

# Experience :-

→ From Historical Data

# Supervised

Petal width	Petal height	color	flower
-	-	-	-
-	-	-	-

features

Instance  
Record  
sample

## Features

### Selection

- Select More weight feature.
- In ML - you have do feature selection
- In DL - NN do it by itself.

## Redundant features

which

- features to add more meaning for prediction

## Classification

SVM

DA

LDA

PDA

Naive

Ensemble  
Methods

Logistic

## Regression

Linear Reg

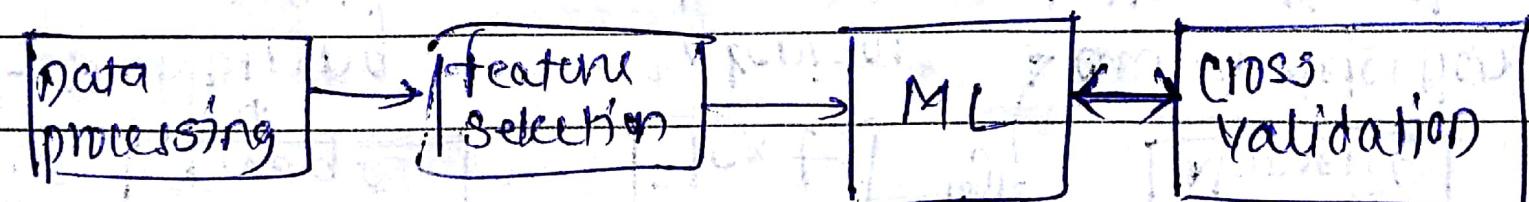
GLM

SVR.

## clustering

# Bike sharing demand - kaggle

Import  
Data



Select  
best  
Model

Trained  
Model

Hyper  
parameter  
tuning

Deploy  
app, cloud  
web

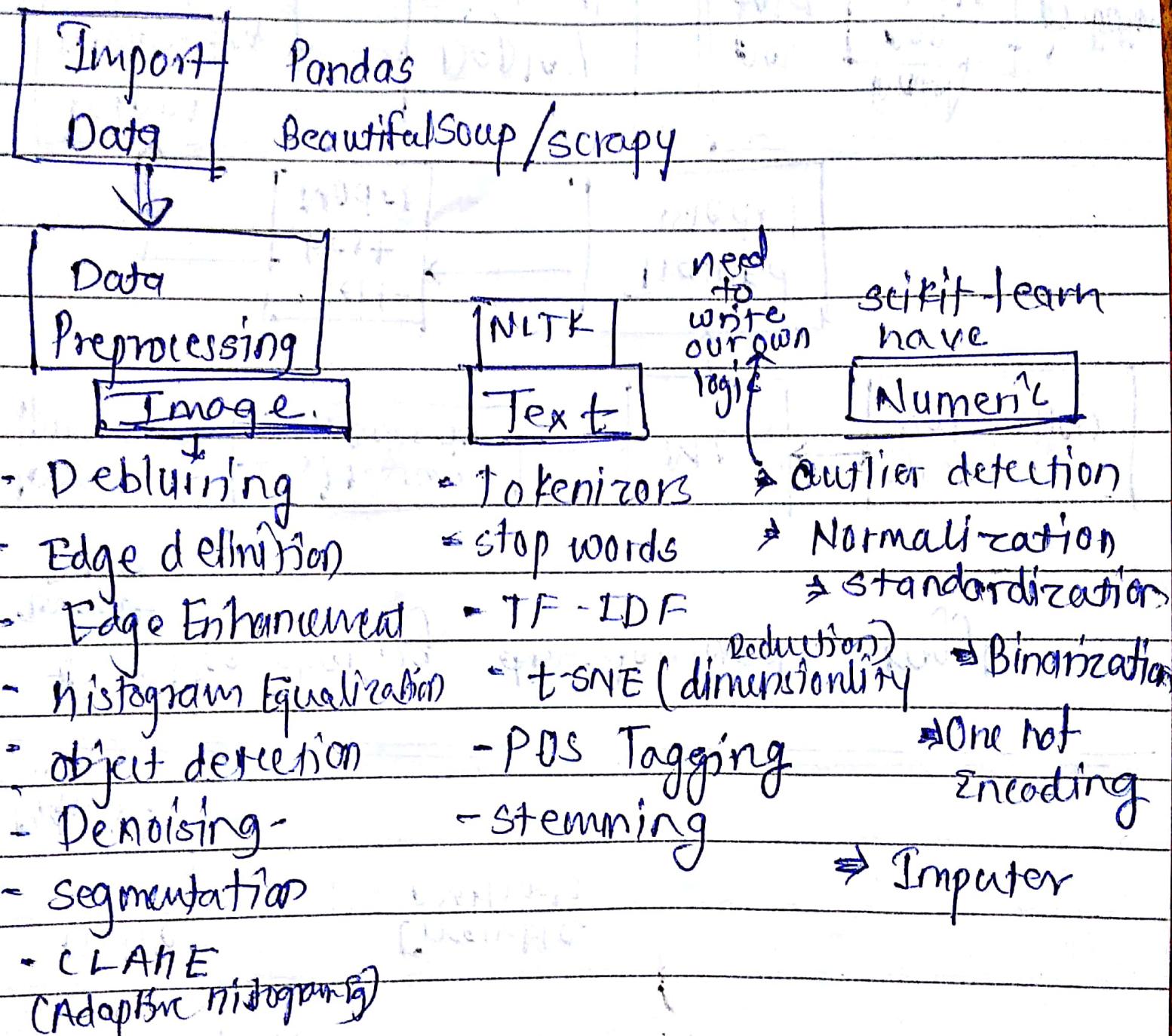
new  
data

Model  
App,  
website  
joblib

prediction

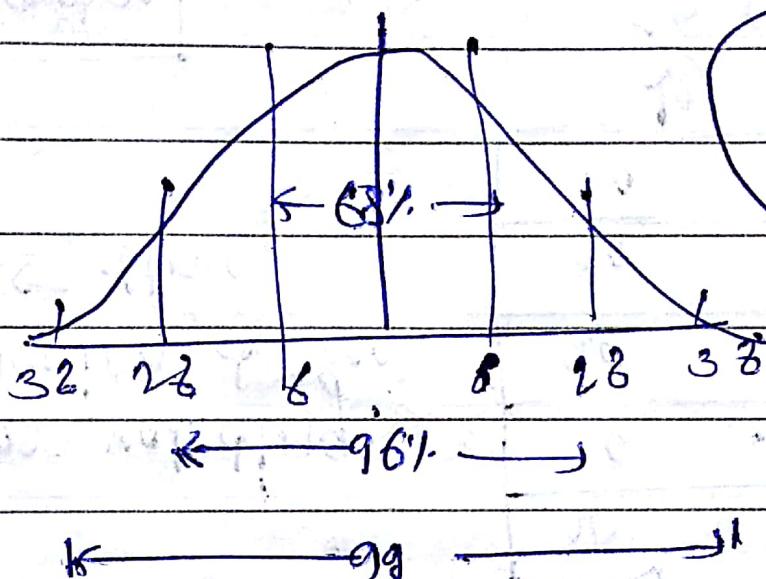
# # ML Workflow #

Data Analysis:  
—> scitensor  
—> Engineer



## Thumbs rule

- If data points beyond the 2 or 3 std. ~~variance~~ deviation from Mean it is Outliers



Gaussian

distribution

Data  
preprocessing

feature selection

Extraction

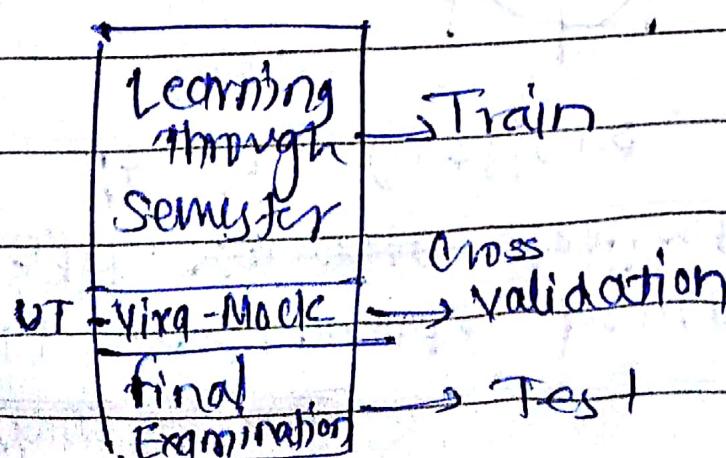
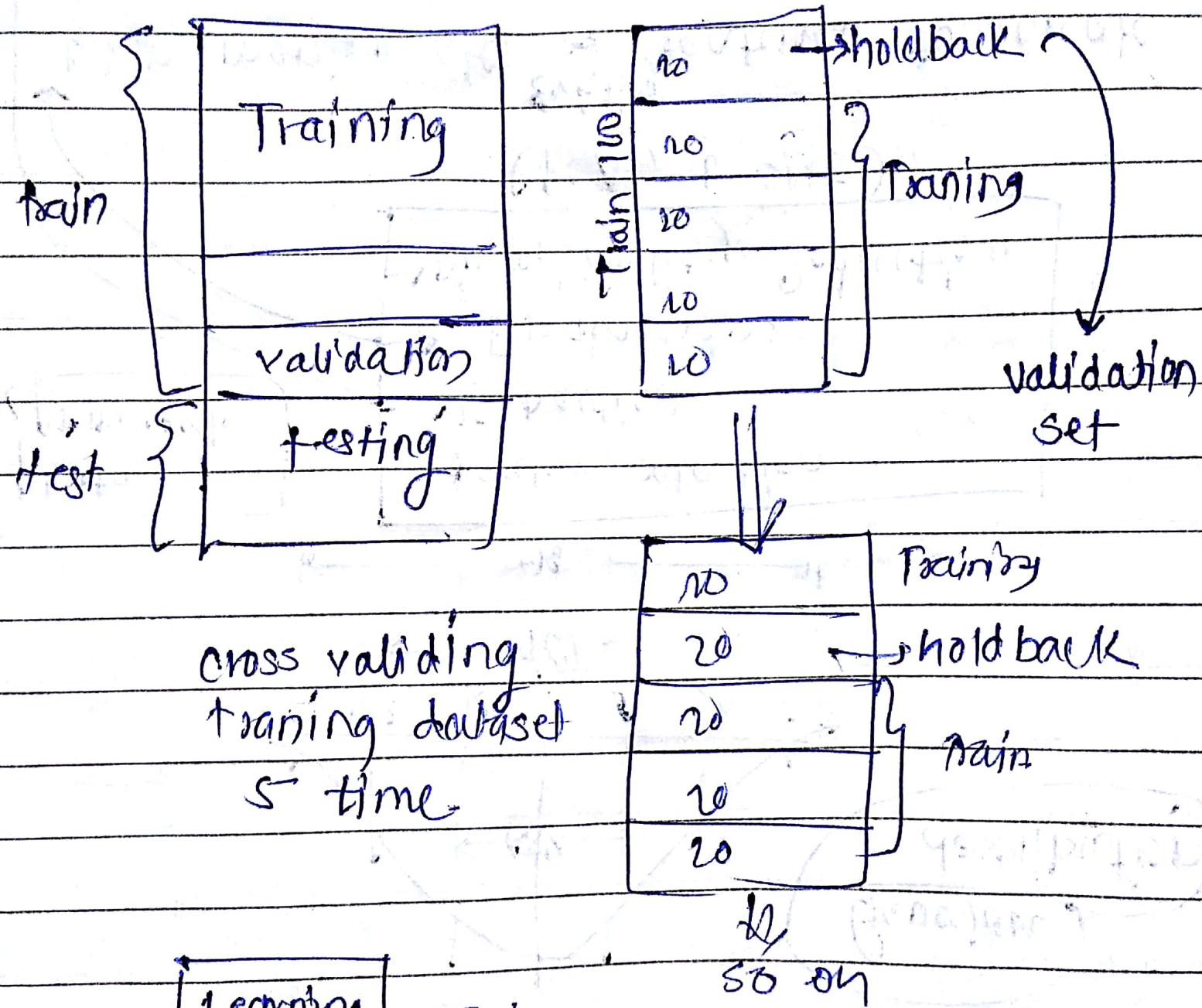
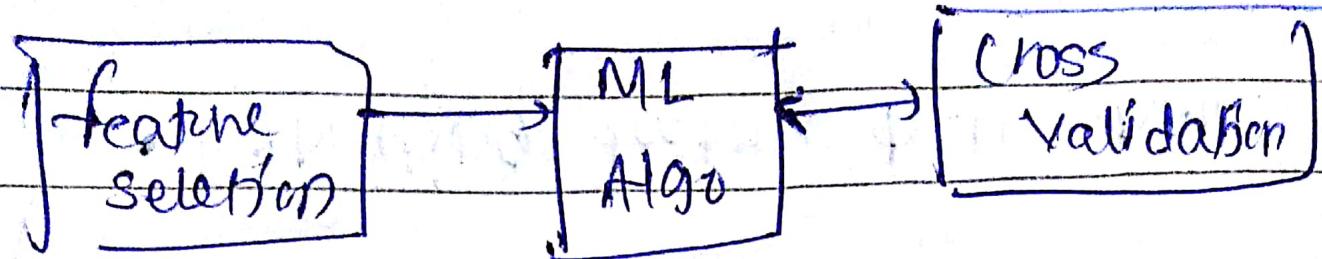
Engineering

Dimensionality Reduction

(PCA, t-SNE)

When manipulate <sup>existing</sup> ~~new~~ features to create new features

Extracting features from Data.

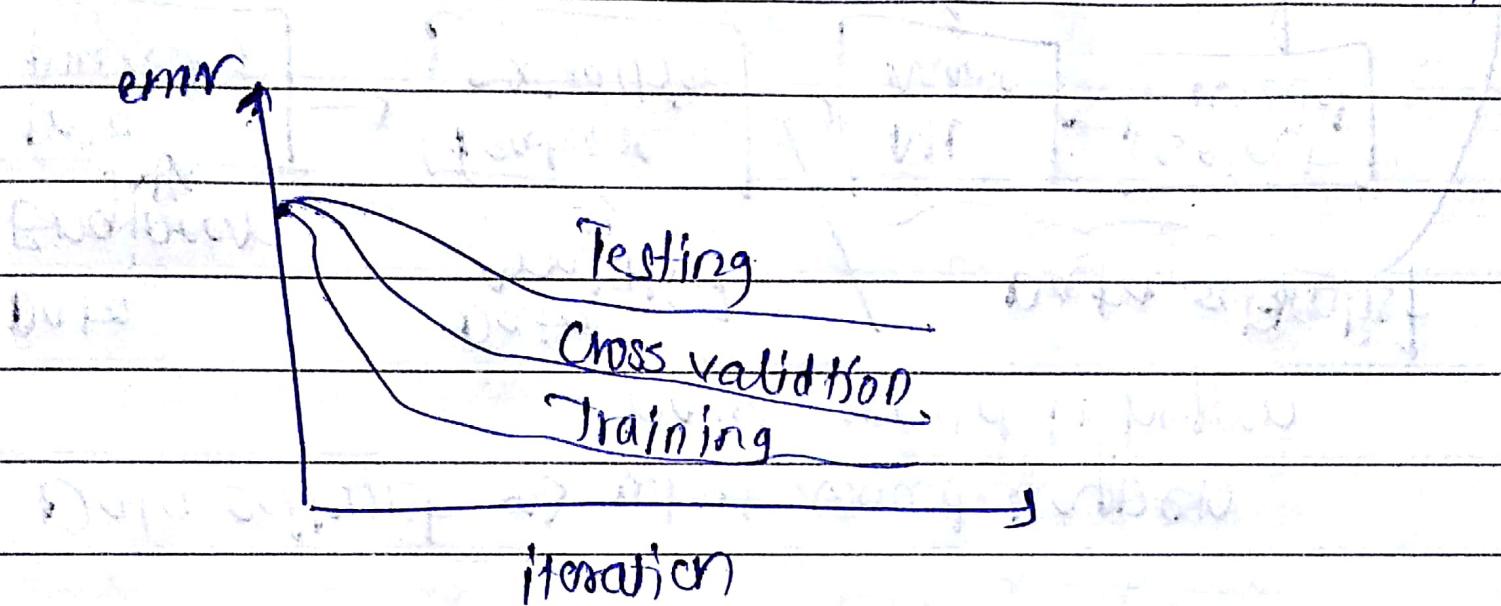


## # Cross validation

→ ~~K-fold~~ → cross validation  
→ fold

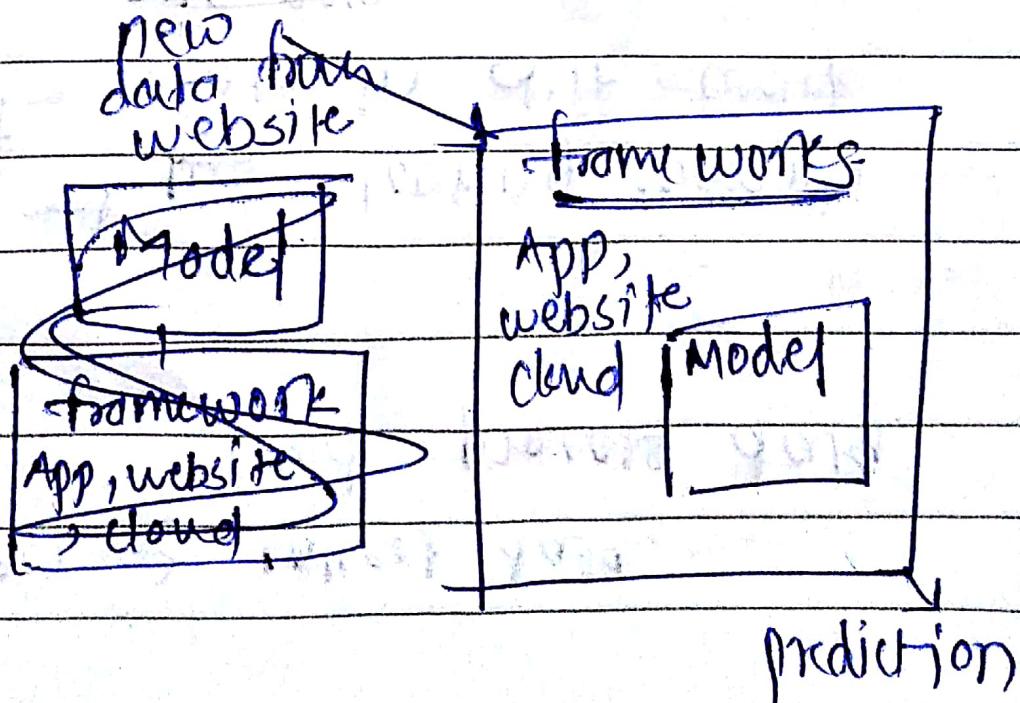
→ shuffle split cross validation

- LOOCV (leave one out cross validation)



## # Hyper Parameter Tuning :-

### # Deploy

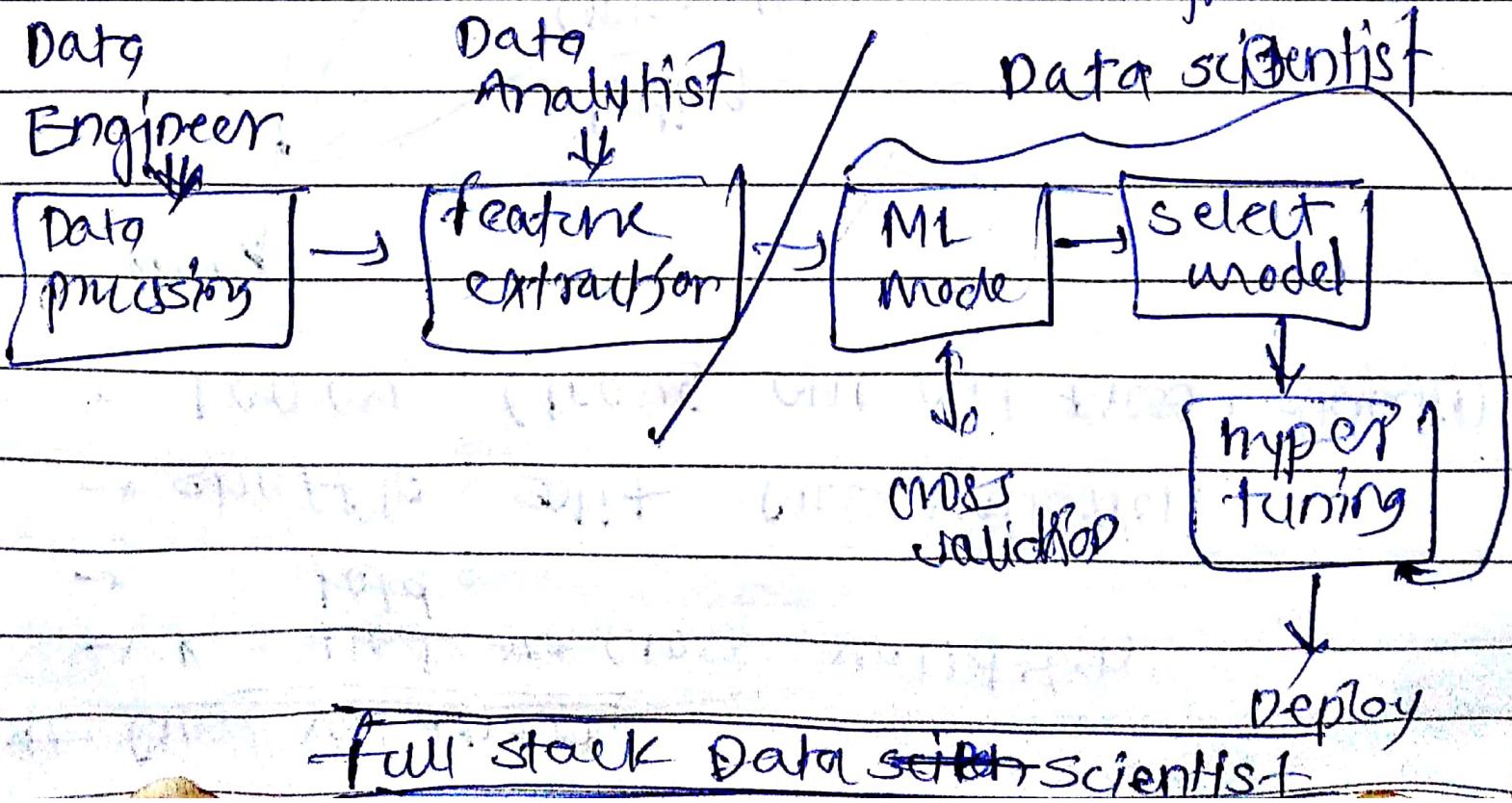


Data Engineer  $\Rightarrow$  collect data  
and process data.

Data ~~Analyst~~  $\Rightarrow$  ~~How~~ looking towards  
~~Analyst~~ data in diff. way  
~~new~~

- just analysing data
- what happened
- how happened

Data scientist  $\Rightarrow$  what would happen  
how would it happen

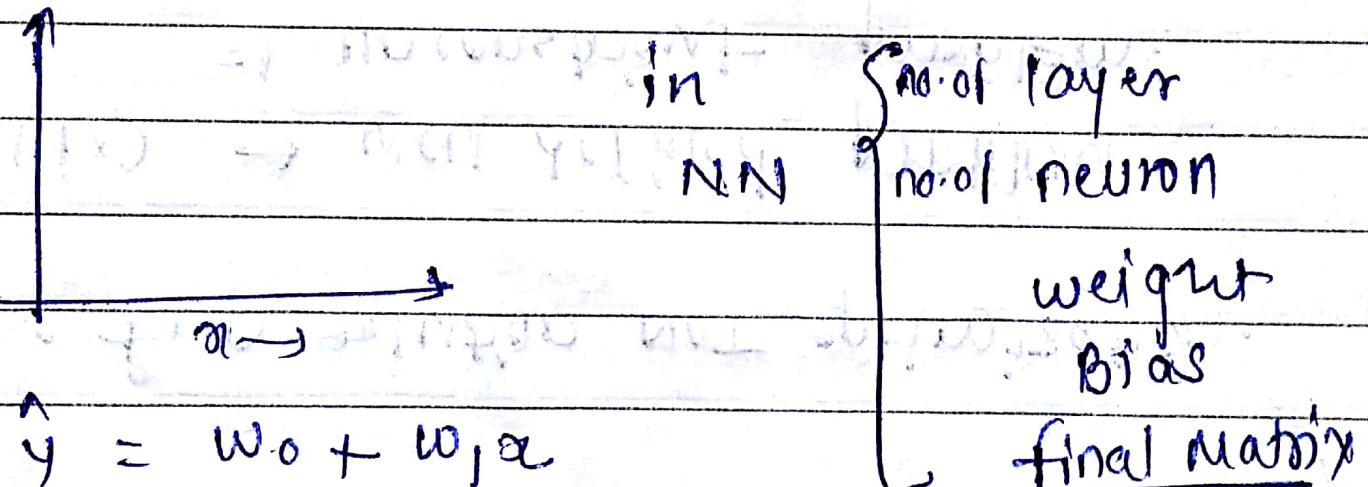


Model , Algo , Data

$$y = f(x)$$

~~Model = Algo (Data)~~

Manual Computation prediction



learnt model  $(w_0, w_1)$

Learned Model

$\hat{w}_0$  = Best value for  $w_0$

= optimal point

a	4
1	4.8
3	11.3
5	17.2
7	?

objective  $f''$

$$f(x) = 2x^2 - 5x + 3$$

Close form solution - can solve by manually

close form solution NOT optimization.

- $\min (fx) \rightarrow$  well defined problem  
 $\Rightarrow$  unconstraint problem
- $\min f(x)$  s.t.  $1 \leq x \leq 10$   $f(2x^2) \geq 5$

optimization problem  
most of time we have  
constraint

Ques.  $\arg \min_a f(a)$  ?

→ find argument  $a$  for which  $f(a)$  is minimum

Optimization problem.

required

objective  
function

constraint  
(optional)

# Problem formulation of LR:- q-predicted

$$\textcircled{1} \quad \begin{aligned} \text{Error or loss } f^n &= \sum_{i=1}^N (\hat{y}_i - y_i) \\ &\quad y = \text{actual value} \end{aligned}$$

$N$  = total no. of instances.

[But its wrong objective of  $f^n$ ]

- giving false impression of minimization of error

now . P.T.O

$$② L = \sum_{i=1}^N |\hat{y}_i - y_i|$$

necessary  
(and)

sufficient  
cond

$$\frac{\partial f}{\partial x} = 0$$

$$\frac{\partial^2 f}{\partial x^2}$$

$\frac{\partial^2 f}{\partial x^2} = +ve$  minima

$$\frac{\partial f}{\partial x} = 0$$

$\frac{\partial^2 f}{\partial x^2} = -ve$  maxima.

But

it's not

differentiable

~~absolute function not differentiable~~

$\therefore$  ~~not~~ if  
not optimis.  
objective  
fn.

$$③ L = \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

DSS - Residual ~~some~~ sum of square  
SSR - sum of square of residual

$f^n$  - parabolic

still its' not better solution

- (W) if increasing Monotonously  
learning rate is not high increases  
so need to normalization objective  
function.

$$L = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

# its Most logical objective  
function for optimization

$$\hat{w}_i = \frac{\langle x_i y \rangle - \bar{x} \bar{y}}{\langle x_i^2 \rangle - \langle x \rangle^2}$$
$$= \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

$d^2$	$a$	$y$	(approx.)
1	1	4.8	( $1 \times 4.8$ )
9	3	11.3	( $3 \times 11.3$ )
25	5	17.2	( $5 \times 17.2$ )

$$\bar{y} = \frac{\sum y}{3}$$

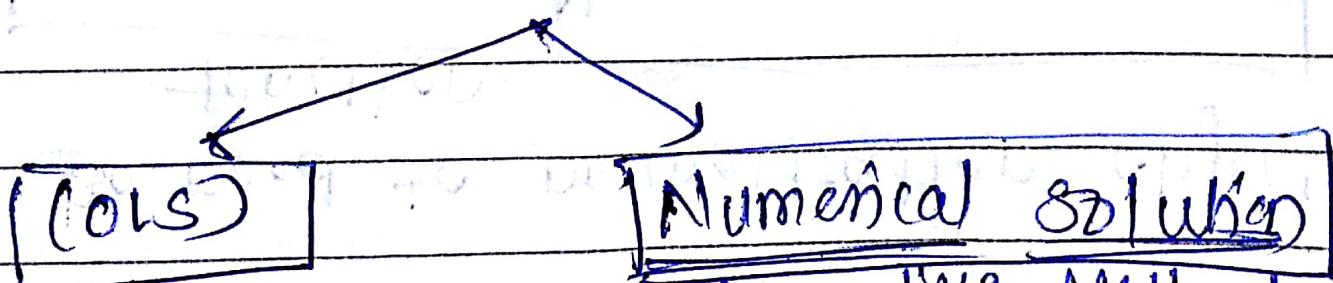
$$y = w_0 + w_1 x$$

$$w_0 \approx \bar{y} - w_1 \bar{x}$$

$$L = 3.01$$

$$\bar{y} = 1.8$$

need to check.



ordinary  
least  
square

Analytical  
solution

$\left( \frac{\partial L}{\partial w_d} \right)$  = gradient of  
L w.r.t.  $w_d$

Total update  $\rightarrow$  Direction of update from gradient

(y)  $\rightarrow$  step size

• update rule of gradient descent

$$w_0^{k+1} = w_0^k - \alpha \left( \frac{\partial L}{\partial w_0} \right) \xrightarrow{\sum (\hat{y} - y)^2}$$

$$w_i^{k+1} = w_i^k - \alpha \left( \frac{\partial L}{\partial w_i} \right) x_i$$

$\Rightarrow$  This is batch gradient descent / Vanilla gradient descent  
improvisation :-

- ① ~~stoc~~ ~~stoch~~ stochastic G.D.
- ② Mini-Batch G.D.