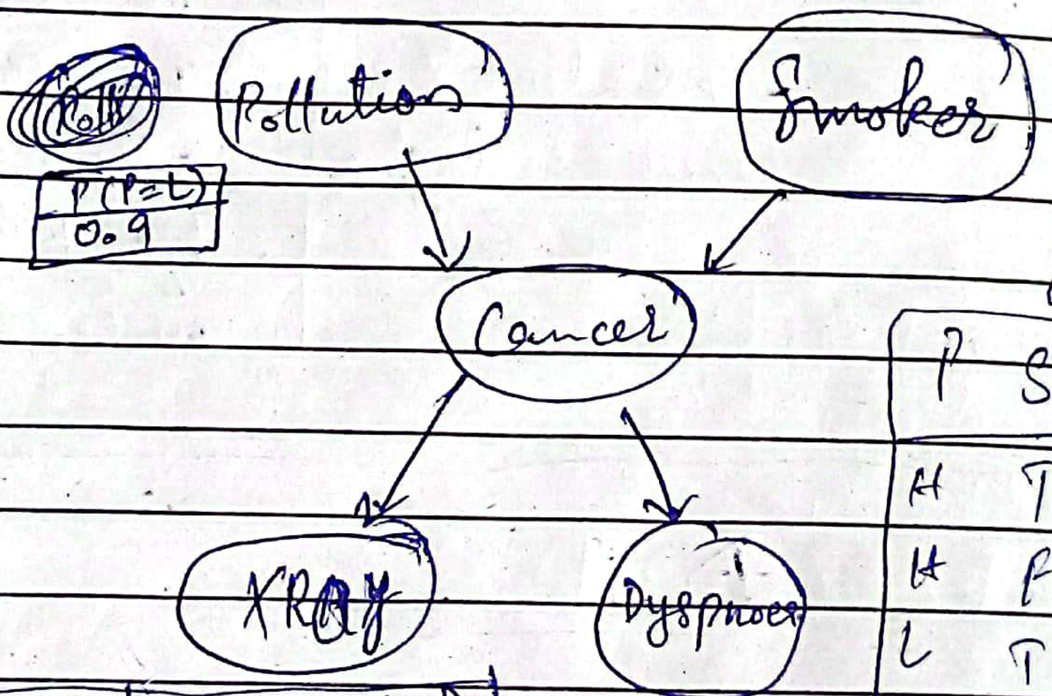
Bayesian Networks



P(P=L)
0.9

P(S=T)
0.3

P	S	P(C=T|P,S)
H	T	0.05
H	F	0.02
L	T	0.03
L	F	0.001

C	P(X=pos|C)
T	0.9
F	0.2

C	P(D=T|C)
T	0.65
F	0.30

Calculate: $P(\text{Cancer}) = 0.05 + 0.02 + 0.03 + 0.001$
$= 0.101$.

$\therefore P(A/B) = P(B|A)\,P(A)$

KNN :-

Q2

Signals	Distance	Power	Class
1	8	20	Normal
2	4	18	Normal
3	5	16	Abnormal
4	10	15	Normal
5	32	10	? ? $\rightarrow$ Abnormal.

$d_1 = \sqrt{(8-32)^2 + (20-10)^2} = 5.29$

$d_2 = \sqrt{(4-32)^2 + (18-10)^2} = 4.69$

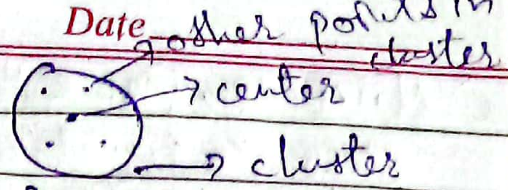
$d_3 = \sqrt{(5-32)^2 + (16-10)^2} = 4.58$

$d_4 = \sqrt{(10-32)^2 + (15-10)^2} = 5$

nearest, so class = Abnormal

A.I Final

Date



(1) K-Mean Clustering

Steps to solve numericals

(1) Choose as many points from given as many as you want clusters i.e., 3 clusters = choose 3 points from given points as centers for 3 clusters.

(2) Calculate distance $\{\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}\}$ of each point from the choosen centers, and cluster as per the lesser distance into clusters.

(3) Now, we have each point in a cluster. Take mean of each cluster by summing all x-values in cluster and divide by total points in cluster, same for y-values, then we will have new center.

$$\text{new x-value for center} = \frac{\text{sum of x-values in cluster}}{\text{Total values in clusters}}$$

$$\text{new y-value for cluster} = \frac{\text{sum of y-values in cluster}}{\text{Total values in clusters}}$$

new center = (new x, new y).

↑ centroid ↑ centroid

→ point can have x, y, z, a, b — many ~~attributes~~ dimensions.

(4) Run step (2) again with new centers for each cluster.

(5) Keep running steps (3) and then (2) until there is no any point which changes cluster, and mean of each cluster remains the same for ~~2 iteration~~ previous and current ~~steps~~ of iteration.

Table:

point	Distance Mean 1 (x_1, y_1)	Distance Mean 2 (x_2, y_2)	Cluster
A1			
A2			
A3			

Date

Naive Bayes Classifier:

~~Steps~~ Formulas to solve numericals:

Probability → A given that B

(i) $P(A|B) = \dfrac{P(B|A) \cdot P(A)}{P(B)}$

(ii) $P(\text{Attribute set} \mid B) = P(\text{Attribute } 1 \mid B) \times P(\text{Att } 2 \mid B) \times \ldots \times P(\text{Att } n \mid B)$

Fruit = { Yellow, Sweet, long }

Attribute

Attribute set.

→ It is used to find posterior probability.

Conditional Probability:

Prior probability = initial probability

given in question.

Posterior probability = revised probability after considering data.

Formulas:-

(i) $P(A|B) = \dfrac{P(A \text{ AND } B)}{P(B)}$ or $\dfrac{P(A \cap B)}{P(B)}$.

Prob. where A and B both are true.

→ if A and B are independent:

$P(A \cap B) = P(A) * P(B)$

→ if A and B are dependent:

$P(A \cap B) = P(A|B) * P(B)$.

You can calculate $(A \cap B)$ from ~~Table~~ contigency table.

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Contingency Table → Joint Probability Distribution

Given Info	Attribute 1	Attribute 2	Row Total
classifier 1	50	10	60
classifier 2	20	30	50
Column Total	70	40	110

~~Ex:~~

	~~catch~~	~~¬catch~~
~~cavity~~	~~0.108~~	~~0.012~~
~~¬cavity~~	~~0.016~~	~~0.064~~

Contingency Table:-

	Attribute 1	Attribute 2
classifier 1	50/110	10/110
classifier 2	20/110	30/110

Ex: Classifiers ← Toothache, ¬Toothache
Attributes ← catch, ¬catch

①

	Toothache		¬Toothache	
	catch	¬catch	catch	¬catch
cavity	0.108	0.012	0.072	0.008
¬cavity	0.016	0.064	0.144	0.576

cavity, ¬cavity → Attributes

②

Sweet, Long, Yellow → Attributes

	Sweet	Long	Yellow
Orange			
Banana			
Others			

Classifier ← Orange, Banana, Others

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(ii) $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$

or

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

(iii) If A and B are independent:

$$P(A \mid B) = P(A).$$

Date

Q: 6 (c) (1) Calculate P(Cancer).

$\cancel{P(C = T) = 0.05 + 0.02 + 0.03 + 0.001}$

$\cancel{= 0.101}$

$P(Cancer = T) = P(Cancer = T \mid H, T) * P(H, T) + P(C = T \mid H, F) * P(H, F) + P(C = T \mid L, T) * P(L, T) + P(C = T \mid L, F) * P(L, F).$

$P(Cancer = T) = 0.05 * ((1 - 0.9) * (0.3))$
$+ 0.02 ((1 - 0.9) * (1 - 0.3))$
$+ 0.03 ((0.9) * (0.3))$
$+ 0.001 ((0.9) * (1 - 0.3)).$

$P(Cancer = T) = 0.0015 + 0.0014 + 0.0081 + 0.00063$

$\boxed{P(Cancer = T) = 0.01163}$

$P(Cancer = F) = 1 - 0.01163$

$\boxed{P(Cancer = F) = 0.98837}$

(2) Calculate P(Pollution | Cancer).

Solution:

$P(P = H \mid C = T) = ?$

$P(P = H \mid C = F) = ?$

$P(P = L \mid C = T) = ?$

$P(P = L \mid C = F) = ?$

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$$P(P=H \mid C=T) = \frac{P(C=T \mid P=H) * P(P=H)}{P(C=T)}$$

$$P(C=T \mid P=H) = P(C=T \mid P=H, S=T) \times P(S=T) + P(C=T \mid P=H, S=F) \times P(S=F)$$

$$= 0.05 * 0.3 + 0.02 * 0.7$$

$$\Rightarrow \boxed{P(C=T \mid P=H) = 0.029}$$

$$P(P=H \mid C=T) = \frac{0.029 * 0.1}{0.01163}$$

$$P(P=H \mid C=T) = 0.25.$$

ॐ Waheguru

A.I Notes
Final

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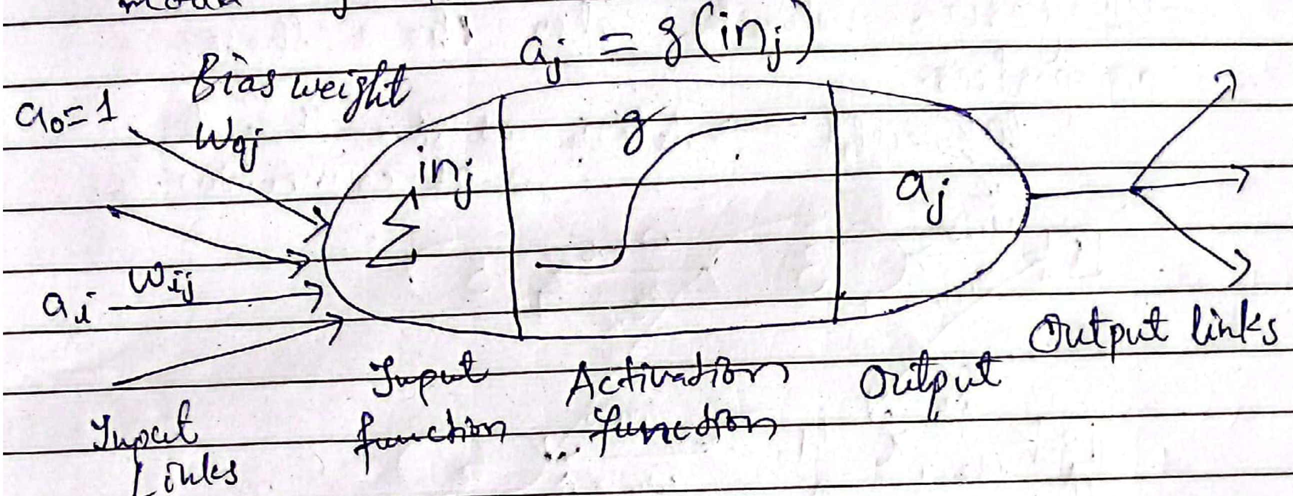
(1) Neural Networks:-

→ Also called connectionism, parallel distributed processing, and neural computation.

→ Below given is a simple mathematical model of the neuron:



→ It "fires" when a linear combination of its inputs ~~exces~~ exceeds some (hard or soft) threshold - that is, it implements a linear classifier.

→ The unit's output activation is

$$\boxed{a_j = g\left(\sum_{i=0}^{n} w_{i,j} a_i\right)}$$

where a_i is the output activation of unit i and $W_{i,j}$ is the weight on the ~~link~~ link from unit i to this unit

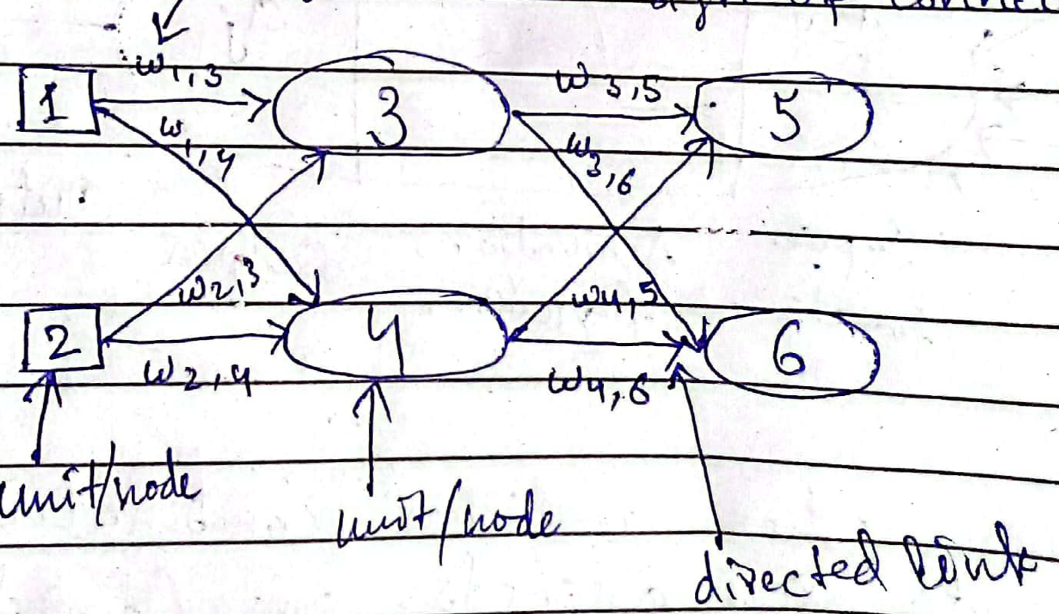
→ A neural network is just a collection of units connected together; the properties of the network are determined by its topology and the properties of the "neurons".

→ Much more detailed and realistic models have been developed, both for neurons and for larger systems in the brain, leading to the modern field of computational neuroscience.

→ Abstract properties of neural networks → Perform distributed computation
→ Tolerate noisy inputs
→ Learn.

→ Bayesian networks also have these properties.

link weight → determines strength and sign of connection.



→ A link from i to j ~~serves to~~ propogates the activation (output) a_i from i to j.

Neural
~~Neural~~ weights with and without bias

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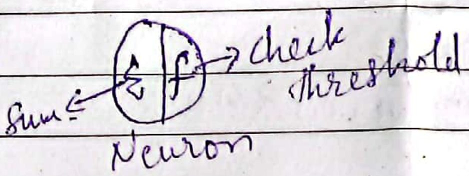
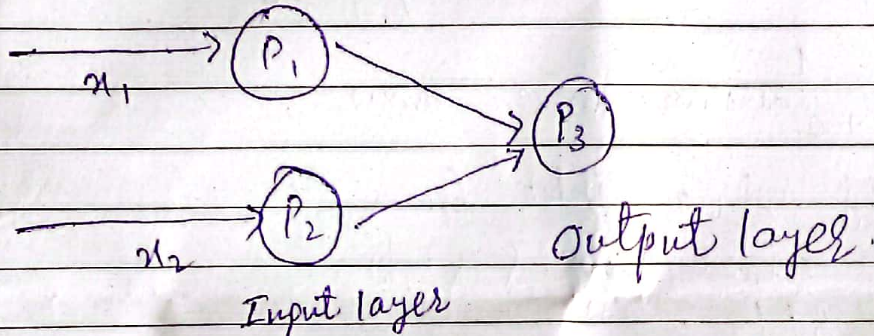
Less than threshold → Inhibit state 0

Greater than threshold → Exhibit state 1

$x_1 w_1 + x_2 w_2 + \ldots x_j w_j + \text{bias } [0-1]$.

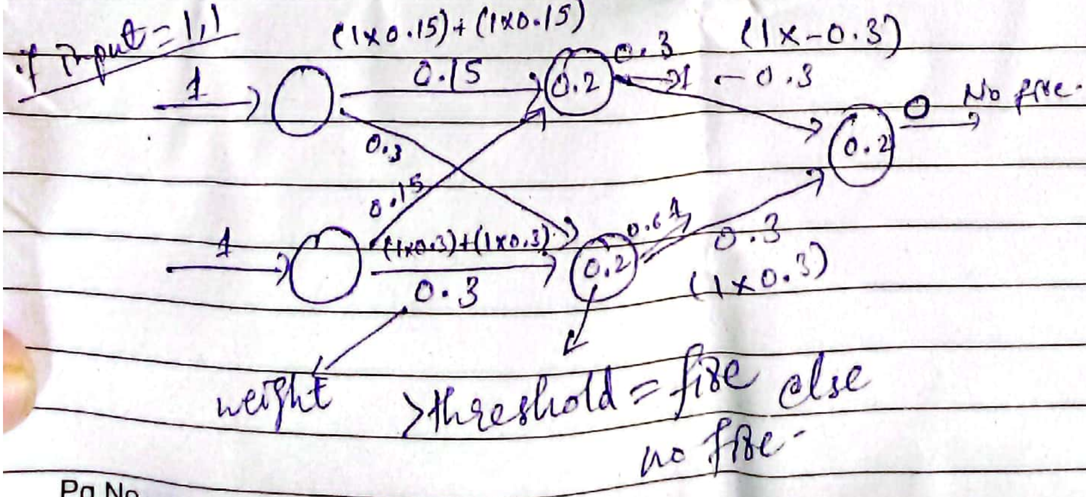


Linear separable



linear seperable are those ~~which~~ whose output can be separated by drawing just one separator. They can be solved by neural networks without hidden layers, but for those which can not be separated by one separator ~~or say cluster~~ ~~of two & two or~~ used at least one hidden layer of neurons to solve.

Example Network for XOR Gate:



Product of

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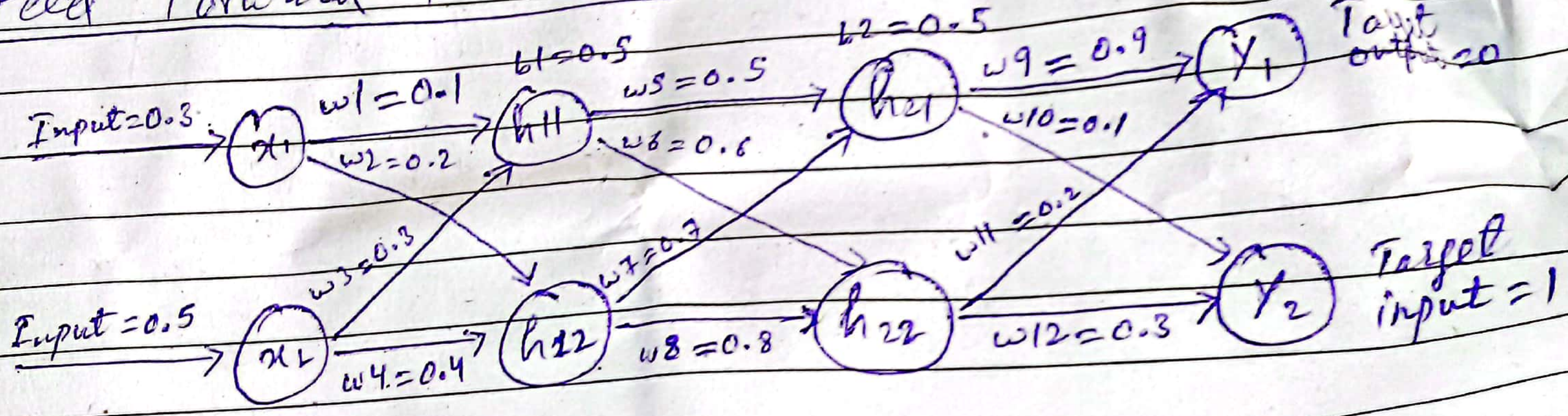
Feed Forward Neural Network



Activation function = $Af = \sigma = \dfrac{1}{1+e^{-\theta}}$

where $\dfrac{1}{1+e^{-w1x1+w2x2+w3x3...-wnxn}}$

Threshold value take from this after solving simply:

like for h11

$(0.3 \times 0.1) + (0.5 \times 0.3) + \overset{\text{bias}}{0.5} =$

Probability: Prior and Posterior Probabilities:-

Markov Model ⟶ we design probabilistic model depending on diff factors.

Bay's Theorem.
~~Mark~~ simple Markov model
Hidden Markov model.

Conditional Probability:- A conditional probability is defined as the chances of occurrance of event depending upon another event.

* $P(B|A)$ = Probability of ~~B~~ B given A is true.

* $P(B|A) = \frac{P(B \text{ AND } A)}{P(A)}$

Prior Probability:
Refers to initial probability assigned to an event or the hypothesis before any evidence is taken into an account. It represents what we believe about the likelihood of an event ~~of occur~~ occurring based on real knowled ge (some times it can be extracted from experience or evidence).

Posterior Prob:- It refers to revised probability of an event or the hypothesis after considering new evidence or data.

$$P(B|A) * P(A) = \boxed{P(B \text{ AND } A)}$$

$$\cancel{P(B|A)}\ \boxed{P(B|A) * P(A) = P(A|B) * P(B)}$$

$$P(A|B) = \frac{P(A \text{ AND } B)}{P(B)}$$

$$P(A|B) * P(B) = \boxed{P(A \text{ AND } B)}$$

$P(A \cup B) = P(A) + P(B) - P(A \cap B)$

$P(\text{Cavity} \vee \text{toothache})$

$$\boxed{P(B|A) = \frac{P(A|B) * P(B)}{P(A)}}$$ Baye's Theorem.

Example :-

$P(B) = \text{Rain} = 0.2$
$P(A) = \text{Cloud} = 0.45$
$P(A|B) = 0.6$
find $P(B|A) = ?$

$$P(B|A) = \frac{P(A|B) * P(B)}{P(A)} = \frac{0.6 * 0.2}{0.45}$$

$$\boxed{P(B|A) = 0.267}$$

Toothache and Cavity Problem

	Toothache		~Toothache	
	Catch	~Catch	Catch	~Catch
Cavity	0.108	0.012	0.072	0.008
~Cavity	0.016	0.064	0.144	0.576

1) P(Cavity) = ?
2) P(~Cavity) = ?
3) P(Toothache) = ?
4) P(~Toothache) = ?
5) P(Cavity ∨ toothache) =
6) P(Cavity | toothache) = ?
7) P(Cavity | toothache ∨ Catch) = ?

1) 0.108 + 0.012 + 0.072 + 0.008
P(Cavity) = 0.2
2) P(~Cavity) = 0.8
3) P(Toothache) = 0.2
4) P(~Toothache) = 0.8
5) P(Cavity ∨ toothache) = 0.2 + 0.2 − 0.12
= 0.28

6) 0.12
7) 0.12 +

1. Genetic Algorithms.
2. CSP problems.
3. Naive Based problems.
4. Baysian Networks.
5. KNN.
6. Supervised Learning.
7. Probablistic Models.
8. Confusion Matrix
9. Artificial Neural Networks.
10. Machine Learning overview.
11. Multilayered Neural networks.
12. Hidden Markov Model.
13.

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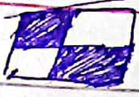
9/5/2024

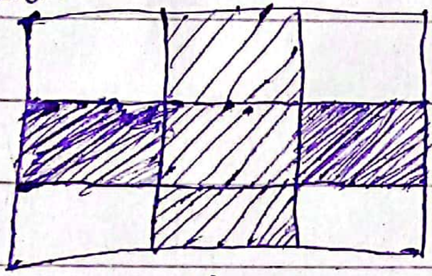
Q:1 Pattern  find the output of this new pattern  either its close to 'A' or 'B'.

Use synchronous update to solve if required:

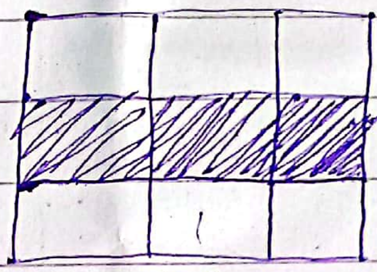
~~0101 1010~~

Q:2

010111010   000111000

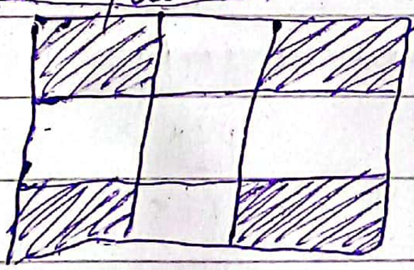


X

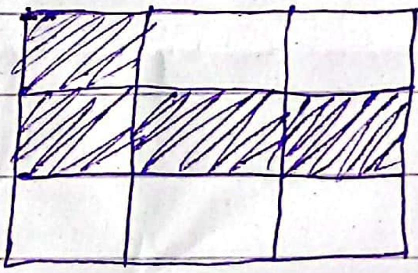


Y

New pattern



U



V

$$W = \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{array} \begin{bmatrix} 0 & 0 & 2 & -2 & -2 & -2 & 2 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -2 & 0 \\ 2 & 0 & 0 & -2 & -2 & -2 & 2 & 0 & 2 \\ 2 & 0 & -2 & 0 & 2 & 2 & -2 & 0 & -2 \\ 2 & 0 & -2 & 2 & 0 & 2 & -2 & 0 & -2 \\ 2 & 0 & -2 & 2 & 2 & 0 & -2 & 0 & -2 \\ 2 & 0 & 2 & -2 & -2 & -2 & 0 & 0 & 2 \\ 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 2 & -2 & -2 & -2 & 2 & 0 & 0 \end{bmatrix}$$

Serial	i	Inv	weight	outvec c	Counts
1	1	0 0 2 -2 -2 -2 2 0 2 101000101	6	101000101	
2	2	-2 101000101	0	111000101	
3	3	2 0 0 -2 -2 -2 2 0 2 111000101	6	111000101	
4	4	2 0 -2 0 2 2 -2 0 -2 111000101	-4	111000101	
5	5	2 0 -2 2 0 2 -2 0 -2 111000101	-4	111000101	
6	6	2 0 -2 2 2 0 -2 0 -2 111000101	-4	111000101	
7	7	2 0 2 -2 -2 -2 0 0 2 111000101	6	111000101	
8	8	0 2 0 0 0 0 0 0 0 111000101	2	111000111	
9	9	2 0 2 -2 -2 -2 2 0 0 111000111	6	111000111	

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$P(Yes) = \frac{9}{14}$. $P(No) = \frac{5}{14}$.

Outlook :-

	Yes	No
Sunny	2/9	3/5
Overcast	4/9	0/5
Rain	3/9	2/5

Temp

	Yes	No
Hot	2/9	2/5
Mild	4/9	2/5
Cool	3/9	1/5

Humidity :-

	Yes	No
High	3/9	4/5
Normal	6/9	1/5

Wind

	Yes	No
Weak	3/9	2/5
Strong	3/9	3/5

Date

<outlook = Rainy, temp = Mild, Humidity = Normal and Wind = Strong>.

<outlook = Sunny, temp = Cool, Humidity = Normal and Wind = Strong>.

$P(yes \mid new\ instance) = P(yes) * P(R \mid Y) * P(M \mid yes) * P(N \mid S) * P(S \mid Y)$

$= \frac{9}{14} * \frac{3}{9} * \frac{4}{9} * \frac{6}{9} * \frac{3}{9}$

$= 0.021$

$P(No \mid New\ Instance) = P(No) * P(R \mid N) * P(M \mid No) * P(N \mid N) * P(S \mid N)$

$= \frac{5}{14} * \frac{2}{5} * \frac{2}{5} * \frac{1}{5} * \frac{3}{5}$

$= 0.006$.

Its a Yes.

$P(Yes \mid New\ Instance) = P(Y) * P(S \mid Y) * P(C \mid Y) * P(N \mid Y) * P(S \mid Y)$

$=$

A.I

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Decision Trees:-

Decision trees' mapping is close to human mind.

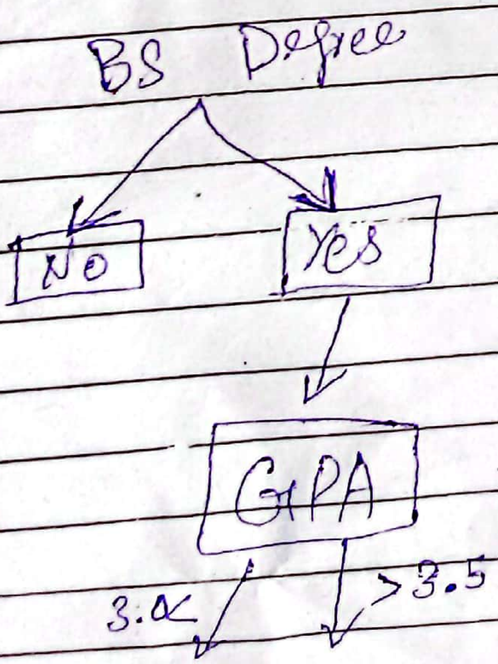
→ human brain → 65

Decision Trees → 71

For Admission in Masters
→ Country
→ Cost
→ University.
→ ~~GPA requirement~~
→ ~~[illegible]~~ Program.
→ Offered courses.

For Admission in Masters

1- Degree of BS
2- Cost of living.
3- Course availability.
4- Country.
5- Ranking of university.
6- GPA requirement.
7- Job placements.
8- Scholarship.
9- Major subjects.
10- Fees structure.
11- Visa.



① Identify attributes
② Define entropy.
③ Make tree.