x}_2^1 = 2$$

12

$$x^1 = [1, 2, 3]$$

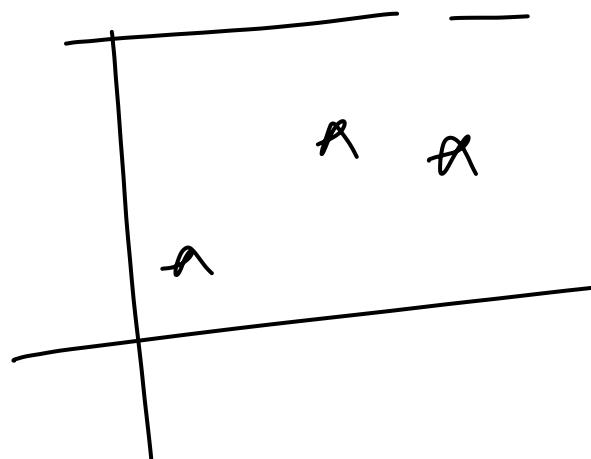
$$x^2 = [4, 5, 9] \vee$$

$$x_2^2 = 5$$

13.

## ~~Supervised Learning~~

### ↳ Curve-fitting



- Given:

$$\left\{ \underset{i=1}{\overset{n}{\downarrow}} (x_i^1, y_i^1), (x_i^2, y_i^2), \dots (x_i^n, y_i^n) \right\} \rightarrow \text{Training data.}$$

- Find a model  $f$  such that  $f(x_i^i)$  is close to  $y_i^i$

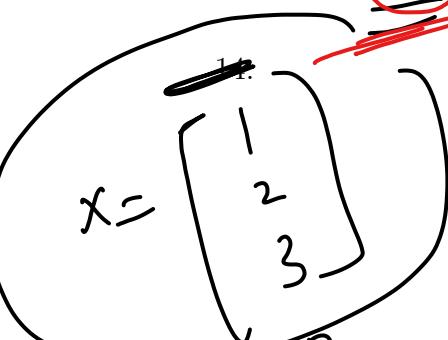
- Algorithm outputs a model:  $f: \mathbb{R}^d \rightarrow \mathbb{R}$

$$\boxed{\text{Loss}[f] = \frac{1}{n} \sum_{i=1}^n (f(x_i^i) - y_i^i)^2}$$

$$\boxed{f(x) = \bar{w}^T x + b = \sum_{j=1}^d w_j x_j + b}$$

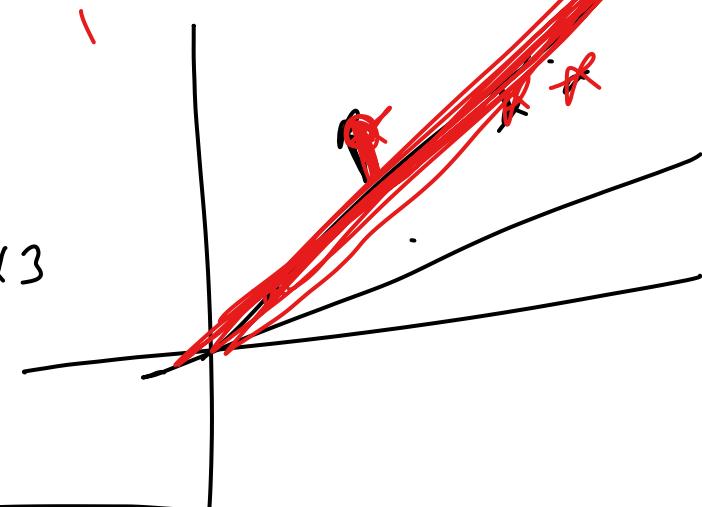
$$= w_1^T \underline{x_1} + w_2^T \underline{x_2} + w_3^T \underline{x_3} + b.$$

$$= \underline{\omega_1} (\# \text{ rooms}) + \underline{\omega_2} (\text{ Cured}) \\ + \underline{\omega_3} (\text{ distance}) + b$$



$$A_{3 \times 2} \quad B_{2 \times 3}$$

$$AB = [ \quad ]_{3 \times 3}$$



$$f(x) = \omega_1 x_1 + \omega_2 x_2 + \omega_3 x_3$$

$$= [\omega_1 \quad \omega_2 \quad \omega_3]_{3 \times 3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}_{3 \times 1}$$

$$= w^T x$$

$$w = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}$$

Absolute:

1 2 3 4 5

15.

$$\text{Variance} = \frac{1}{n} \sum (m - \bar{x})^2$$

11

$d=1$

$x$	$y$	$f$	$g$
[1]	2.1	2	5
[2]	3	4	6
[3]	6.5	6	7
[4]	11.5	8	8

$$f = \underline{\underline{2y}}$$

$$g(x) = x + 4$$

$$\text{Loss}(f) = \frac{1}{n} \sum (f(x^i) - y^i)^2$$

$$= \frac{1}{4} \left[ (2-2.1)^2 + (4-3)^2 + (6-6.5)^2 + (8-11.5)^2 \right]$$

= —

$$^{16.} \text{Loss}[g] = \frac{1}{4} \left[ (5-2.1)^2 + (6-3)^2 + (7-6.5)^2 + (8-11.5)^2 \right]$$

= —

$x_1$ Rooms	$x_2$ Area	$x_3$ distance	Incl(y)	f	g
3	9	1	✓ 5.0	5	5
2	7	2.2	✓ 3.5	—	—
4	10	3.0	✓ 6.5	5	—
5	12	0.8	✓ 8.0	—	—

$w_1 \propto \text{Rooms} + w_2 \propto \text{distance}$

$$f = 2 \times \text{Rooms} - \text{distance}$$

$\rightarrow \text{loss}[f] < \text{loss}[g]$

$$g = \text{Rooms} + 2 \times \text{distance}$$

$$f = 2x_1 - \cancel{x_2}$$

16

$$\text{Loss}[f] = \frac{1}{n} \sum \underbrace{(f(x^i) - y^i)^2}_{\text{expression}} = \frac{1}{n} ( )$$

17.

$$\text{Loss}[g] = \frac{1}{n} \sum (g(x^i) - y^i)^2 = \frac{1}{n} ( ) \leq$$

# Classification #

expression  
 $f: \mathbb{R}^d \rightarrow \mathbb{R}$

Training data:-

$$\left\{ \underbrace{(x^1, y^1), (x^2, y^2), \dots, (x^n, y^n)}_{\text{spam not spam}} \right\}$$

$$x^i \in \mathbb{R}^d, y^i \in \{+1, -1\}$$

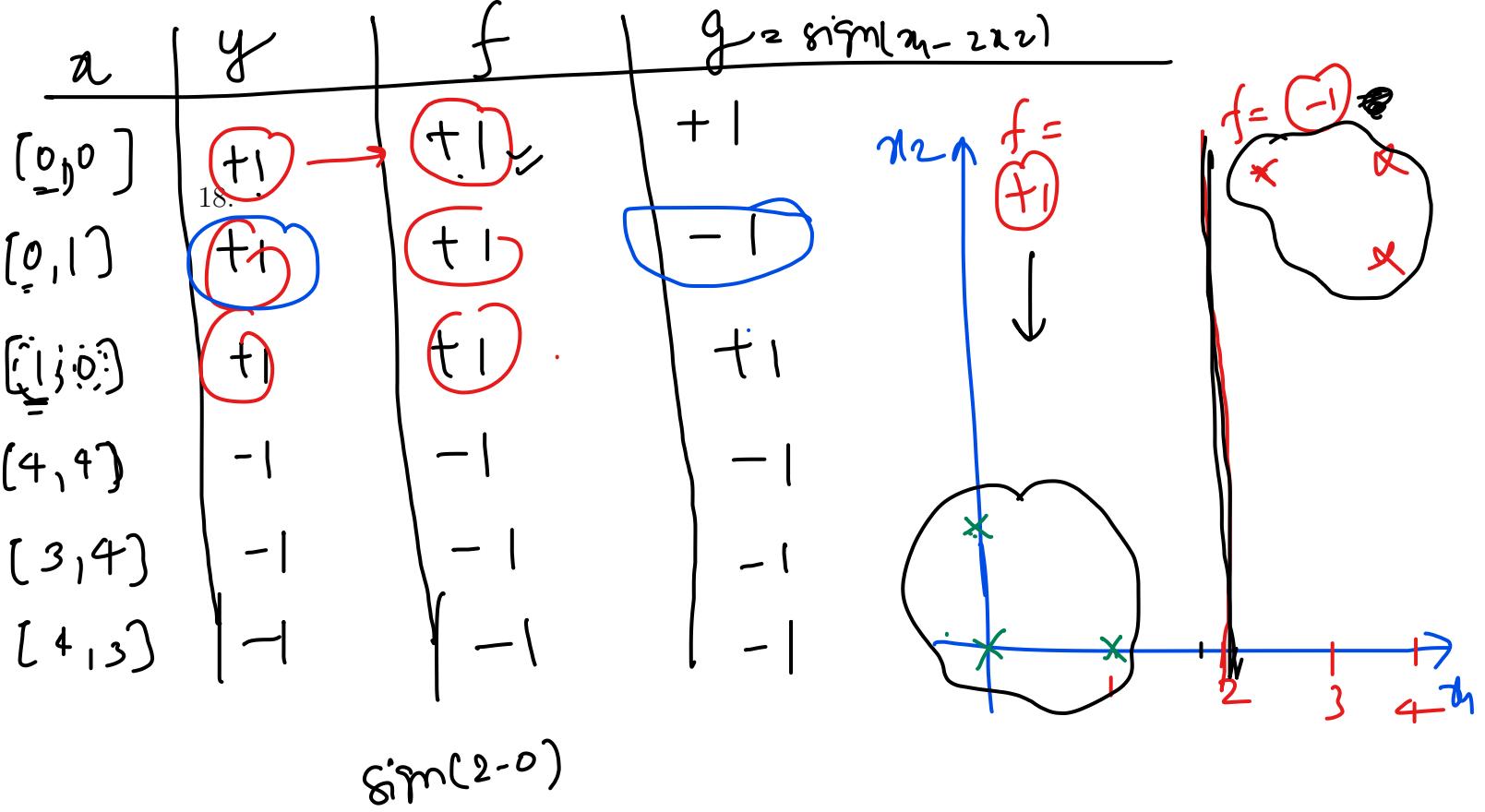
Algorithm outputs a model  $f: \mathbb{R}^d \rightarrow \{+1, -1\}$

$$\text{Loss}[f] = \frac{1}{n} \sum_{i=1}^n \mathbf{1}(f(x^i) \neq y^i)$$

= fraction of training data wrong by  $f$

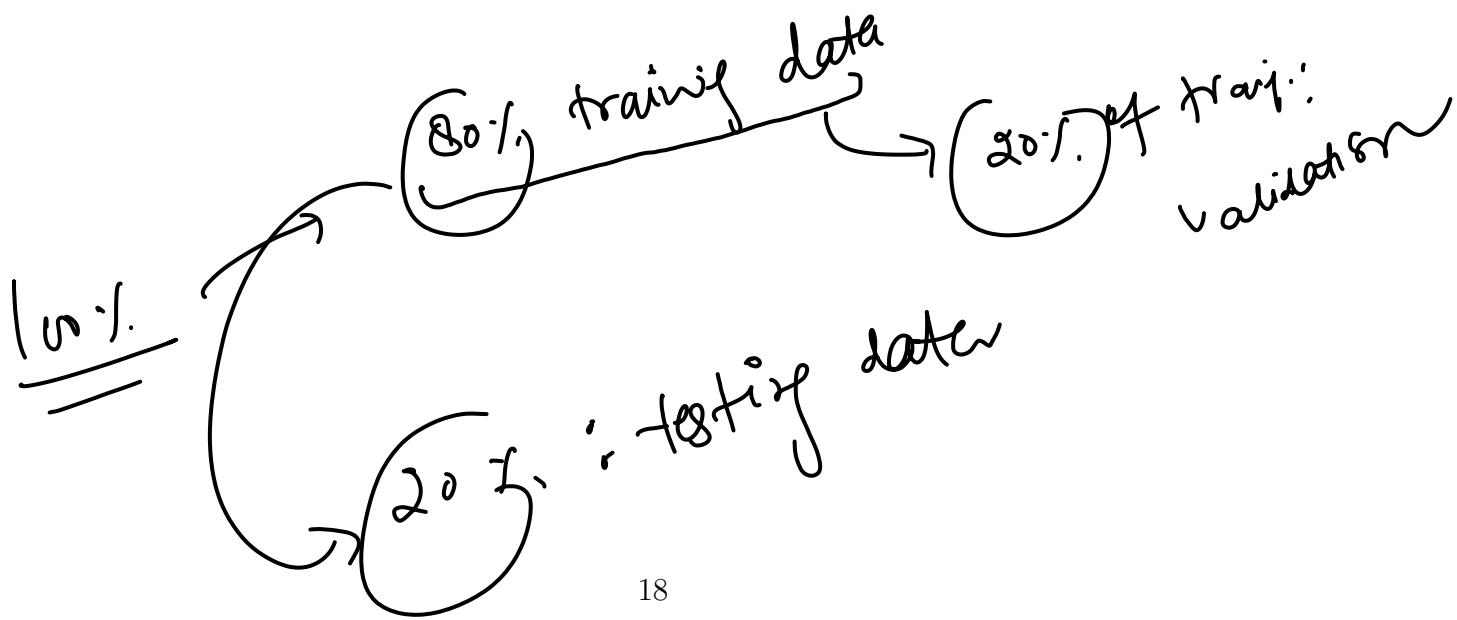
$$f(x) = \text{sign}(\underline{w^T x + b})$$

17



$$f(x) = \text{sign}(2 - x_1) \quad \text{Loss}[f] = \frac{1}{6}(0) = 0$$

$$g(x) = \text{sign}(x_1 - 2x_2) \quad \text{Loss}[g] = \frac{1}{6}(1) = \frac{1}{6}$$



Training: practice questions you solve at

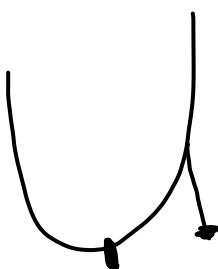
19.

Validate: A mock test that helps us check whether my preparation method is working.

Adjust my hyperparameters

Test: the final exam

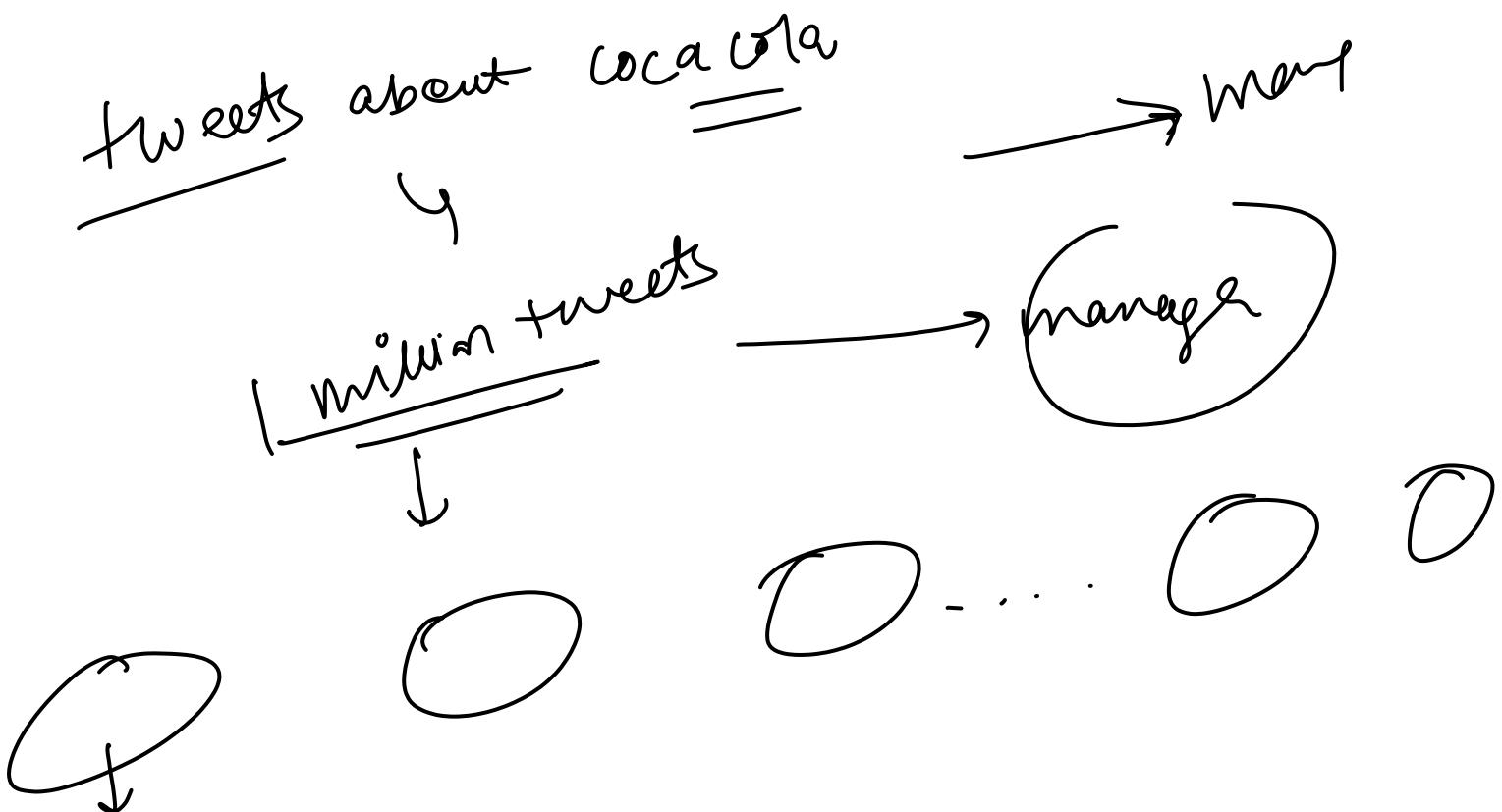
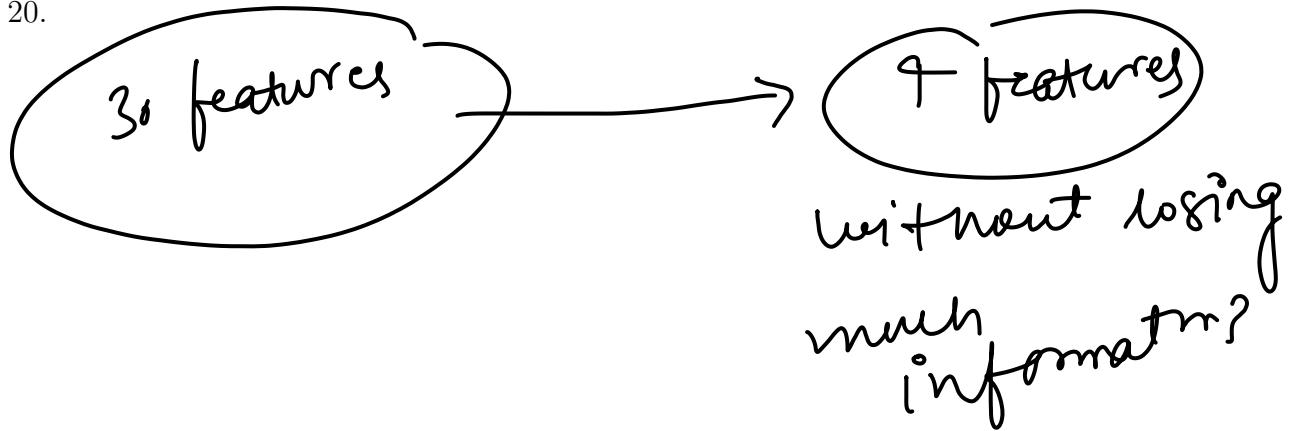
train  $\rightarrow$  70%  
validate  $\rightarrow$  15%  
test  $\rightarrow$  15%



$$f(x^{t+1}) = \text{○} - \text{m}$$

# Unsupervised Learning

20.



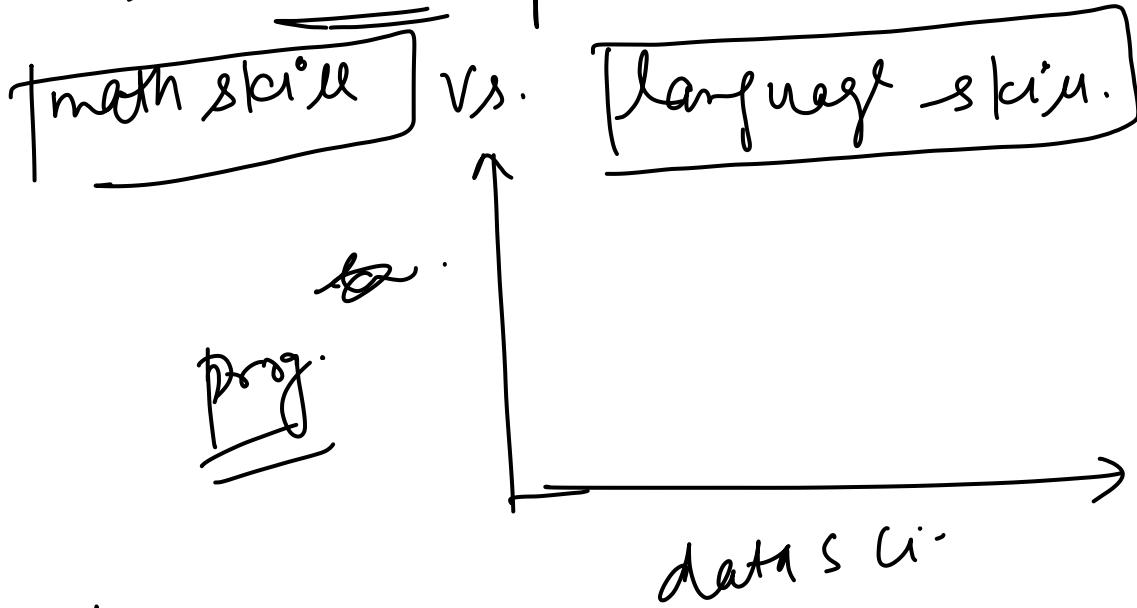
III Understanding data

Build models that compress, explain & group data

Ex: → I give you exam marks in 10 subjects  
21. for each student.

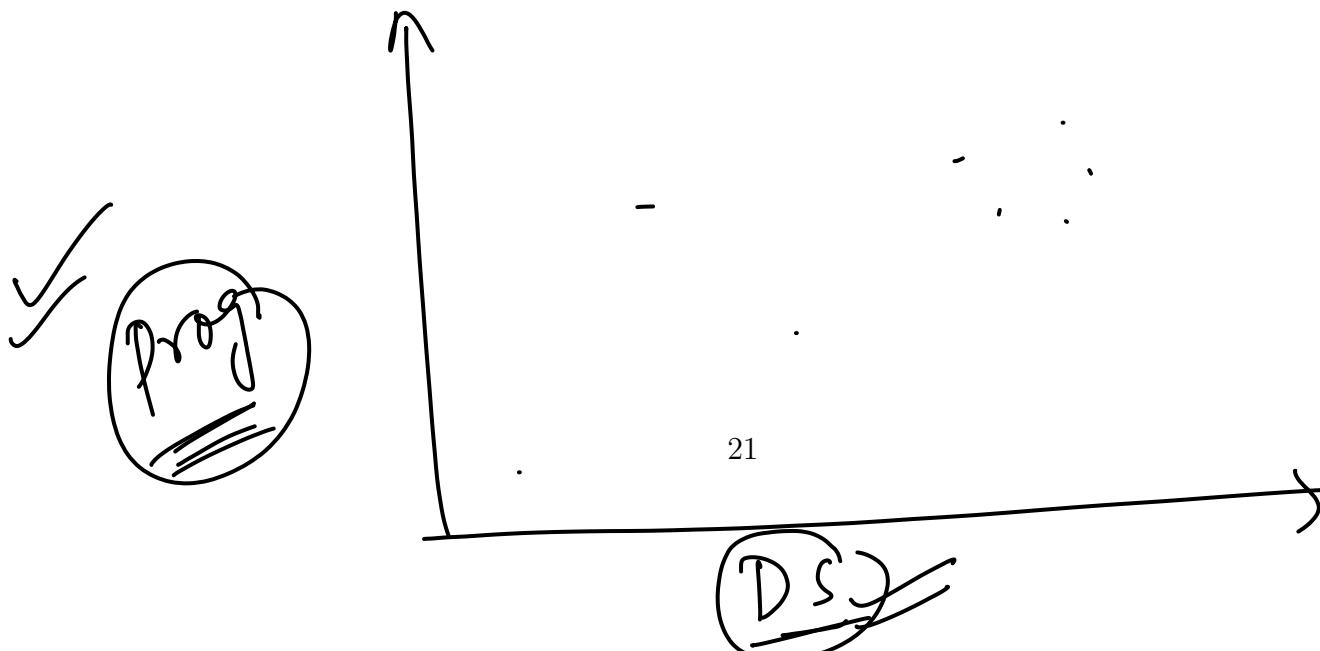
=  
dimensionality reduction!

reduces to 2 components:



Diploma level  
12 subjects 4000

Too many dimensions.



S1 S2 S3 S4 S5 - - - S12

22.

you

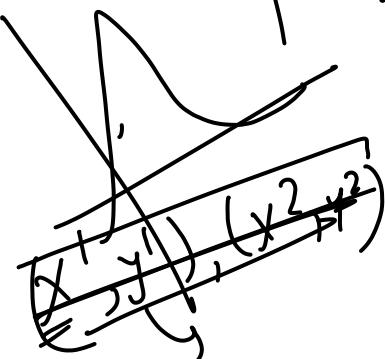
Image comp = reduce the amount of data needed  
to present an image while  
keeping it visually meaningful.

e.g.: A  $100 \times 100$  pixel image = 1,000,000 numbers

~~PCA~~

most imp. features in  
your image  
data.

Top-k principal components



$100 \times 100 \rightarrow$   
50

50 principal components:  
mean =  
var =

Data:  $\{x^1, x^2, \dots, x^n\}$

23.  $x^i \in \mathbb{R}^d$

$$d' < d$$

- Encoder  $f: \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$
- decoder  $g: \mathbb{R}^{d'} \rightarrow \mathbb{R}^d$

Goal:  $g(f(x^i)) \approx x^i$

Loss =  $\frac{1}{n} \sum_{i=1}^n \| g(f(x^i)) - x^i \| ^2$

$d=2$ , $d'=1$	$f$	$g$	$f$	$g$
$[1, 0.8]$	0.2	$[0.2, 0.2]$	$\underline{0.9}$	$[0.9, 0.9]$
$[2, 2.2]$	-0.2	$[-0.2, -0.2]$	$\underline{2.1}$	$[2.1, 2.1]$
$[3, 3.2]$	-0.2	$[-0.2, -0.2]$	$\underline{3.1}$	$[3.1, 3.1]$
$[4, 3.8]$	0.2	$[0.2, 0.2]$	$\underline{3.9}$	$[3.9, 3.9]$

$f(x) = \underline{x_1 - x_2} = -$

$g(u) = [u, u]$

models

23

$$\tilde{f}(x) = \frac{x_1 + x_2}{2} ; g(u) = [u, u] \quad \left. \begin{array}{l} \text{models} \\ \text{24.} \end{array} \right\}$$

$x$

$$\tilde{g}(u) = [u, u]$$

$$g(f(x)) = \left[ \begin{matrix} x_1 \\ x_2 \\ x_3 \end{matrix} \right] \quad \boxed{\|g(f(x)) - x\|^2}$$

$$x = \left[ \begin{matrix} x_1 \\ x_2 \\ x_3 \end{matrix} \right] \quad \|x\|^2 = x_1^2 + x_2^2 + x_3^2$$

$$[0.2, 0.2]$$

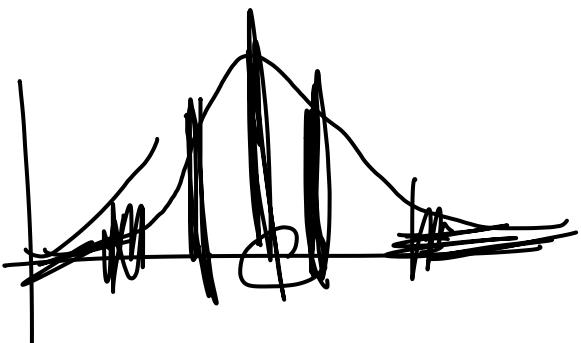
$$(1, 0.8)$$

$$\frac{1}{4} \left[ (0.2 - 1)^2 + (0.2 - 0.8)^2 + \dots \right]$$

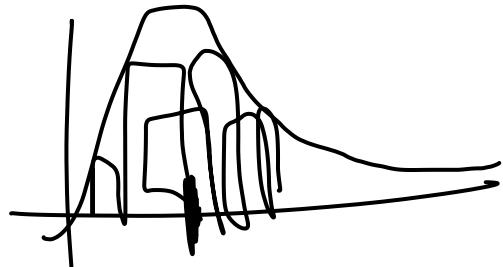
Density estimation

- Process of estimating the prob. distn of data.
- Helps us understand ~~to~~ how data is spread.

↳ detects rare/ unusual patterns (outliers)



24



Fraud detection:-

25.

Normal transaction = high-density areas

Fraudulent = low-density area

Data:  $\{x^1, x^2, \dots, x^n\}$

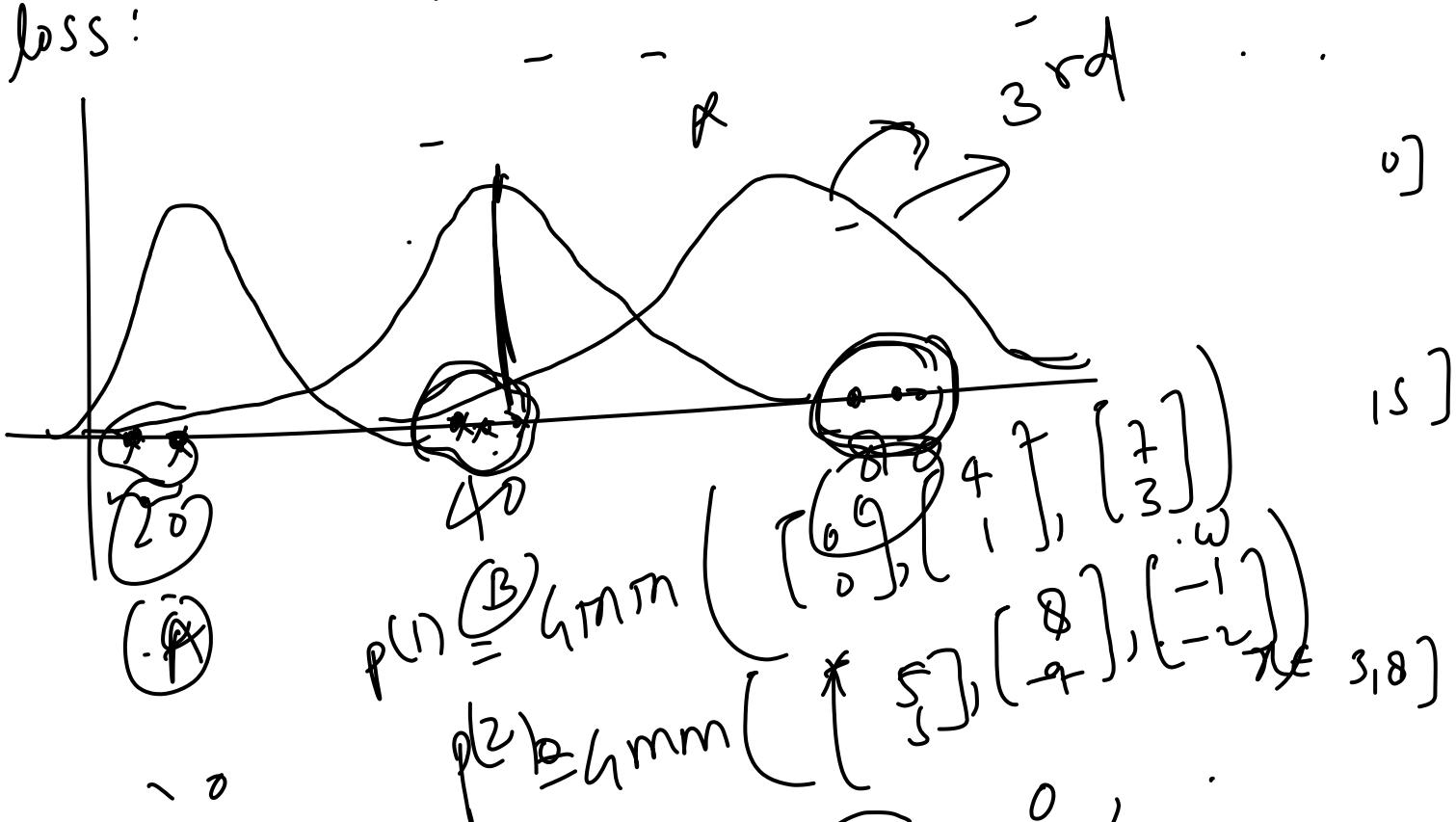
$x^i \in \mathbb{R}^d$

$$\sum p_i = 1$$

Prob. mapping  $P: \mathbb{R}^d \rightarrow \mathbb{R}_+$ , that sums to one

Goal:  $P(x)$  is large if  $x \in \text{data}$  & low otherwise

loss:



1.9  
4.3  
9.8

$y_{10}$

-15  
-15  
-15

25

$$\text{loss}(P^1) =$$

$$(1) \log(1)$$

$$\text{loss}(P^2) =$$