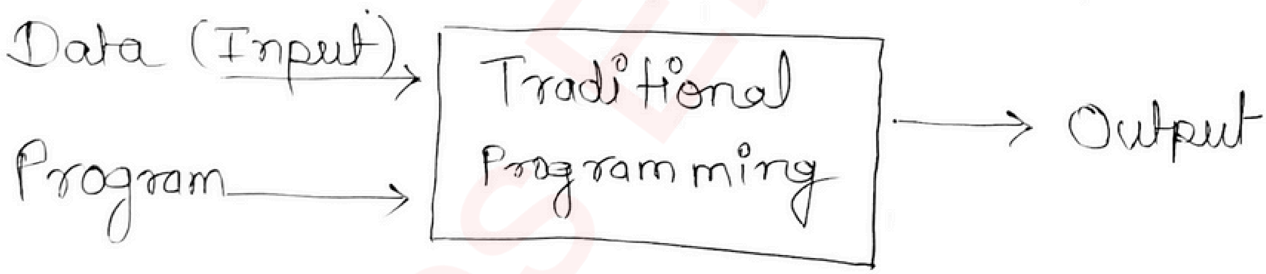
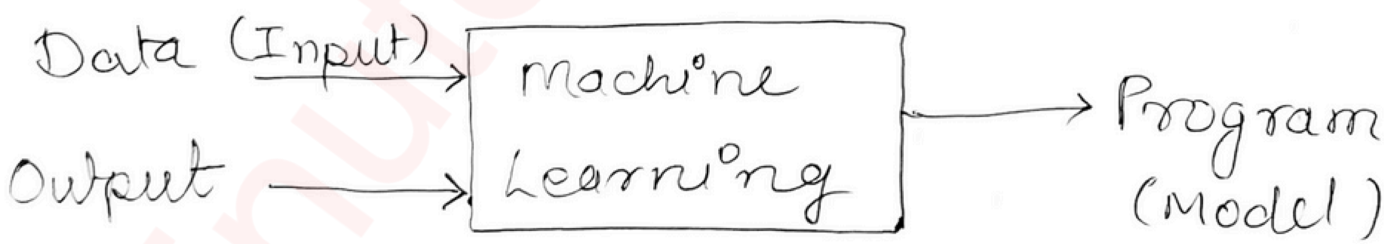
ML

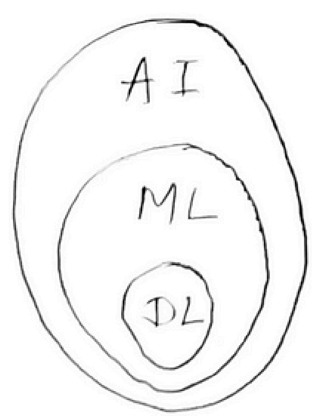
Machine | Learning

- Capability to learn without being explicitly programmed.

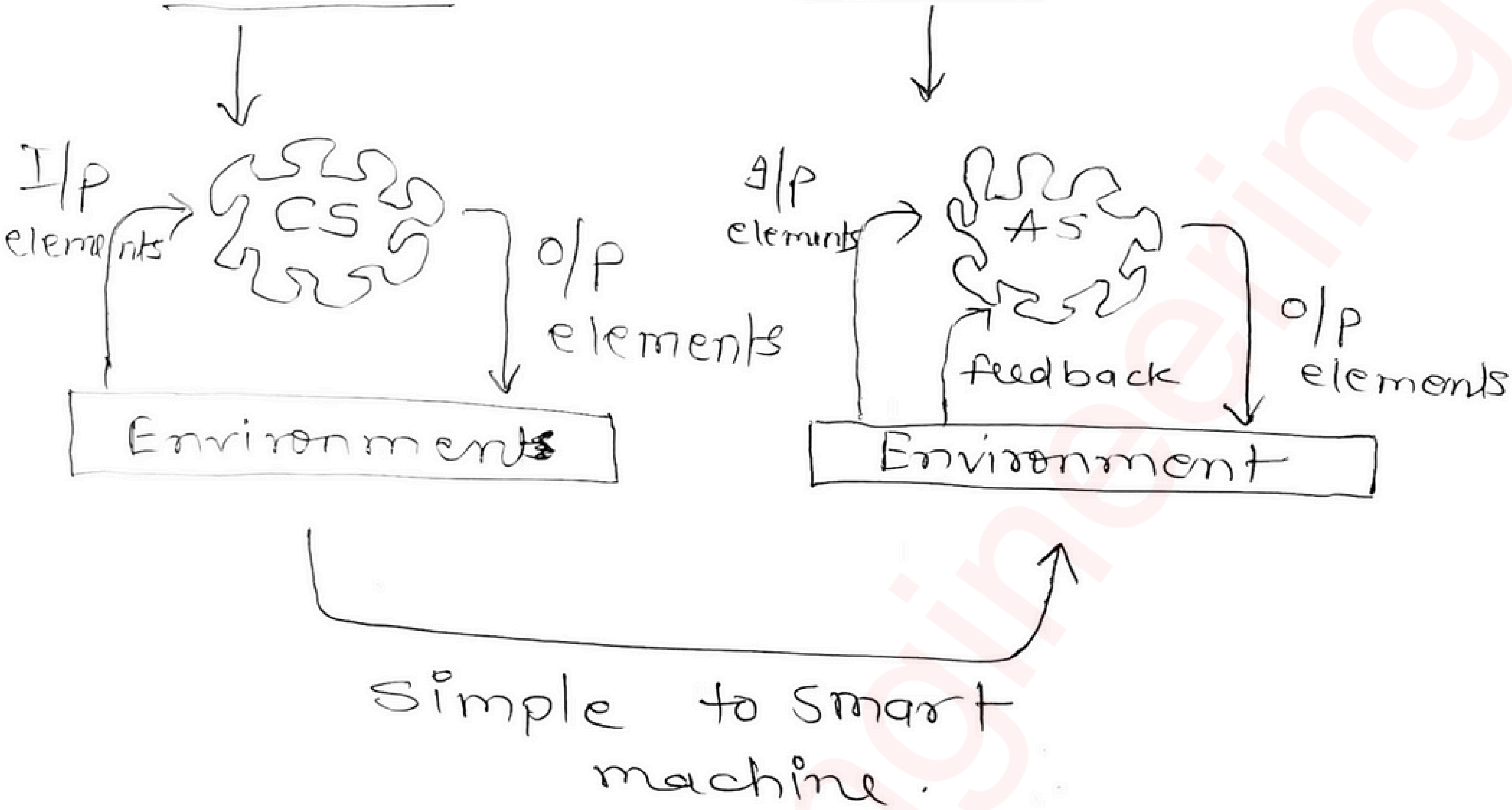
(without being actually programmed)







- Classic & Adaptive machines



- Machine Learning cycle:

1. Problem Understanding
2. Data collection
3. Data preparation
4. Model selection
5. Model building
6. Model Evaluation
7. Model Tuning
8. Deployment
9. Monitoring

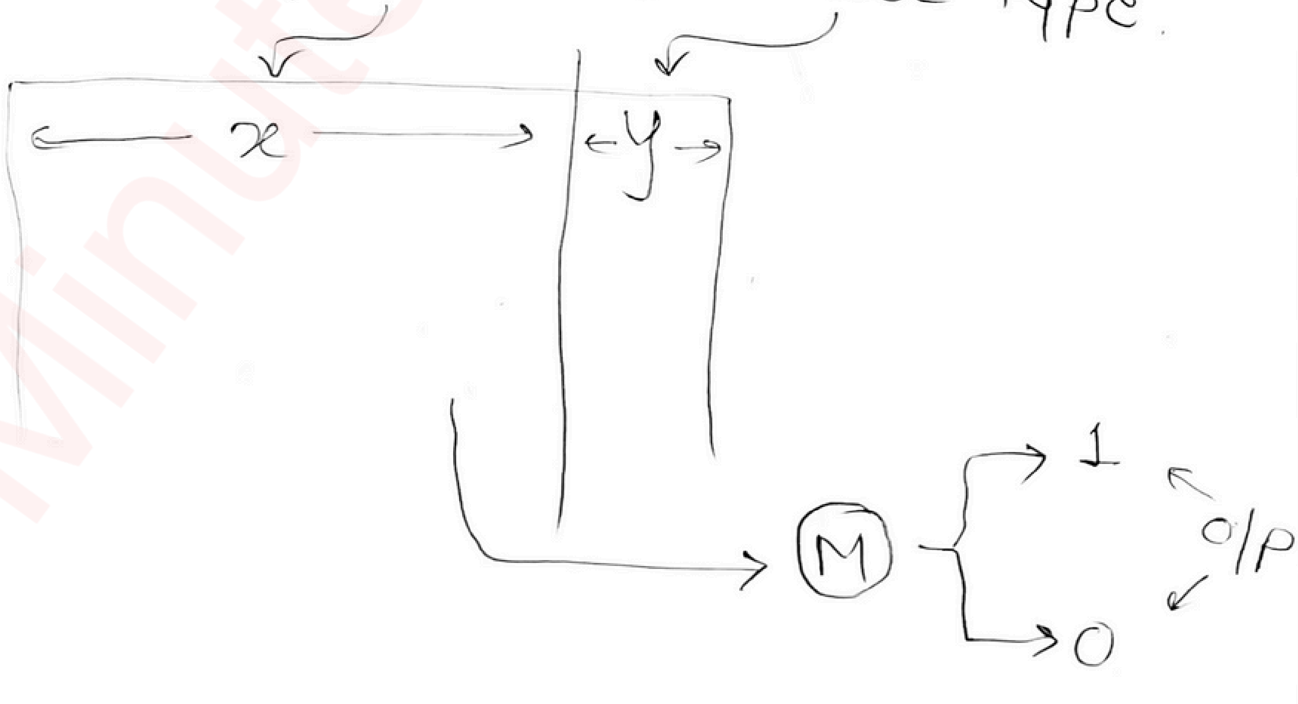
- **Data** :- facts, figs, statistics, observations.
- **Information** : meaningful, useful, relevant data.
- **Labelled data**: I/p + O/p

* Types of Learning :

① Supervised Learning
② Unsupervised Learning
③ Reinforcement Learning.

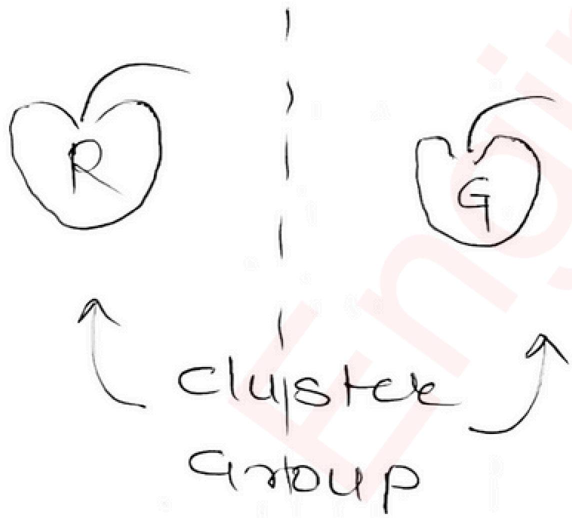
① Supervised Learning:

- → I/p + O/p (labelled data).
- → Question & Answer type.



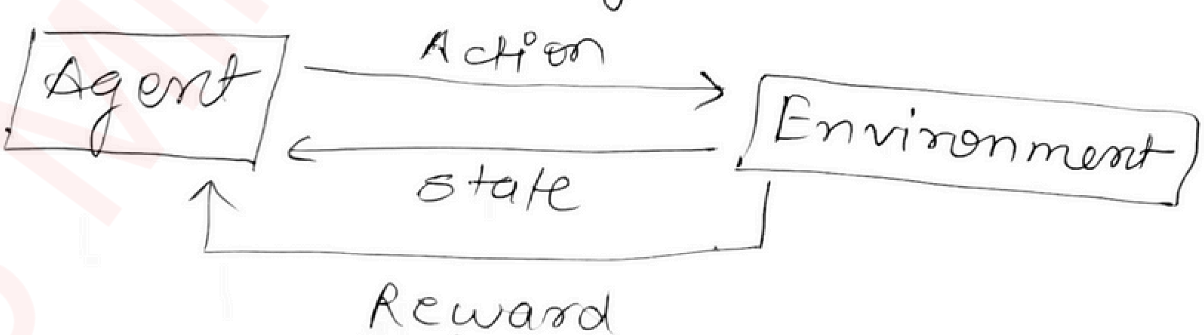
② Unsupervised Learning:

- Only I/p NO output
- Only Question type
- Unlabelled data
- Look out for similarity.

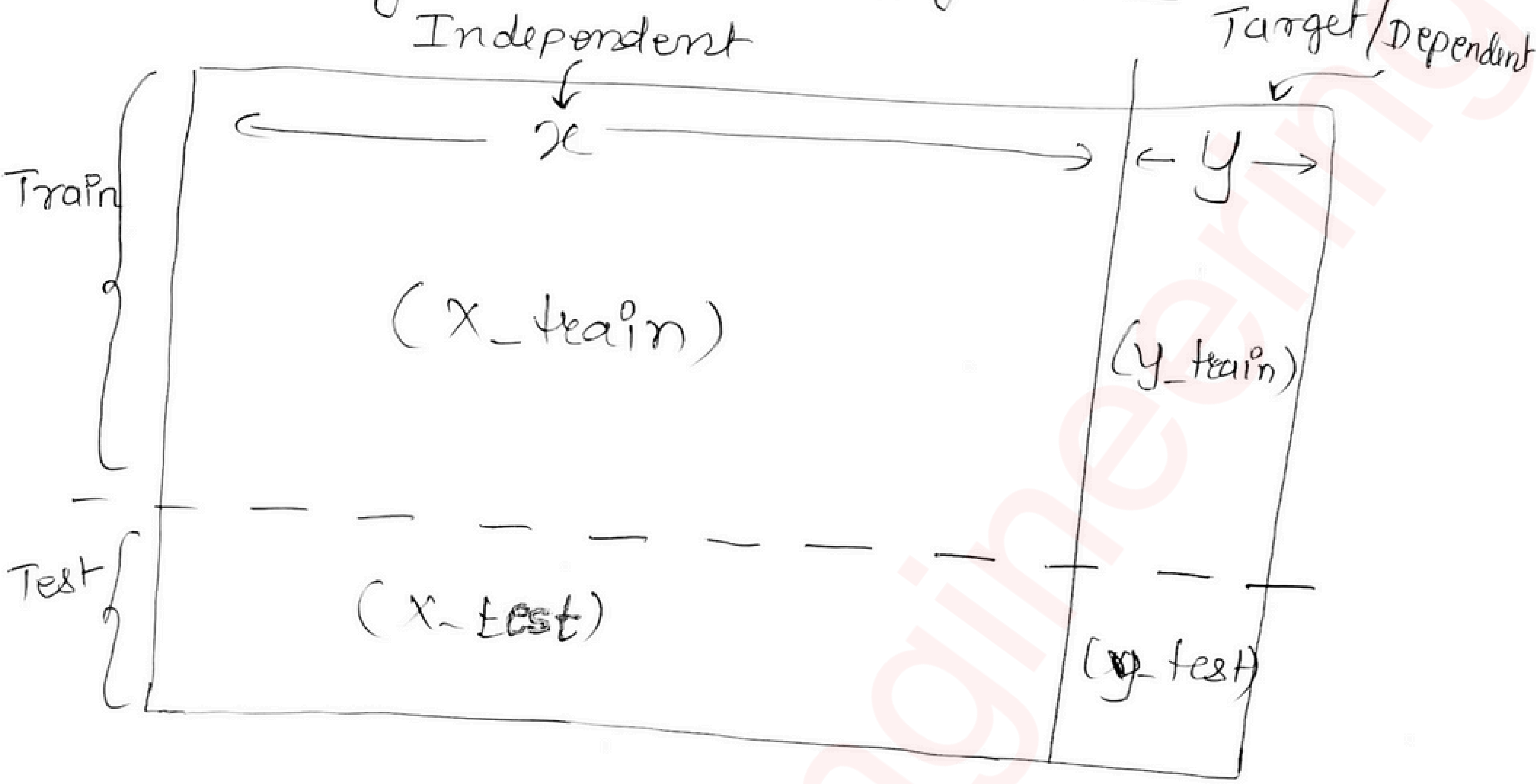


③ Reinforcement Learning:

- Reward / penalty based learning.



* Testing & Training Data



(x_test)

↓

(x_train, y_train) → TM → Trained Model

↓

y_predicted

y_test (actual) ⟷ y_predicted (predicted)

↑

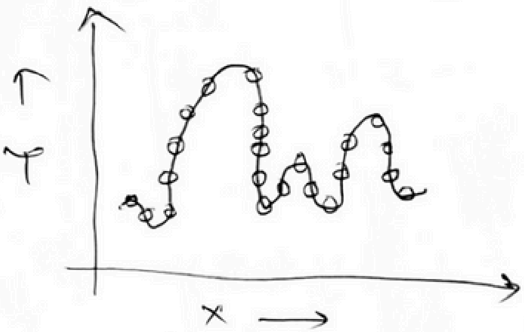
Error

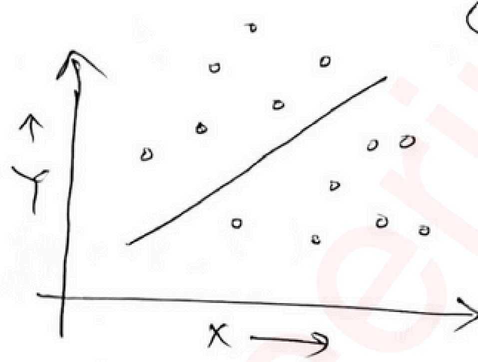
↓

Cost function.

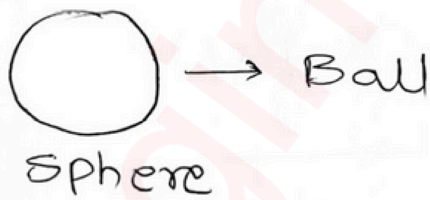
$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_p)^2$$

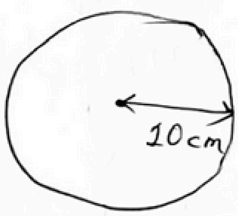
Overfitting & Underfitting



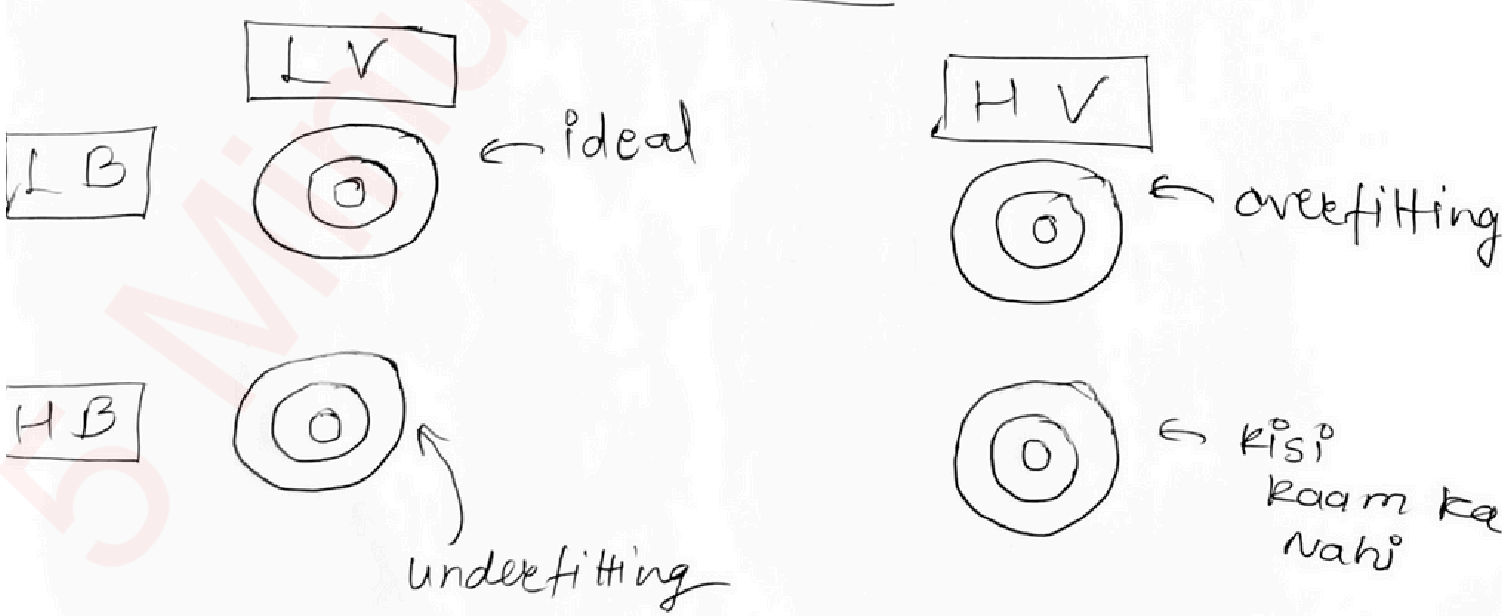


- Sphere
- Play
- Eat
- Radius = 5cm





Bias & Variance



- **Confusion Matrix:**

Predicted

Actual

165	NO	Yes	
NO	50 [TN]	10 [FP]	60
Yes	5 [FN]	100 [TP]	105
	55	110	

- **Accuracy** = $\frac{TP + TN}{TN + TP + FN + FP} = \frac{100 + 50}{165}$

$= 0.91$

- **Error**: $1 - \text{Accuracy}$

or

$\frac{FP + FN}{\text{Total}} = 0.09$

- **Precision**: $\frac{TP}{TP + FP} = \frac{100}{110} = 0.909$

- **Recall**: $\frac{TP}{\text{Actual Yes}} = \frac{TP}{TP + FN} = \frac{100}{105}$

$= 0.95$

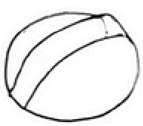
Curse of Dimensionality

M1	M2	M3	m4	M5	M6	M7
2	4	8	10	12	100	1000

ATE↓

Sphere Eatable Play Red

① 

② 

F1 score

TP = 50
FP = 10
TN = 10
FN = 30
P = 0.83
R = 0.62

(P) \ (A)	+	−
+	TP	FP
−	FN	TN

$$P = \frac{TP}{TP+FP}$$

$$R = \frac{TP}{TP+FN}$$

$\boxed{1, 2, 3, 4, 5}$

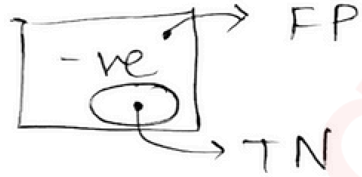
$$\rightarrow HM = \frac{5}{\frac{1}{1}+\frac{1}{2}+\frac{1}{3}+\frac{1}{4}+\frac{1}{5}}$$

$$\rightarrow f1score = \frac{2}{\frac{1}{P}+\frac{1}{R}} = \frac{2 \times P \times R}{P+R}$$

$$= TP / TP + \frac{1}{2}(FP+FN)$$

$\rightarrow \boxed{0.70}$

- Specificity $= \dfrac{TN}{TN + FP}$

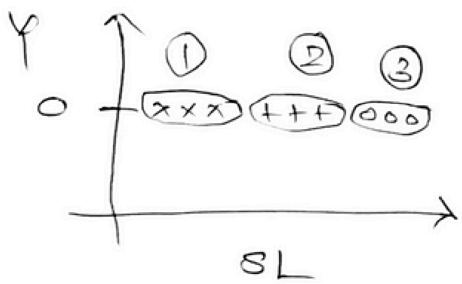


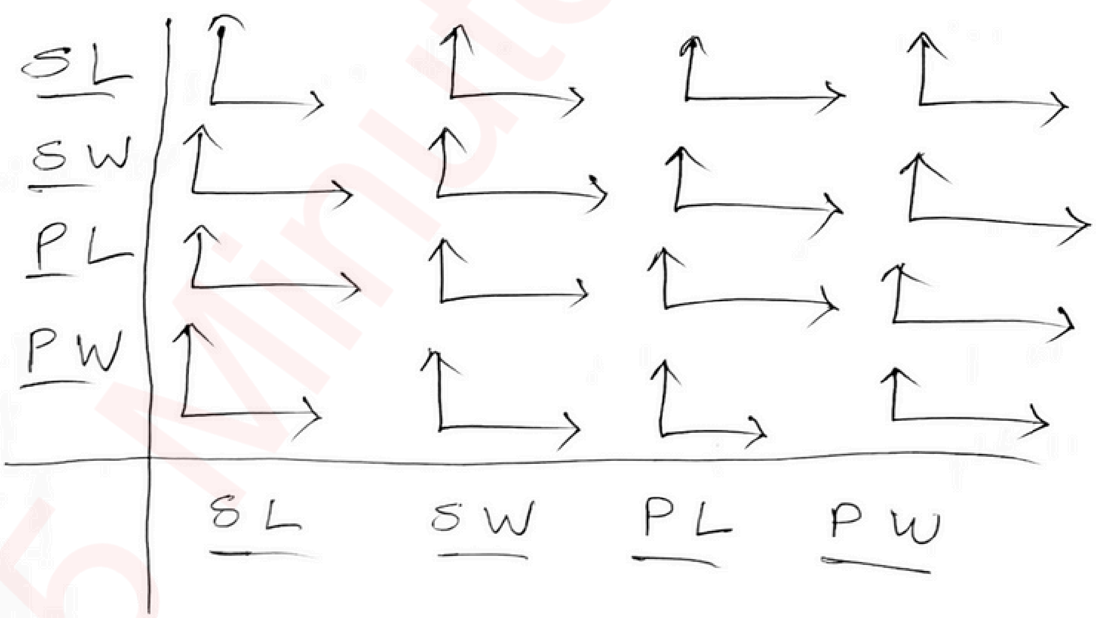
- Sensitivity = Recall $= \dfrac{TP}{TP + FN}$

* Uni, Bi, Multi
Variate Analysis

SL SW PL PW

- setosa
- versicolor
- virginica





- Preprocessing

① Normalization [MinMax Scaler]

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \{0 - 1\}$$

② Standardization [Standard Scaler]

($\mu \to 0$ & $\sigma \to 1$)

$$x' = \frac{x - \mu}{\sigma}$$

③ Robust Scaler

→ IQR (Interquartile Range)

⇒ 10, 20, 30, 30, 45, 50, 55, 60, 70, 80

1st Quartile = 25% P = 30

2nd Quartile = 50% P = 47.5

3rd Quartile = 75% P = 58.75

4rd Quartile = 100% P = 80

$$x' = \frac{x - x_{med}}{Q_3 - Q_1}$$

(4) Label Encoding

eg:-

f	
Pune →	0
Goa →	1
Mumbai →	2
Pune →	0
Punjab →	3
Goa →	2

Pune → 0
Goa → 1
Mumbai → 2
Punjab → 3

(5) One hot encoding

eg:

f	Pune	Goa	Mumbai	Punjab
Pune →	1	0	0	0
Goa →	0	1	0	0
Mumbai →	0	0	1	0
Pune →	1	0	0	0
Punjab →	0	0	0	1
Goa →	0	1	0	0

ML

- Supervised
  - Classification
    - Decision Tree
    - Logistic Reg.
    - Naive Bayes
    - SVM
    - Random forest
    - KNN
  - Regression
    - Linear Reg.
    - Polynomial
    - Ridge & Lasso
    - Decision Tree
    - Random Forest
    - SVM Reg.
- Unsupervised
  - Clustering
    - Kmeans
    - Hierarchical
    - DBSCAN
- Reinforcement
  - Decision Making
    - Q Learning

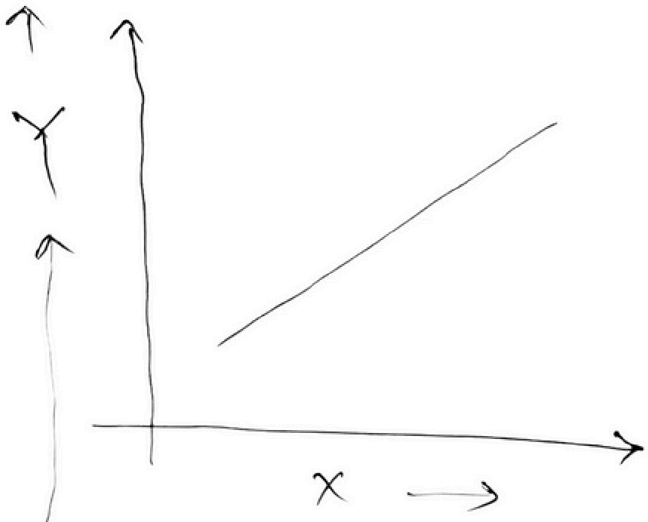
* Regression:

- → Continuous data
- → Relationship betn Independent & dependent variables

① Linear regression

- → Simple (1 IV)
- → Multiple (>1 IV)

Simple Linear Regression :



$$\Rightarrow \quad y = mx + c$$

$$\downarrow$$

$$y_p = b_0 + b_1 X$$

$$\uparrow$$

1 IV

eg:- Marks = $b_0 + b_1$(Hours)

Multiple Linear Regression

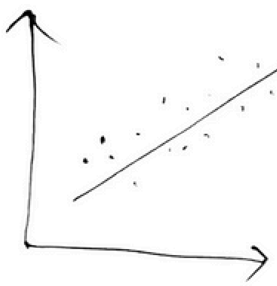
x1	x2	x3	y

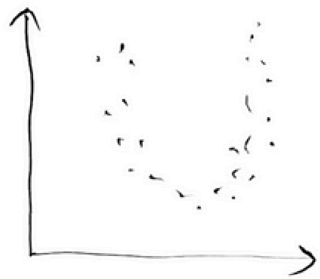
$\rightarrow$

Hours	Attend.	Assig.	Marks

Marks = $b_0 + b_1$(Hours) + b_2(Attendance) + b_3(Assignment)

Polynomial Regression





$y = b_0 + b_1 x 1$

$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4$

$y = \alpha_0 + \sum_{i=1}^{m} b_i x_i$

0 degree poly : $y =$ constant

1 degree poly : $y = mx^1 + c$

2 degree poly : $y = ax^2 + bx + c$

$y = b_0 + b_1 x + b_2 x^2 + b_3 x^3 + \cdots + b_n x^n$

$$\boxed{y = b_0 + \sum_{i=1}^{m} b_i x_i + \boxed{f_p}}$$

polynomial feature

- **Ridge Regression** ← **Regularization** → **Lasso Regression**

$$RR = Loss + \alpha \|W\|^2$$

(penalty)

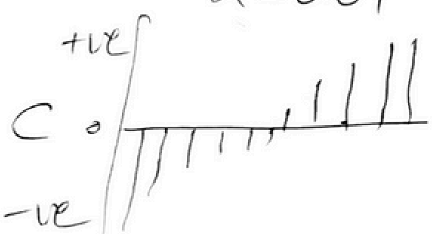
$$LR = Loss + \alpha \|W\|$$

absolute value.

(can be zero)

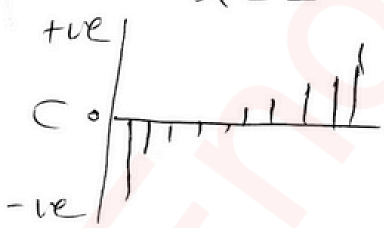
$$\|W\|^2 = W_1^2 + W_2^2 + W_3^2 + W_4^2 + \cdots W_n^2$$

$\alpha = 0.01$



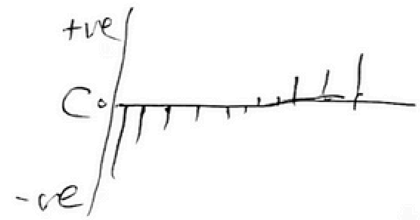
✓

$\alpha = 1$



✓

$\alpha = 2$



✓

$$y = 0.9 + 1.2x_1 + 20x_2 + 39x_3$$

$$\Downarrow$$

$$y = 0.9 + 0.7x_1 + 2x_2 + 5x_3$$

- **ElasticNet Regression** (Hybrid)

$$RR = Loss + \alpha \|W\|^2$$

$$LR = Loss + \alpha \|W\|$$

$$ER = Loss + \alpha_1 \|W\|^2 + \alpha_2 \|W\|$$

(multicollinearity) RR

(feature selection) LR

- Decision Tree, SVM, KNN, Random forest

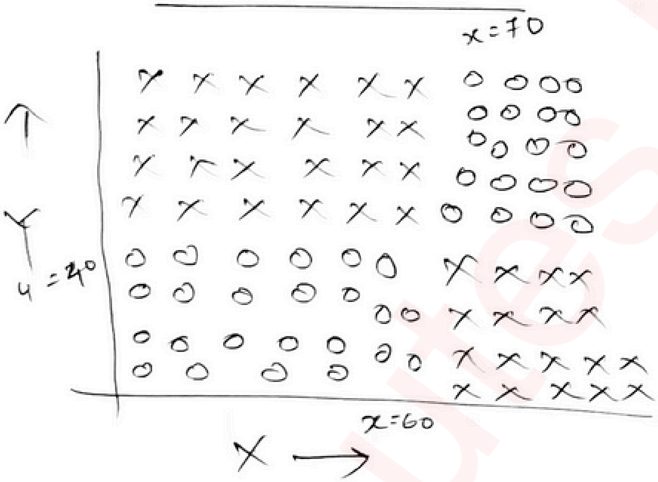
Regression — y — Continuous

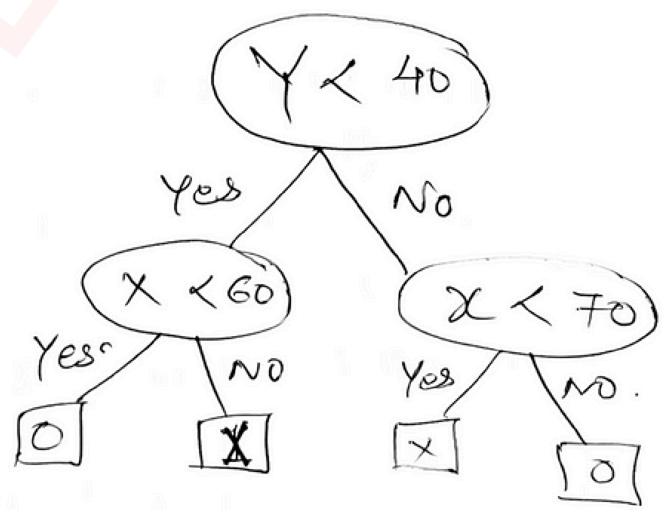
(Mean/Average)

Classification — y — Categorical

(Majority)*

* Decision Tree





$$\text{Entropy}(E) = -P(+)\log_2 P(+) - P(-)\log_2 P(-)$$

$P(+)$: Probability of +ve class

$P(-)$: Probability of -ve class.

eg:

5(1), 2(0) → 5(1), 2(0)

$$\Rightarrow -\left(\frac{5}{7}\right)\log_2\left(\frac{5}{7}\right) - \left(\frac{2}{7}\right)\log_2\left(\frac{2}{7}\right)$$

$$\Rightarrow 0.85$$

eg:- 2 features

- (SME): Y, N
- (book): Y, N

P : 16
F : 14

① SME

P : 16, F : 14 → $E(\text{Parent}) = -\left(\frac{16}{30}\right)\log_2\left(\frac{16}{30}\right) - \left(\frac{14}{30}\right)\log_2\left(\frac{14}{30}\right)$

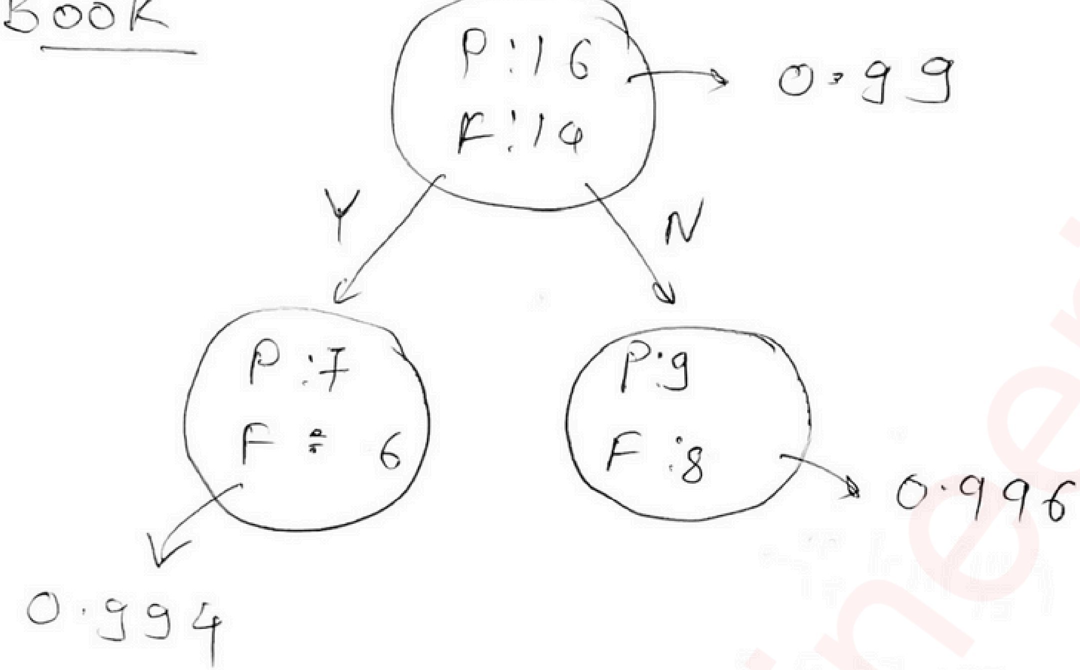
$= 0.99$

- Y → P : 12, F : 1 → 0.39
- N → P : 4, F : 13 → 0.79

$$\Rightarrow \frac{13}{30} \times 0.39 + \frac{17}{30} \times 0.79 = 0.62$$

$$\therefore 0.99 - 0.62 = \underline{0.37} \rightarrow IG.$$

② Book



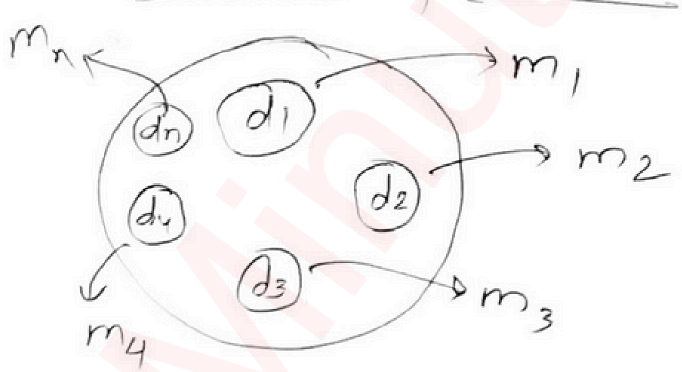
$$\Rightarrow \frac{13}{30} \times 0.994 + \frac{17}{30} \times 0.996$$

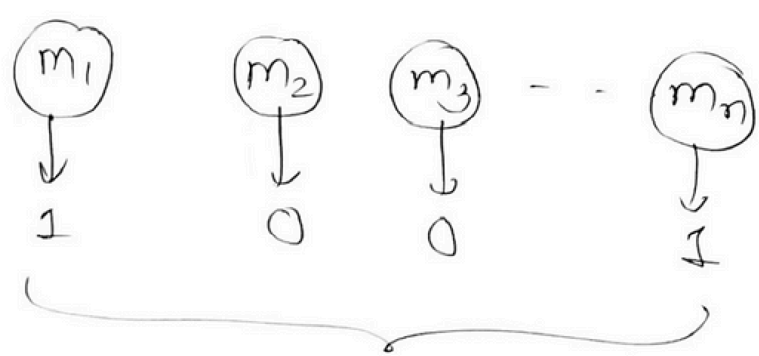
$$\Rightarrow 0.99$$

$$\rightarrow \quad 0.99 - 0.99 = 0.00 \rightarrow IG$$

$$\boxed{0.37 > 0.00}$$

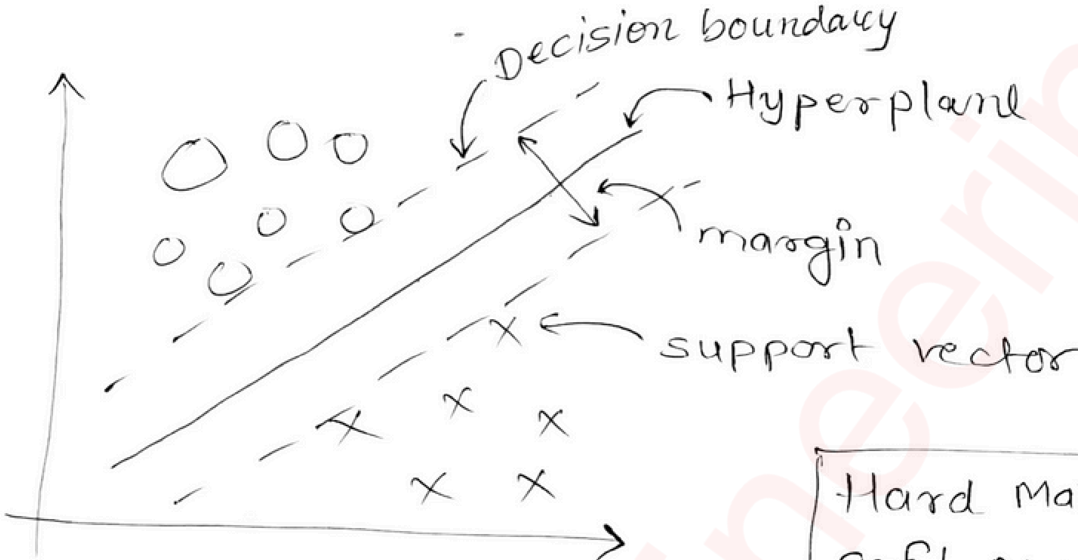
→ Random forest





Majority wins.

- SVM : Support Vector Machine



Hard Margin
Soft Margin

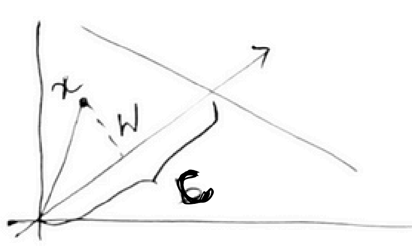
⇒ Binary classification

+1   −1

Hyperplane eqⁿ = $w^T x + b = 0$
(H)

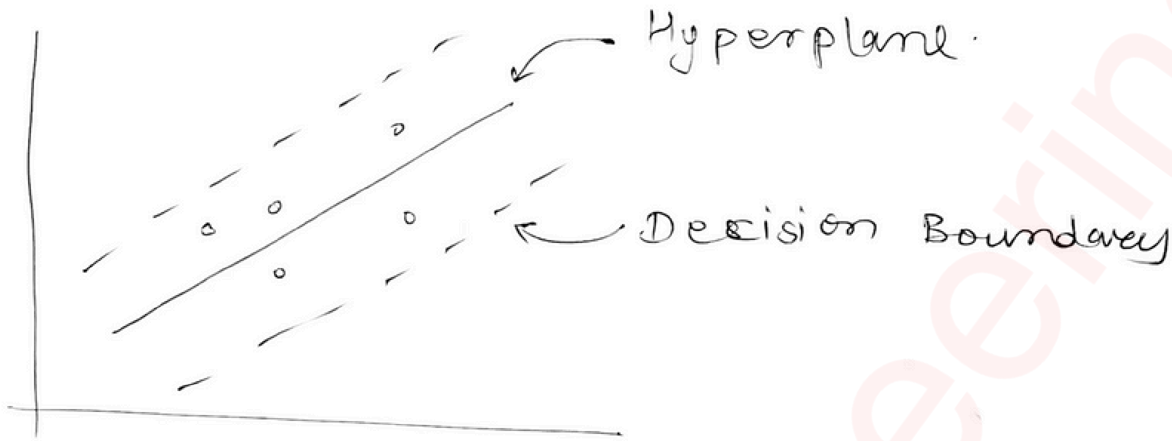
Normal vector to hyperplane.
(direction ⊥)

Linear SVM : $y_p = \begin{cases} +1 & : w^T x + b \geq 0 \\ -1 & : w^T x + b < 0 \end{cases}$



$\vec{x} \cdot \vec{w} = c$ (on H)
$\vec{x} \cdot \vec{w} > c$ (+ve)
$\vec{x} \cdot \vec{w} < c$ (−ve)

SVR (Regression)



→ Best hyperplane that has max number of points.

eqn of (H)

↳ $Y = wx + b$

eqn of DB

↳ $wx + b = +a$

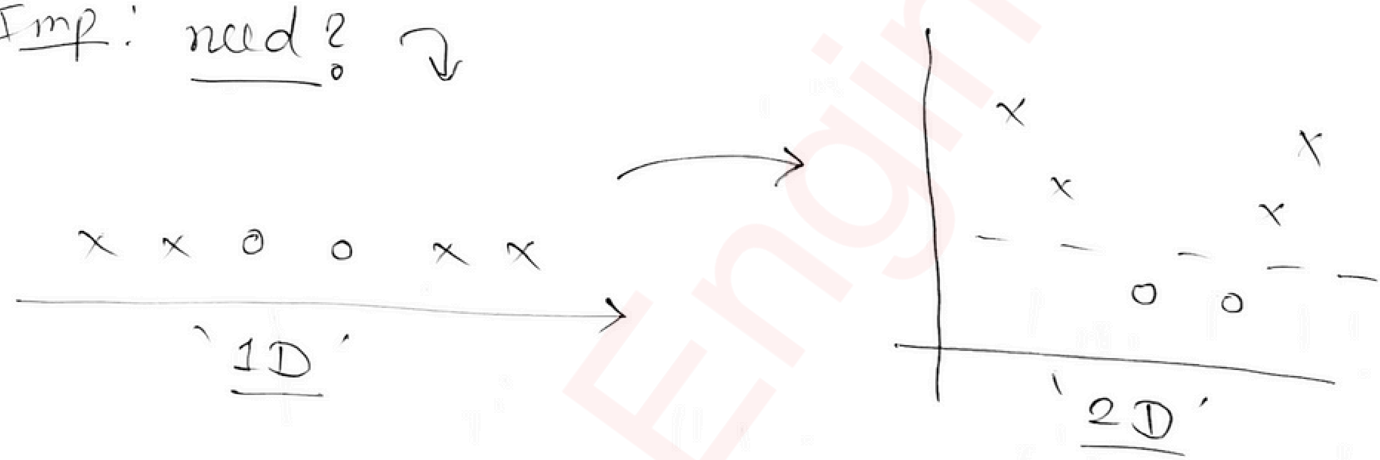
$wx + b = -a$

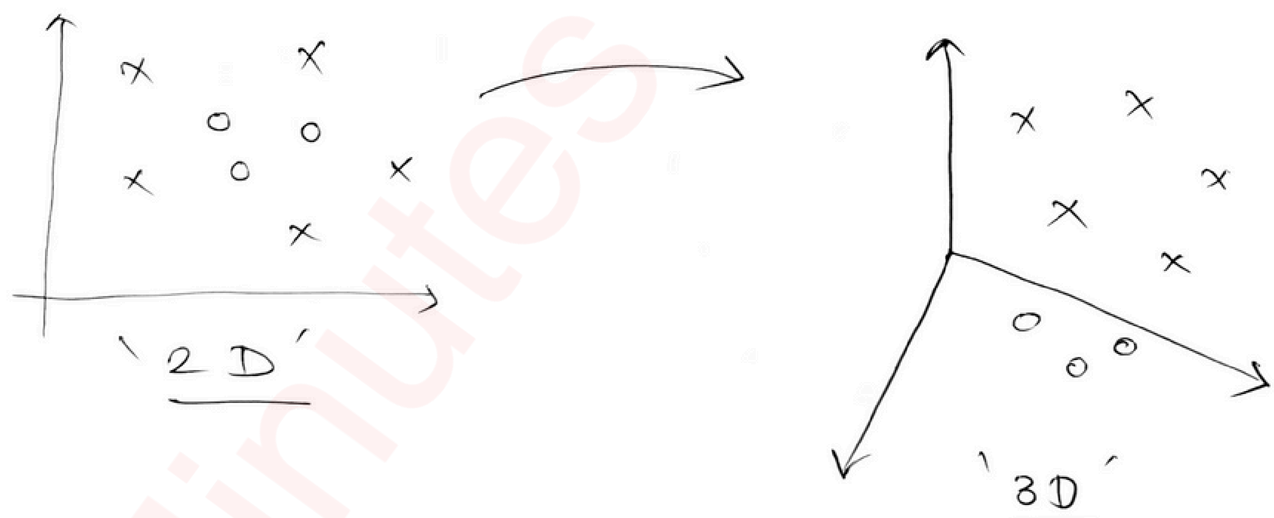
Range: → $-a < Y - wx + b < +a$

- SVM kernel function:
  - → Higher 'D' $\xleftarrow{\text{To}}$ Lower 'D'

→ Linear
→ polynomial
→ RBF

Imp: need?





Linear kernel

→ $k(x, x') = x \cdot x'$ $\quad [f(x) = x]$

Polynomial kernel

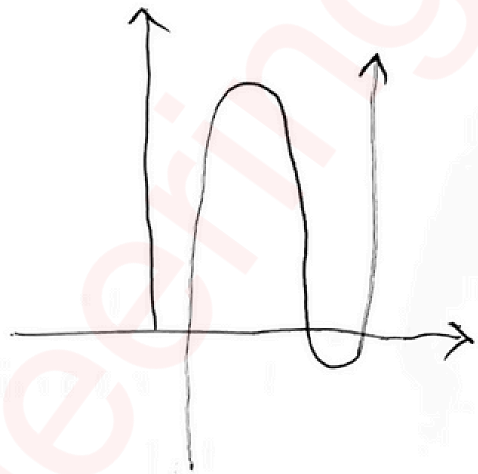
→ $k(x, x') = (1 + x^T x')^D$

$$f(x_1, x_2) = (1 + x_1^T \cdot x_2)^{D=2}$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \cdot \begin{bmatrix} x_1 & x_2 \end{bmatrix}$$

$$\Downarrow$$

$$\begin{bmatrix} x_1^2 & x_1 \cdot x_2 \\ x_1 \cdot x_2 & x_2^2 \end{bmatrix}$$



$\Rightarrow \quad x_1, \; x_2, \; x_1^2, \; x_2^2, \; x_1 \cdot x_2$

RBF kernel

"$(x_2 \mid y)$"

$$K(x, x') = e^{-\gamma \|x - x'\|^2}$$

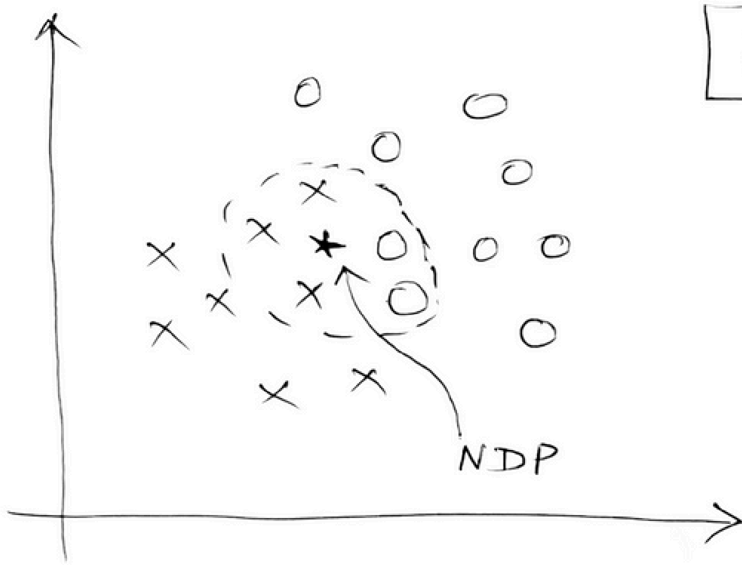
Euclidean (d) distance betn (x_1, x_2) or (x, x').

$$\gamma = \frac{1}{2\sigma^2}$$

$$= e^{-d\gamma}$$

KNN (K-nearest neighbors).

$\boxed{k=5}$

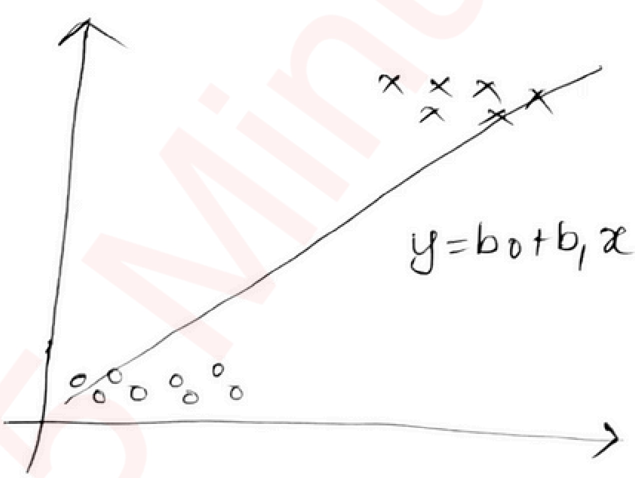


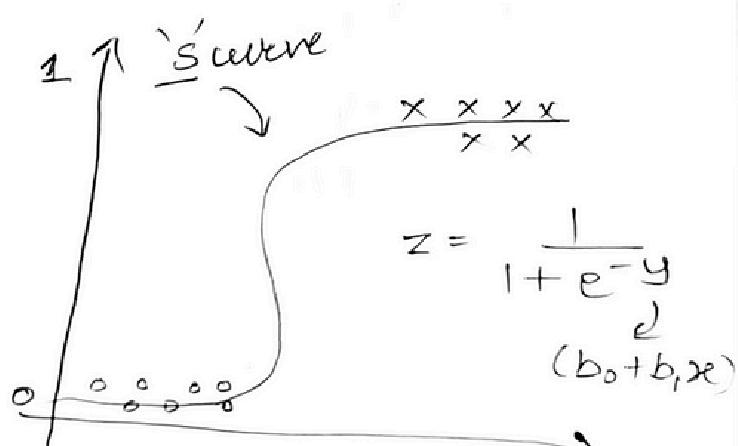
Classification (Majority)

Regression (Average/mean).

$$\frac{y_1 + y_2 + y_3 + y_4 + y_5}{K=5} = y_{avg}$$

Logistic Regression

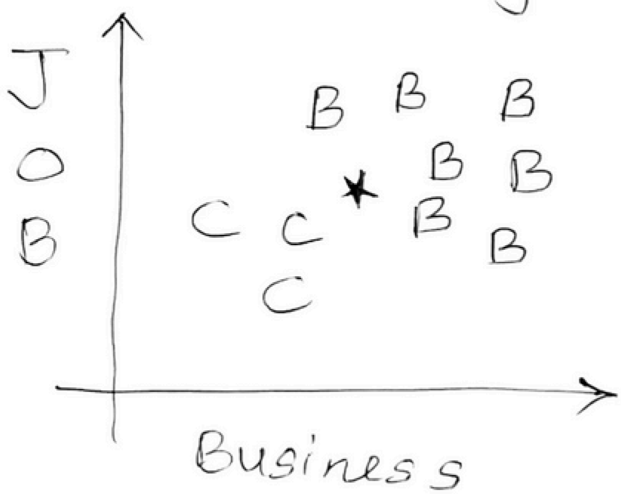




$$z = \frac{1}{1+e^{-y}}$$

$y = (b_0 + b_1 x)$

Naive Bayes



B : Bike
C : Car

✓ $P(A/B) = \dfrac{P(B/A) \cdot P(A)}{P(B)}$ ← Bayes theorem.

✓ $P(y/x) = \dfrac{P(x/y) \cdot P(y)}{P(x)}$

✓ $P(y \mid x_1, x_2, x_3 \ldots x_n) =$

$$\frac{P(x_1/y) \times P(x_2/y) \times \ldots P(x_n/y) \times P(y)}{P(x_1) \times P(x_2) \times \ldots P(x_n)}.$$

$x_1 \rightarrow$ Yes, No

$x_2 \rightarrow$ Yes, No

$y \rightarrow$ Bike, Car.

$P(\text{Car}) = \frac{3}{10} = 0.3$

$P(\text{Bike}) = \frac{7}{10} = 0.7$

$$P(\text{Car} / J, B) = \frac{P(J/\text{Car}) \times P(B/\text{Car}) \times P(\text{Car})}{P(J) \times P(B)}$$

$$= 1/3 \times 2/3 \times 3/10$$

$$= 2/30 = 0.066$$

$$P(\text{Bike} / J, B) = \frac{P(J/\text{Bike}) \times P(B/\text{Bike}) \times P(\text{Bike})}{P(J) \times P(B)}$$

$$= 2/7 \times 5/7 \times 7/10$$

$$= 0.142$$

- Gaussian NB

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

5MF → Yes [80, 70, 90, 75, 70, 86, 96, 80, 65]

5MF → NO [70, 90, 91, 95, 85]

$\mu(Y) \rightarrow 79.1$ $\qquad \sigma(Y) \rightarrow 10.2$

$\mu(N) \rightarrow 86.2$ $\qquad \sigma(N) \rightarrow 9.7$

$P(Marks = 74 \mid SME = Y)$

$$= \frac{1}{\sqrt{2\pi}(10.2)} e^{-\frac{(74-79.1)^2}{2(10.2)^2}}$$

$$= \underline{0.034}$$

$P(Marks = 74 \mid SME = N)$

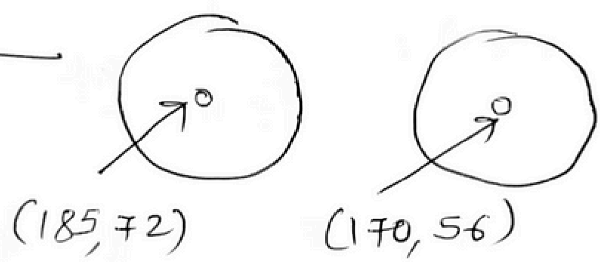
$$= \frac{1}{\sqrt{2\pi}(9.7)} e^{-\frac{(74-86.2)^2}{2(9.7)^2}}$$

$$= 0.018$$

* Unsupervised Learning:

(1) K means:

	Height	Weight
1	185	72
2	170	56
3	168	60
4	179	68
5	182	72
6	188	77
7	180	71
8	180	70
9	183	84
10	180	88
11	180	67
12	177	76



$$ED = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

ED for ③ :-

$$k1 \rightarrow \sqrt{(168-185)^2 + (60-72)^2}$$

$$d1 \rightarrow 20.80$$

$$k2 \rightarrow \sqrt{(168-170)^2 + (60-56)^2}$$

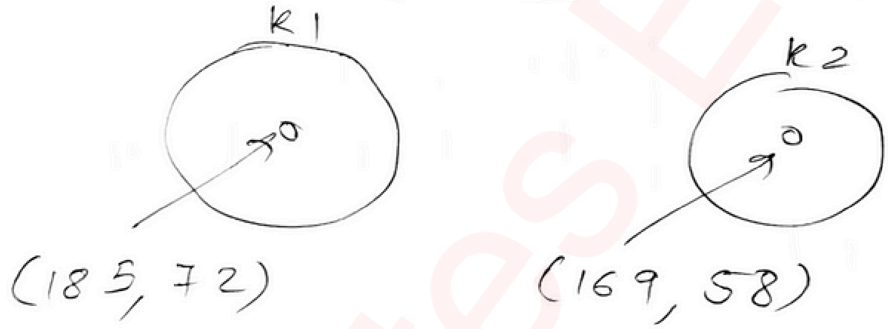
$$d2 \rightarrow 4.48$$

$$d_2 < d_1$$

$$③ \longrightarrow k_2 \checkmark$$

New centroid calculation:

$$\text{for } k_2 = \left(\frac{170+168}{2}, \frac{60+56}{2}\right) = (169, 58)$$



$$\text{ED for } k1 \rightarrow \sqrt{(179-185)^2 + (68-72)^2}$$

$$d_1 \rightarrow 7.21$$

$$\text{for } k2 \rightarrow \sqrt{(179-169)^2 + (68-58)^2}$$

$$d_2 \rightarrow 14.14$$

Ans :- $k1 \longrightarrow \{1, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$

$k2 \longrightarrow \{2, 3\}$

② k medoids clustering

	X	Y	K1	K2	Cost	K1	K2	Cost
①	8	2	0	6	0	0	2	2
②	3	5	8	2	2	8	6	6
③	4	7	9	3	3	9	7	7
④	8	4	2	4	2	2	0	2
⑤	5	5	6	0	0	6	4	4
					7			21

$\Rightarrow |x_2 - x_1| + |y_2 - y_1|$

$= |5-8| + |5-2|$

$= 3 + 3 = 6$

$\Rightarrow |3-8| + |5-2|$

$= 5 + 3 = 8$

$\Rightarrow |3-5| + |5-5|$

$= 2$

$\Rightarrow |4-8| + |7-2|$

$= 4 + 5 = 9$

$\Rightarrow |4-5| + |7-5|$

$\Rightarrow 1 + 2 = 3$

$\Rightarrow |8-8| + |4-2| = 2$

$\Rightarrow |8-5| + |4-5| = 4$

$\rightarrow |8-8| + |4-2| = 2$

$\rightarrow |3-8| + |5-2| = 8$

$\rightarrow |3-8| + |5-4| = 6$

$\rightarrow |4-8| + |4-7| = 7$

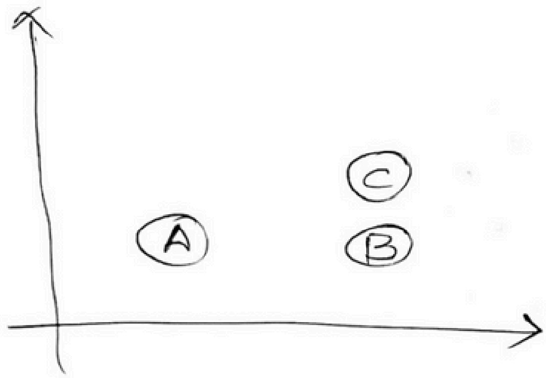
$\rightarrow |5-8| + |4-5| = 4$

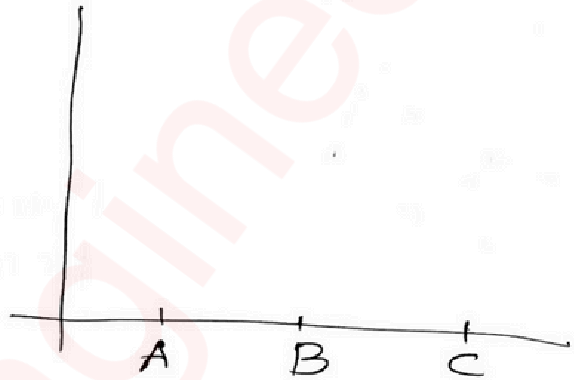
③ Hierarchical clustering:

→ Agglomerative

→ Divisive

* Dendrogram.

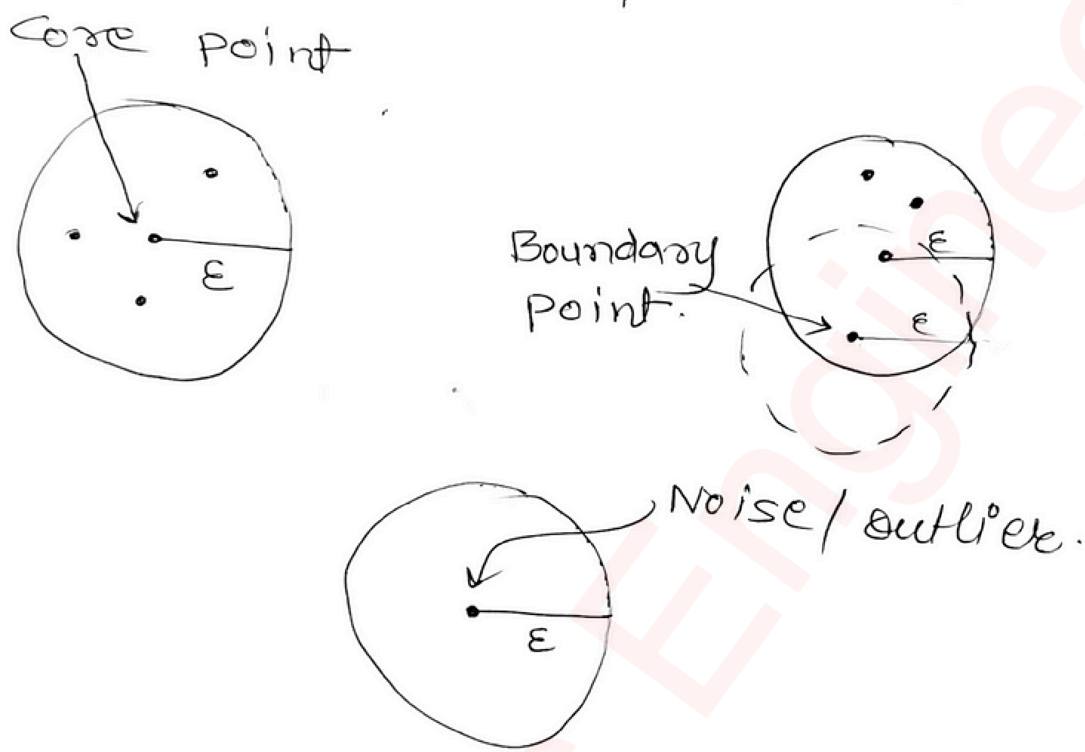




④ DBSCAN

↳ Density Based spatial clustering of Applications with Noise.

'ε' & 'minpoint'



⑤ PCA (Principal Component Analysis)

↳ Dimension Reduction Techniques

Steps:

1. $D+1 \longrightarrow D$
2. Compute μ for every D.
3. Calculate Covariance matrix.
4. Calculate eigen value & eigen vector.
5. Top k - eigen values.
6. $(\text{feature vector})^T \times (\text{Original Dataset})^T = \text{New data.}$

Eg:

X	Y
2.5	2.4
0.5	0.7
2.2	2.9
1.9	2.2
3.1	3.0
2.3	2.7
2	1.6
1	1.1
1.5	1.6
1.1	0.9
$\bar{X} = 1.81$	$\bar{Y} = 1.91$

$$Cov(x, y) = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{x})}{n-1}$$

$$C = \begin{bmatrix} Cov(x,x) & Cov(x,y) \\ Cov(y,x) & Cov(y,y) \end{bmatrix}$$

$\Rightarrow$

X	$X - \bar{X}$	$(X - \bar{X})(X - \bar{X})$
2.5	0.6	0.476
0.5	-1.31	1.716

Sum = 5.5490

$\Rightarrow$

Y	$Y - \bar{Y}$	$(Y - \bar{Y})(Y - \bar{Y})$
2.4	0.49	0.2401
0.7	-1.21	1.4641

Sum = 6.449

$\Rightarrow$

X	Y	$X - \bar{X}$	$Y - \bar{Y}$	$(X - \bar{X})(Y - \bar{Y})$
2.5	2.4	0.69	0.49	0.3381
0.5	0.7	-1.31	-1.21	1.5851

sum = 5.5390

$$C = \begin{bmatrix} 0.6165 & 0.6154 \\ 0.6154 & 0.7165 \end{bmatrix}$$

$$\Rightarrow \quad C - \lambda I = 0$$

$$\begin{bmatrix} 0.6165 & 0.6154 \\ 0.6154 & 0.7165 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = 0$$

$$\begin{bmatrix} 0.6165 - \lambda & 0.6154 \\ 0.6154 & 0.7165 - \lambda \end{bmatrix}$$

$$\Rightarrow \quad \lambda^2 - 1.333\lambda + 0.0630 = 0$$

$$\lambda_1 = 0.0490$$

$$\lambda_2 = 1.2840$$

$$\Rightarrow \quad C\vec{v} = \lambda \vec{v}$$

$$\begin{bmatrix} 0.6165 & 0.6154 \\ 0.6154 & 0.7164 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = 0.0490 \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

$$\Rightarrow 0.6165\,x_1 + 0.6154\,y_1 = 0.0490\,x_1$$

$$\Rightarrow 0.6154\,x_1 + 0.7165\,y_1 = 0.0490\,y_1$$

$$\Rightarrow \quad 0.5674\,x_1 = -0.6154\,y_1$$

$$\Rightarrow \quad 0.6154\,x_1 = -0.6674\,y_1$$

$$\rightarrow \quad x_1 = -1.0845\,y_1$$

$$\begin{bmatrix} -1.0845 \\ 1 \end{bmatrix} = \frac{1.17614 + 1}{\sqrt{2.17614}} = 1.47517$$

$$\Rightarrow \begin{bmatrix} -0.7351 \\ 0.6778 \end{bmatrix} \leftarrow v_1$$

<u>then</u>, $x_2 = 0.92194\ y_2$

$$\rightarrow \begin{bmatrix} 0.92194 \\ 1 \end{bmatrix} = 0.8499 + 1$$

$$= \sqrt{1.8499}$$

$$= 1.3601$$

$$\Rightarrow \begin{bmatrix} 0.6778 \\ 0.7351 \end{bmatrix} \leftarrow v_2$$

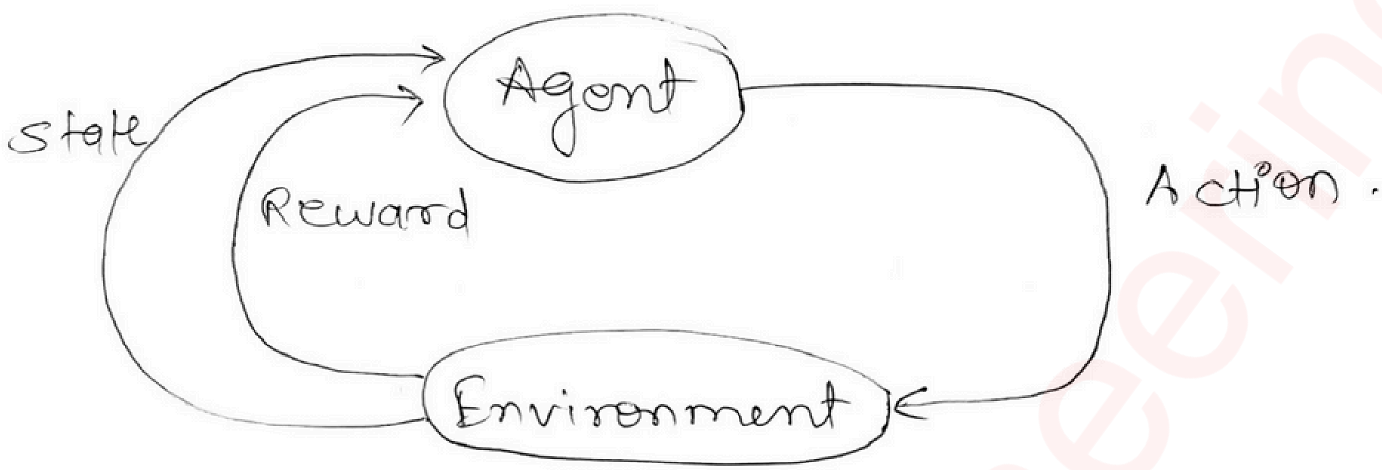
$\Rightarrow$ Sum of λ_1 & λ_2 $= 1.2840 + 0.0490$

$= 1.33$

$$\lambda_1 > \lambda_2$$

So, $v_1 \rightarrow$ is our principal component.

* Reinforcement Learning:



Elements of RL
- → Policy
- → Reward fn
- → Value fn

① Policy: Defines agents behavious for a given state/time.

$$\text{state} \xrightarrow{\text{mapping}} \text{Action}$$

② Reward f^n: It provides a numerical score based on state of environment

③ value f^n: value of state is total amount of reward an agent can expect to gain over the future starting from that particular state.

① Q Learning

- → Initialize Q-table
- → Choose an action
- → Perform action
- → Measure reward
- → Update Q-table

① Initialize Q table

↳ It's a simple lookup table where we calculate max. expected future rewards for action at each state.

Actions: ↑ → ↓ ←

	↑	→	↓	←
S	0	0	0	0
B	0	0	0	0
H	0	0	0	0
E	0	0	0	0

Rows :- no. of states
Column: no. of actions

Start, Blank, Hole, End

② choose an action:

S			
	H		H
			H
H			E

'→' or '↓'

③ Perform '↓'

Rewards → Reaching goal = 1
Hole = 0
Blank = 0

- Update Q table
  - ↳ using Q function
    - ↳ uses Bellman eqn.

⇓

$$\underbrace{NQ(s,a)}_{\text{New Q value}} = \underbrace{Q(s,a)}_{\text{Current Q value}} + \underbrace{\alpha}_{\text{Learning Rate}} \Big[\underbrace{R(s,a)}_{\text{Reward for taking 'a' at 's'}} + \underbrace{\gamma}_{\text{Discount Rate.}} \underbrace{\max Q'(s',a')}_{\text{Max future reward.}} - Q(s,a)\Big]$$

* Ensemble Learning

- → Bagging (Random forest)
- → Boosting
  - → Ada Boost
  - → Gradient boosting.

◦ Boosting:

weak learners.

$$D \rightarrow M_1 \rightarrow M_2 \rightarrow M_3 \dashrightarrow M_n \rightarrow y$$

Sequence

not parallel.

$$\alpha_1 M_1 + \alpha_2 M_2 + \alpha_3 M_3 - - - + \alpha_n M_n$$

$\alpha \rightarrow$ weights / Importance / Influence.

1. Dataset:

1	1/5
2	1/5
3	1/5
4	1/5
5	1/5

} equal sample weight.

2. Get the best model.

→ DT (Highest IG)

3. Calculate the 'α'

→ $\frac{1}{2} \log \frac{1 - TE}{TE}$ ← Miss-classified.

Performance $= \frac{1}{2} \log \frac{1 - TE}{TE}$

$$\alpha = \frac{1}{2} \log \frac{1 - 1/5}{1/5}$$

$$\boxed{\alpha = 0.69}$$

4. New SW

	SW	NSW	NNSW
1	1/5	0.10	0.126
2	1/5	0.10	0.126
3	1/5	0.39	0.493
4	1/5	0.10	0.126
5	1/5	0.10	0.126
		0.79	→ 0.997

$$NSW = OW * e^{\pm\alpha}$$

'−' → correct

'+' → wrong

$$\underset{\text{(correct)}}{NSW} = \frac{1}{5} * e^{-0.69} = 0.1004$$

$$\underset{\text{(wrong)}}{NSW} = \frac{1}{5} * e^{+0.69} = 0.3988$$

5 Bins / Bucket

	NNSW	Bins
1	0.126	0 − 0.126
2	0.126	0.126 − 0.252
3	0.493	0.252 − 0.745
4	0.126	0.745 − 0.871
5	0.126	0.871 − 0.997

6 Random selection (0 − 1)

→ 0.011 → 1

→ 0.33 → 3

→ 0.45 → 3

→ 0.60 → 3

→ 0.90 → 5

$\left.\begin{matrix}0.33 \\ 0.45 \\ 0.60\end{matrix}\right\}$ 3 times.

→

1
3
5

New dataset → M_2

Voting classifier

→ Hard voting

Test → C_1, C_2, C_3, C_4, C_5

C_1	C_2	C_3	C_4	C_5
1	1	0	1	1

Prediction → '1' (Majority

→ soft voting

Test → C_1, C_2, C_3

C_1		C_2		C_3	
0.9	0.1	0.8	0.2	0.4	0.6
(1)	(0)	(1)	(0)	(1)	(0)

$$(1) = \frac{0.9 + 0.8 + 0.4}{3} = 0.7 \checkmark$$

$$(0) = \frac{0.1 + 0.2 + 0.6}{3} = 0.3$$

Gradient Boosting

Age	Income	P1	E1	P2	E2
20	10k	20k	-10k	19.9k	-9.9k
30	30k	20k	10k	20.1k	9.9k
35	40k	20k	20k	20.2k	19.8k
25	15k	20k	-5k	19.95k	-4.95k
50	5k	20k	-15k	19.85k	-14.85k

$\mu = 20k$

① Base Model Prediction = 20k.

② Train DT on (Age, E1)

$$I/p \rightarrow \text{BM} \rightarrow \underset{(x,\ E1)}{\text{DT1}} \rightarrow O/p$$

for I/p

Age	E1
20	-10k

$= 20k + (-10k)$

$= 10k$

③ Introducing LR.

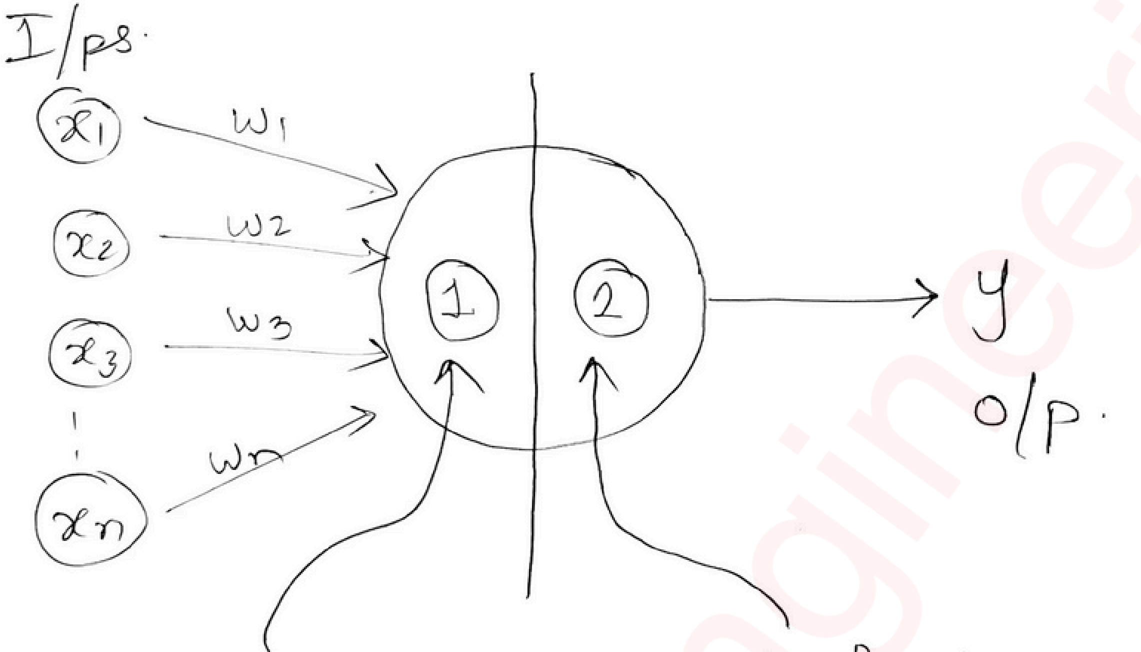
$\Rightarrow$ BMP + LR × DT1

$\Rightarrow$ 20k + (0.01) × (−10k) = 19.9k

Age	E1	P2
30	10k	20.1k
35	20k	20.2k
25	-5k	19.95k
50	-15k	19.85k

• Neural Network :

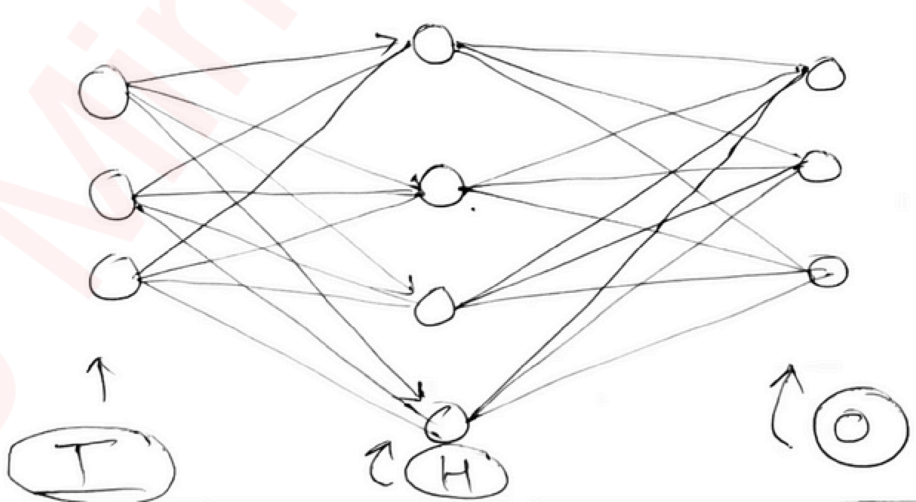
↳ mimic human brain



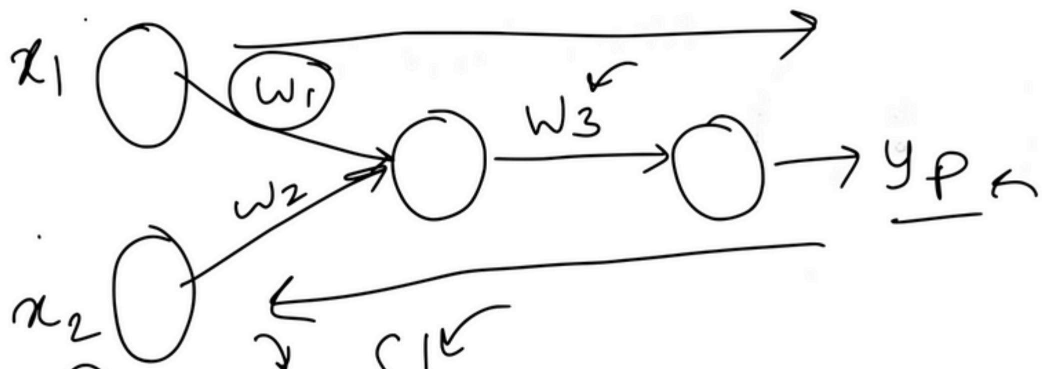
$Z = \sum_{i=1}^{n} x_i w_i + \text{bias}$ → Activation function

Layers :

- → Input
- → Hidden
- → Output.



$$L = (y - y_p)^2$$



$$W3_{new} = W3_{old} - LR \times \frac{\delta L}{\delta W3}$$

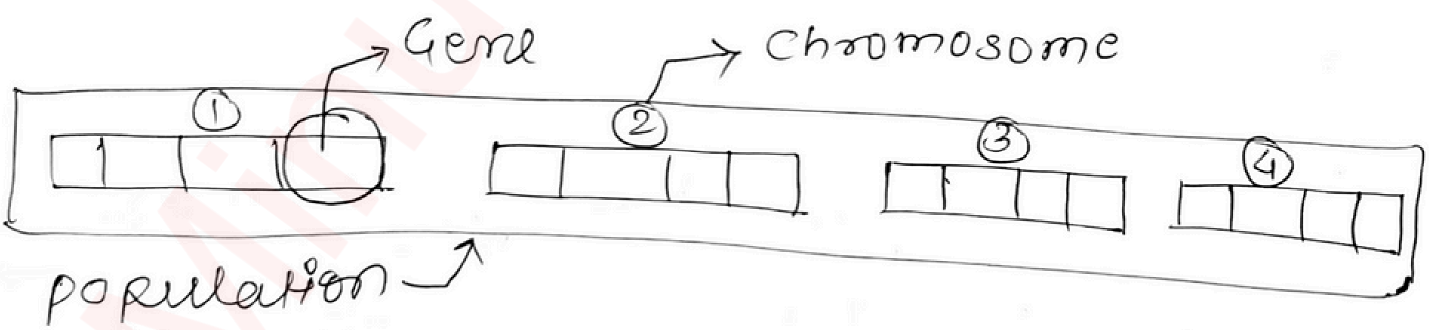
LR: (0.01)

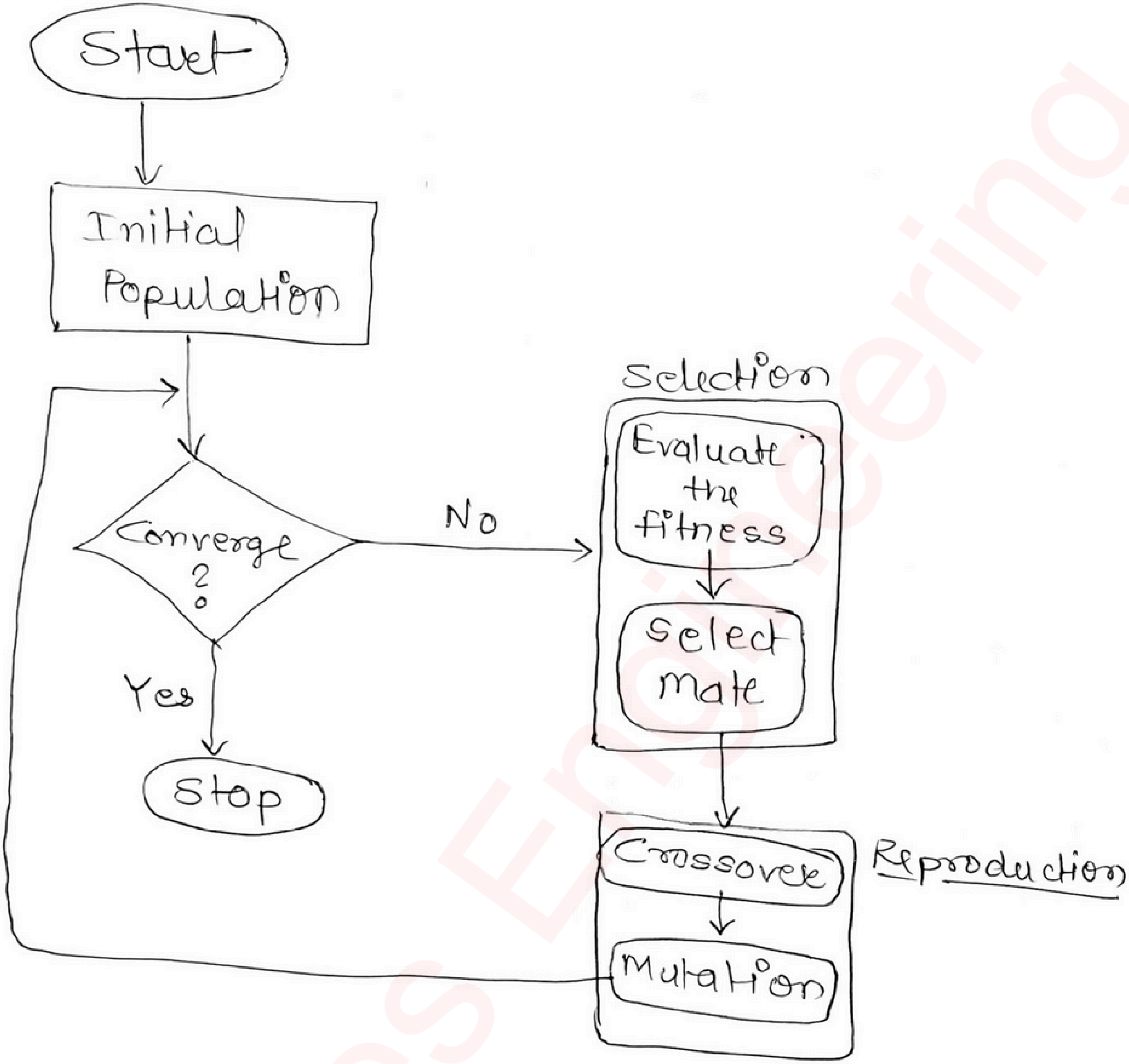
Types of NN

- FFN
- CNN
- RNN
- LSTM

- Genetic Algorithm
  - → Adaptive heuristic search algo. inspired by "DTOE". (Genetics & natural selection)
  - → To generate high Quality soln for optimization problem.
- → Terms
  - → Population
  - → Chromosomes
  - → Gene
  - → Allele
  - → fitness function
  - → Operator of GA
    - → selection
    - → crossover
    - → mutation

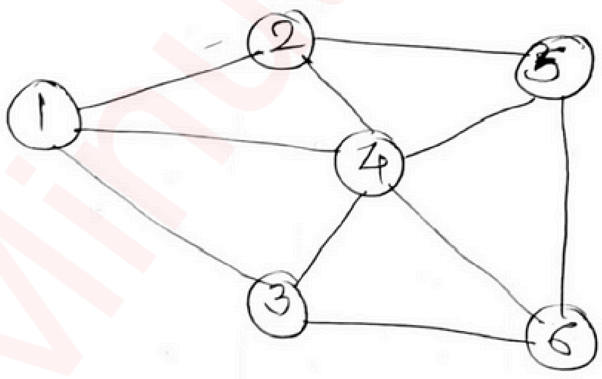
$$\begin{array}{c} \text{Phenotype} \\ \text{Decode} \uparrow \quad \downarrow \text{Encode} \\ \text{Genotype} \end{array}$$





fitness function :

eg:-



P1 : 1 2 5 6 4 3 2 1 → 18

P2 : 1 2 5 4 6 3 1 → 20

P3 : 1 2 4 5 6 3 1 → 12

P4 : 1 2 5 6 3 4 1 → 17

- ## Crossover

P1 :

0	1	1	0	1	0

P2 :

1	1	0	1	0	0

- **single point**

O1 : 0 1 0 1 0 0
O2 : 1 1 1 0 1 0

- **2 point**

O1 : 0 1 0 1 1 0
O2 : 1 1 1 0 0 0

- **Multipoint**

O1 : 1 1 0 1 1 0
O2 : 0 1 1 0 0 0

- ## Mutation

Offspring :

0	1	1	0	0	1

MP (Probability :

0	1	0	0	0	1

MO :

0	0	1	0	0	0

or Interchanging ⇒ 0 1 1 0 0 1
or Exchange.

0 0 1 0 1 1