



University of Asia Pacific

Department of CSE

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Course Title: Machine Learning

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"During Examination and upload time I will not take any help from anyone. I will give my exam all by myself."

University of Asia Pacific

Admit Card

Final-Term Examination of Fall, 2020

Financial Clearance PAID



Registration No : 17201012
Student Name : Rashik Rahman
Program : Bachelor of Science in Computer Science and Engineering

SI.NO.	COURSE CODE	COURSE TITLE	CR.HR.	EXAM. SCHEDULE
1	CSE 400	Project / Thesis	3.00	
2	CSE 330	Industrial Training	1.50	
3	CSE 401	Mathematics for computer Science	3.00	
4	CSE 403	Artificial Intelligence and Expert Systems	3.00	
5	CSE 404	Artificial Intelligence and Expert Systems Lab	1.50	
6	CSE 405	Operating Systems	3.00	
7	CSE 406	Operating Systems Lab	1.50	
8	CSE 407	ICTLaw, Policy and Ethics	2.00	
9	CSE 410	Software Development	1.50	
10	CSE 427	Topics of Current Interest	3.00	

Total Credit: 23.00

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Answer to the Q.No.1(a)

In an artificial neural network, the function which takes the incoming signals as input and produces the output signal is known as the activation function.

Some activation function with expression and diagram are given below:

i) Threshold activation function,

$$\text{defined by, } f(x) = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{if } x \leq 0 \end{cases}$$

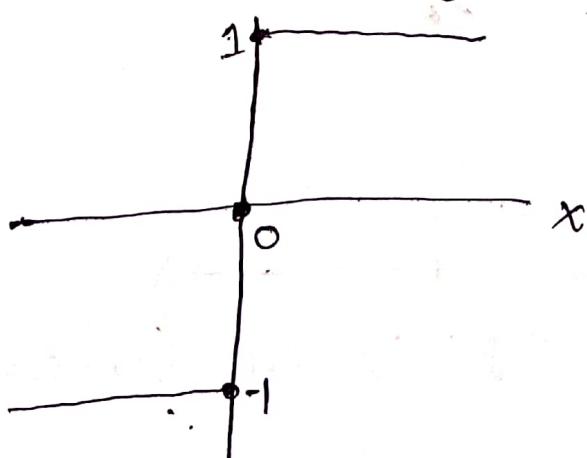


fig: Threshold function

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ii) Unit step function:

definite
 defined by, $f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$

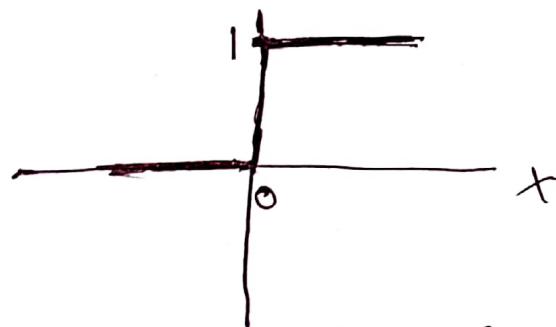


fig: unit step function

iii) Sigmoid activation function:

defined by, $f(x) = \frac{1}{1 + e^{-x}}$

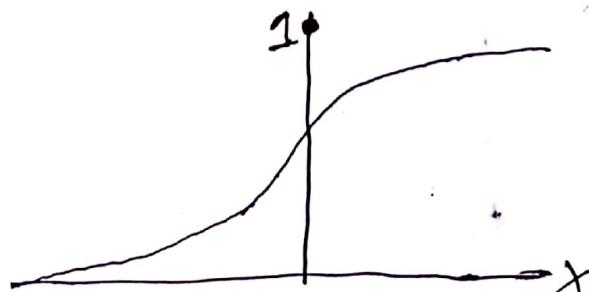


fig: sigmoid function

iv) Linear activation function:

defined by, $f(x) = mx + c$

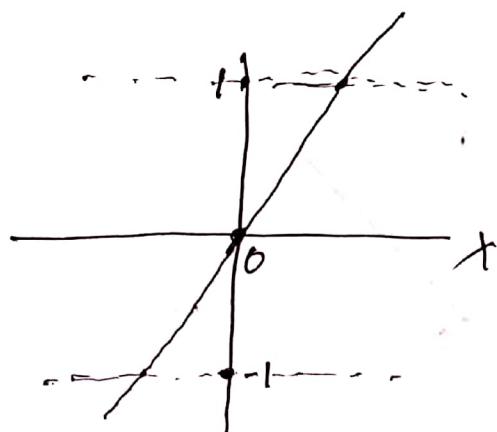


fig: Linear function

v) Hyperbolic tangential activation function:

defined by, $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

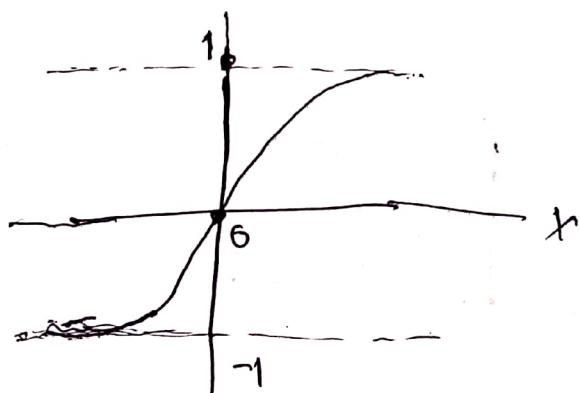


fig. Hyperbolic tangential function

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vi) ReLU activation function:

defined by, $f(x) = \begin{cases} x; & \text{if } x \geq 0 \\ 0; & \text{if } x < 0 \end{cases}$

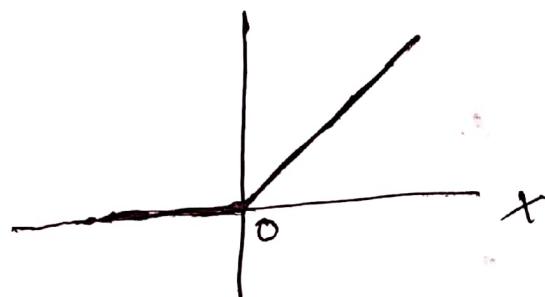


fig. ReLU function

vii) Leaky ReLU activation function:

defined by, $f(x) = \begin{cases} x; & \text{if } x \geq 0 \\ -0.000001; & \text{if } x < 0 \end{cases}$

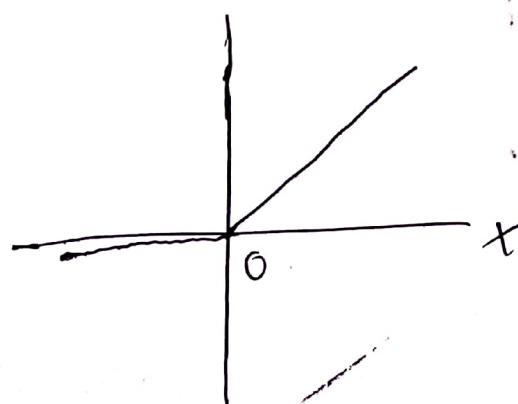


fig. Leaky ReLU function.

Answer to the Q.No. 1(b)

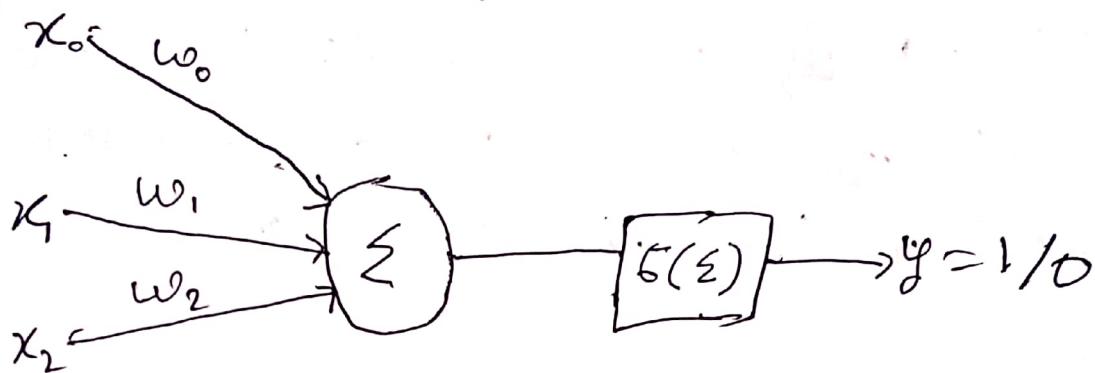


fig: Perceptron model.

AND gate:

A (x_1)	B (x_2)	y
0	0	0
0	1	0
1	0	0
1	1	1

Table: AND gate,

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So if we consider the ~~w_i~~ values as the following fig then we can build an AND gate.

So if we consider the value of $w_0 = -1.5$, $w_1 = 1$, $w_2 = 1$ and $x_0 = +1$ then we can get the same output as the AND gate output from a perception model.

For, $x_1 = 0, x_2 = 0$

$$y = \sigma(x_0 w_0 + x_1 w_1 + x_2 w_2)$$

$$= \sigma(1 \times (-1.5) + 0 \times 1 + 0 \times 1)$$

$$= \sigma(-1.5)$$

$$= 0$$

$$\sigma(x) = \begin{cases} 1; & \text{if } x \geq 0 \\ 0; & \text{if } x < 0 \end{cases}$$

For, $x_1 = 0, x_2 = 1$

$$y = \sigma(x_0 w_0 + x_1 w_1 + x_2 w_2)$$

$$= \sigma(1 \times (-1.5) + 0 \times 1 + 1 \times 1)$$

$$= \sigma(-0.5)$$

$$= 0$$

For, $x_1 = 1, x_2 = 0$

$$y = G(x_0w_0 + x_1w_1 + x_2w_2)$$

$$= G(1 \times (-1.5) + 1 \times 1 + 0 \times 1)$$

$$= G(0.5)$$

$$= 0$$

For, $x_1 = 1, x_2 = 1$

$$y = G(x_0w_0 + x_1w_1 + x_2w_2)$$

$$= G(1 \times (-1.5) + 1 \times 1 + 1 \times 1)$$

$$= G(0.5)$$

$$= 1$$

x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1

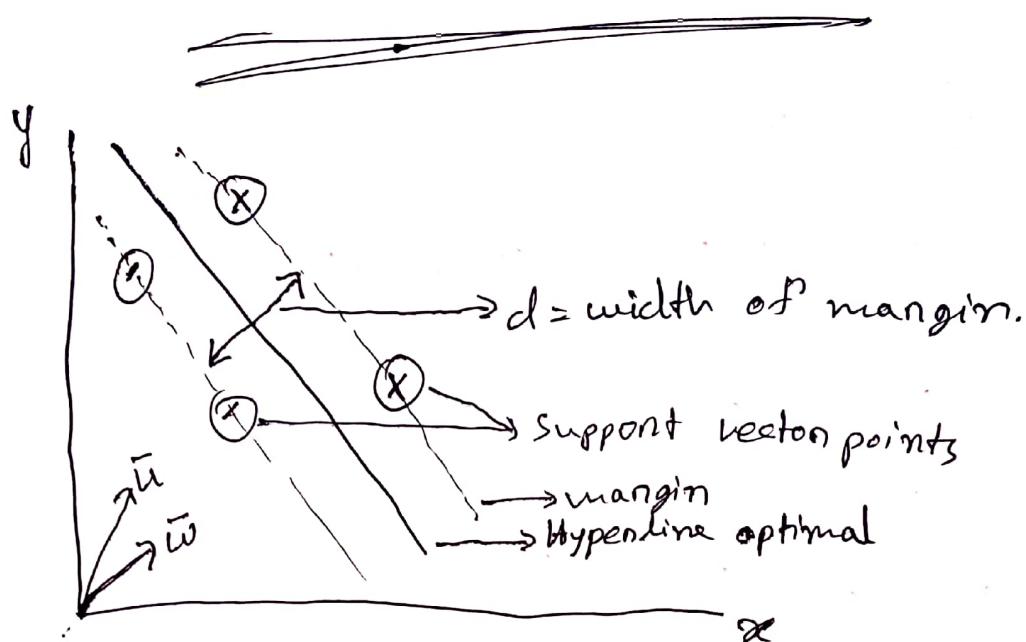
Table: Perception I/O.

~~Thus~~ As both of the table matches we can say we have achieved ~~an~~ AND gate through perceptron model.

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Answer to the Q.No.3 (a)



\bar{w} = weight vector perpendicular to hyperplane

\bar{u} = unknown point vector

Goal is to maximize d

$\bar{w}\bar{u} + b > 0$; for any $(+)$ sample

$\bar{w}\bar{u} + b \leq 0$; for any $(-)$ sample.

Equation for support vector points,

$\bar{w}\bar{x}_+ + b > 0$; for any $(+)$ support vector points

$\bar{w}\bar{x}_- + b \leq 0$; for any $(-)$ n n n

Now,

$$\left. \begin{array}{l} y_i (\bar{w} \cdot \bar{x}_+ + b) \geq 1 \\ y_i (\bar{w} \cdot \bar{x}_- + b) \geq 0 \end{array} \right\}$$

\therefore for all points (positive/negative)

$$y_i (\bar{w} \cdot \bar{x} + b) - 1 \geq 0$$

$$\Rightarrow y_i (\bar{w} \cdot \bar{x} + b) - 1 = 0$$

$$\therefore \vec{w} \cdot \vec{x}_+ + b \geq 1 \Rightarrow \vec{w} \cdot \vec{x}_+ + b = 1 \Rightarrow \boxed{\vec{w} \cdot \vec{x}_+ = 1 - b}$$

$$\vec{w} \cdot \vec{x}_- + b \leq -1 \Rightarrow \vec{w} \cdot \vec{x}_- + b = -1 \Rightarrow \boxed{\vec{w} \cdot \vec{x}_- = -1 - b}$$

Now, maximizing d ,

$$\begin{aligned} d &= (\vec{x}_+ - \vec{x}_-) \frac{\vec{w}}{\|\vec{w}\|} \\ &= \vec{x}_+ \frac{\vec{w}}{\|\vec{w}\|} - \vec{x}_- \frac{\vec{w}}{\|\vec{w}\|} \\ &= (\vec{x}_+ \vec{w} - \vec{x}_- \vec{w}) \frac{1}{\|\vec{w}\|} \\ &= (1 - b + 1 + b) \frac{1}{\|\vec{w}\|} \\ &= \frac{2}{\|\vec{w}\|} \end{aligned}$$

~~scratches~~

$$\begin{aligned} \therefore \max(d) &= \max\left(\frac{2}{\|\vec{w}\|}\right) \\ &\approx \max\left(\frac{1}{\|\vec{w}\|}\right) \\ &\approx \min\left(\frac{1}{\|\vec{w}\|}\right) \\ &\approx \min\left(\frac{1}{2} \|\vec{w}\|^2\right) \end{aligned}$$

Hence,

$$\|\vec{w}\| = \sqrt{\sum_{i=1}^n \lambda_i y_i \vec{x}_i}$$

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$$\cancel{\textcircled{Q}} \sum_{i=1}^l \lambda y_i = 0$$

$$\therefore \min(L) = \frac{1}{2} \|\vec{w}\|^2 - \sum_{i=1}^l \lambda_i (y_i (\vec{w} \cdot \vec{x}_i + b) - 1)$$

$$\therefore L = \sum_{i=1}^l \lambda_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \lambda_i \lambda_j y_i y_j \vec{x}_i^T \vec{x}_j \rightarrow \text{dual soln.}$$

Answer to the Q. No. 3(b)

Given,

class

$$x_1 \quad 2 \quad 1 \quad +1$$

$$x_2 \quad 4 \quad 3 \quad -1$$

Here, $\lambda = 2$

$$\vec{x}_1 = (2, 1) \rightarrow y_1 = +1$$

$$\vec{x}_2 = (4, 3) \rightarrow y_2 = -1$$

$$L(w, b) = \sum_{i=1}^l \lambda_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \lambda_i \lambda_j y_i y_j \vec{x}_i^T \vec{x}_j$$

$$= (\lambda_1 + \lambda_2) - \frac{1}{2} \left\{ \cancel{\lambda_1 \lambda_2} \cancel{y_1 y_2} (\lambda_1 \lambda_2 y_1 y_2, \bar{x}_1 \bar{x}_1 + \lambda_1 \lambda_2 y_1 y_2 \bar{x}_1 \cdot \bar{x}_2 + \lambda_2 \lambda_1 y_2 y_1 \bar{x}_2 \cdot \bar{x}_1 + \cancel{\lambda_1 \lambda_2 y_1 y_2} \bar{x}_2 \cdot \bar{x}_2) \right.$$

$$= (\lambda_1 + \lambda_2) - \frac{1}{2} \left\{ \lambda_1 \lambda_2 (+1)(+1) (2 \times 2 + 1 \times 1) \cancel{+} \right. \\ + \lambda_1 \lambda_2 (+1)(-1) (2 \times 4 + 1 \times 3) \\ + \lambda_2 \lambda_1 (-1)(+1) (4 \times 2 + 3 \times 1) \\ \left. + \lambda_2 \lambda_2 (-1)(-1) (4 \times 4 + 3 \times 3) \right\}$$

L =

$$\boxed{(\lambda_1 + \lambda_2) - \frac{1}{2} \left\{ 5\lambda^2 - 22\lambda_1 \lambda_2 + 25\cancel{\lambda_2^2} \right\}} \quad \leftarrow \textcircled{1}$$

we know,

$$\sum_{i=1}^k x_i y_i = 0$$

$$\Rightarrow \lambda_1 y_1 + \lambda_2 y_2 = 0$$

$$\Rightarrow \lambda_1 x_1 + \lambda_2 (-1) = 0$$

$$\therefore \cancel{\lambda_1} = \cancel{\lambda_2}$$

∴ from ①,

$$L = \lambda_1 + \lambda_2 - \frac{1}{2} \left\{ 5\lambda^2 - 22\lambda_1 \lambda_2 + 25\cancel{\lambda_2^2} \right\}$$

$$= 2\lambda_1 - \frac{1}{2} \left\{ 5\lambda^2 - 22\lambda_1^2 + 25\lambda_1^2 \right\}$$

$$= 2\lambda_1 - 4\lambda_1^2$$

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$$\underline{\underline{f'(x_0) = 0}}$$

$$\frac{\partial}{\partial \lambda_1} (L) = 0$$

$$\Rightarrow \frac{\partial}{\partial \lambda_1} (2\lambda_1 - 4\lambda_1^2) = 0$$

$$\Rightarrow 2 - 2 \times 4\lambda_1 = 0$$

$$\Rightarrow \lambda_1 = \frac{2}{8} = \frac{1}{4}$$

$$So, \lambda_1 = \lambda_2 = \frac{1}{4}$$

So,

$$w = \sum_{i=1}^l \lambda_i y_i \bar{x}_i$$

$$= \lambda_1 y_1 \bar{x}_1 + \lambda_2 y_2 \bar{x}_2$$

$$= \frac{1}{4}(+1)(2, 1) + \frac{1}{4}(-1)(4, 3)$$

$$\Rightarrow \frac{1}{4} \cancel{(2, 1)} - \frac{1}{4}(4, 3)$$

$$= \frac{1}{4}(2 - 4, 1 - 3)$$

$$= \frac{1}{4}(-2, -2) = \left(-\frac{1}{2}, -\frac{1}{2}\right)$$

$$b = \frac{1}{2} (\min_{y_i=+1} \vec{w} \cdot \vec{x} + \max_{y_i=-1} \vec{w} \cdot \vec{x})$$

$$= -\frac{1}{2} [(-\frac{1}{2} \times 2) + (-\frac{1}{2} \times 1) + (-\frac{1}{2} \times 4) + (-\frac{1}{2} \times 3)]$$

$$= -\frac{1}{2} [-1 - \frac{1}{2} - 2 - \frac{3}{2}]$$

$$= -\frac{5}{2}$$

$$f(\vec{x}) = \vec{w} \cdot \vec{x} + b = 0$$

$$= (-\frac{1}{2}, -\frac{1}{2}) \cdot (x_1, x_2) + \frac{5}{2} = 0$$

$$= -\frac{x_1}{2} - \frac{x_2}{2} + \frac{5}{2} = 0$$

$$\Rightarrow \boxed{x_1 + x_2 - 5 = 0} \quad \text{Sohn}$$

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Answer to the Q.No. 4(a)

The criterion for minimization of error in regression problem are as follows:

i) Power rule: $\frac{d}{dx} x^n = n x^{n-1}$.

ii) Constant rule: if $f(x) = c$ then $f'(c) = 0$

iii) A constant times a function: $\frac{d}{dx} m x^n = m n x^{n-1}$

iv) Differentiating a sum: $\frac{dQ}{dx} = \sum_{j=1}^m a_{kj} x_j + \sum_{i=1}^n a_{ik} x_i$

v) Product rule: $\frac{d}{dx} [f(x)g(x)] = f(x)g'(x) + f'(x)g(x)$

vi) Quotient rule: $\frac{d}{dx} \left[\frac{f(x)}{g(x)} \right] = \frac{g(x)f'(x) - f(x)g'(x)}{(g(x))^2}$

vii) Chain rule: $F'(x) = f'(g(x)) g'(x)$

These methods can be used in minimizing errors using derivatives.

Answer to the Q. No. 4(b)

Let A and B any two events in a random experiment. If $P(A) \neq 0$, then.

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \rightarrow \text{Bayes theorem}$$

here, $P(A|B)$ is called posterior probability of A given B.

$P(B|A)$ is called likelihood of B given A.

Freq Table

class	features										Total
	height			weight				foot size			
	5.00	5.50	6.00	130	150	170	180	6	8	10	
male	0	1	3	0	0	2	2	0	1	3	4
female	2	1	1	2	2	0	0	2	2	0	4
Total	2	2	4	2	2	2	2	2	3	3	8

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likelihood table:

Class	Features			Weight				Foot Size		
	height 5.00	5.50	6.00	130	150	170	180	6	8	10
male	0	$\frac{1}{2}$	$\frac{3}{4}$	0	0	1	1	0	$\frac{1}{3}$	1
female	1	$\frac{1}{2}$	$\frac{1}{4}$	1	1	0	0	1	$\frac{2}{3}$	0

Now for person with height = 6, weight = 130 and foot size = 8

height = 6, weight = 130 and foot size = 8

Class	Feature			Weight				Foot Size		
	height 5.00	5.50	6.00	130	150	170	180	6	8	10
male	0	$\frac{1}{4}$	$\frac{3}{4}$	0	0	$\frac{3}{4}$	$\frac{3}{4}$	0	$\frac{1}{4}$	$\frac{3}{4}$
female	$\frac{3}{4}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{3}{4}$	$\frac{3}{4}$	0	0	$\frac{3}{4}$	$\frac{3}{4}$	0

$$P(\text{male}) = \frac{3}{4} \times 0 \times \frac{1}{4} = 0$$

$$P(\text{female}) = \frac{1}{4} \times \frac{2}{4} \times \frac{2}{4} = 0.0625$$

Overall probability,

$$P(\text{male}) = 0 \times \frac{1}{8} = 0$$

$$P(\text{female}) = 0.0625 \times \frac{1}{8} = 0.0078125$$

So we assign the class label ~~for~~
female to the ~~test~~ given test ~~to~~
instance.

Example of Bayes theorem:

$$P(A) = 10\% = 0.1$$

$$P(B) = 5\% = 0.05$$

$$P(B|A) = 7\% = 0.07$$

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

$$= \frac{0.07 \times 0.10}{0.05}$$

$$= 0.14$$

Ans

Answer to the Q.No. 2 (a)

Artificial Neural Network :

An artificial neural network (ANN) is a computing system inspired by the biological neural networks that constitute biological brains. An ANN is based on a collection of connected units called artificial neurons. Each connection between artificial neurons can transmit a signal from one to another. The artificial neuron that receives the signal can process it and then signal other artificial neurons connected to it.

Characteristics of ANN:

An ANN can be defined and implemented in several different ways. The way the following characteristics are defined determines a particular variant of an ANN.

→ The activation function:

This function defines how a neuron's combined input signal are transformed into a single output signal to be broadcast further in the network.

→ The network topology:

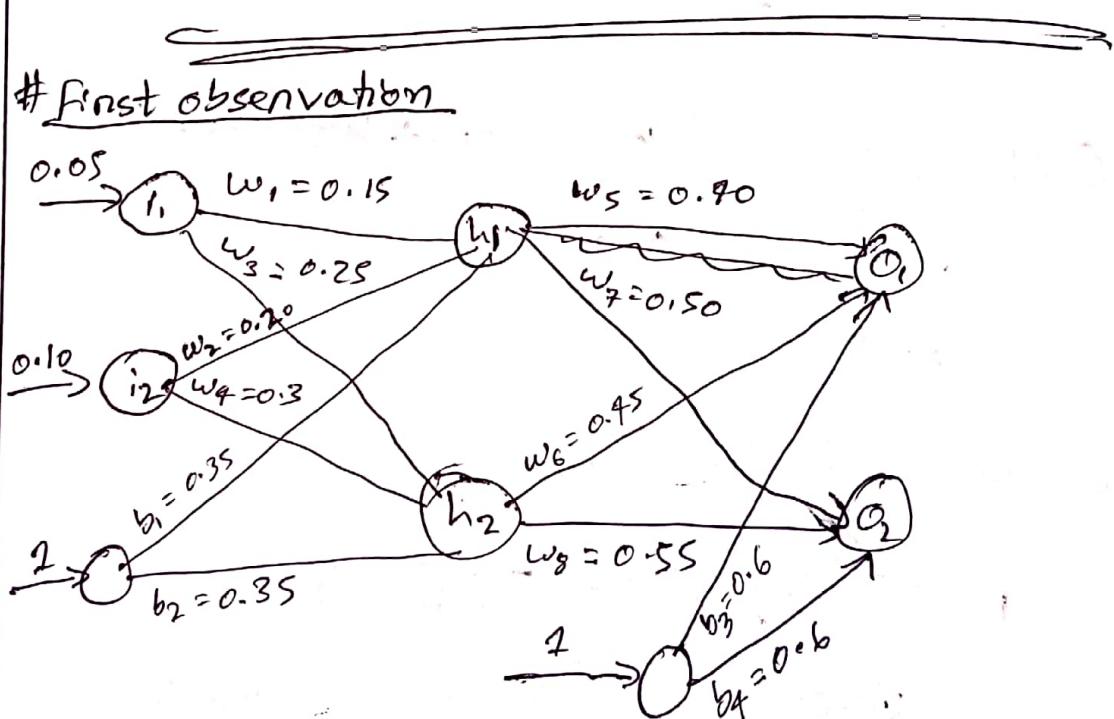
This describes the number of neurons in the model as well as the number of layers and manner in which they are connected.

→ The training algorithm:

This algorithm specifies how connection weights are set in order to inhibit or excite neurons in proportion to the input signals.

Answer to the Q No. 2(b)

First observation



i) Output calculation:

$$\text{Out}_{h_1} = \text{sigmoid}(w_1 i_1 + w_2 i_2 + b_1 \times 1) \quad \left| \begin{array}{l} \text{sigmoid}(x) \\ = \frac{1}{1+e^{-x}} \end{array} \right.$$

$$= \text{sigmoid}(0.3775)$$

$$= 0.59$$

$$\text{Out}_{h_2} = \text{sigmoid}(w_3 i_1 + w_4 i_2 + b_2 \times 1)$$

$$= \text{sigmoid}(0.39)$$

$$= 0.59$$

$$\text{Out}_{o_1} = \text{sigmoid}(w_5 \times \text{Out}_{h_1} + w_6 \times \text{Out}_{h_2} + b_3 \times 1)$$

$$= \text{sigmoid}(1.11)$$

$$= 0.75$$

$$\text{Out}_{o_2} = \text{sigmoid}(w_7 \times \text{Out}_{h_1} + w_8 \times \text{Out}_{h_2} + b_4 \times 1)$$

$$= \text{sigmoid}(0.122)$$

$$= 0.77$$

ii) Error calculation:

$$E = \frac{1}{2} (T_1 - \text{Out}_{o_1})^2 + \frac{1}{2} (T_2 - \text{Out}_{o_2})^2$$

$$= (0.01 - 0.75)^2 + (0.99 - 0.77)^2$$

$$= 0.298$$

iii) Weight adjust. of output layer

Q.

$$\delta_{01} = (T_1 - \text{out}_{01}) \times \text{out}_{01} \times (1 - \text{out}_{01}) \\ = -0.138$$

Q.

$$w_5^+ = w_5 + \eta \times \delta_{01} \times \text{out}_{h1} \\ = 0.358$$

Q.

$$w_6^+ = w_6 + \eta \delta_{01} \text{out}_{h2} \\ = 0.49$$

$$b_3^+ = b_3 + \eta \delta_{01} \cancel{1} \\ = 0.53$$

$$\delta_{02} = (T_2 - \text{out}_{02}) \times \text{out}_{02} \times (1 - \text{out}_{02}) \\ = 0.03$$

$$w_7^+ = w_7 + \eta \delta_{02} \text{out}_{h1} \\ = \cancel{0.59} 0.511$$

$$b_4^+ = b_4 + \eta \delta_{02} \cancel{1} \\ = \cancel{0.61} 0.62$$

$$w_8^+ = w_8 + \eta \delta_{02} \text{out}_{h2} = 0.56$$

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iv) weigh adjust for hidden layer.

$$\delta_{h1} = (\delta_{o1} w_5 + \delta_{o2} w_7) \text{ out}_{h1} \times (1 - \text{out}_{h1}) \\ = -0.008$$

$$w_1^+ = w_1 + \eta \delta_{h1} x_{i1} \\ = 0.05$$

$$w_2^+ = w_2 + \eta \delta_{h1} x_{i2} \\ = 0.19$$

$$b_1^+ = b_1 + \eta \times \delta_{h1} \times 1 = 0.34$$

$$\delta_{h2} = (\delta_{o1} w_6 + \delta_{o2} w_8) \times \text{out}_{h2} \times (1 - \text{out}_{h2}) \\ = -0.009$$

$$w_3^+ = w_3 + \eta \delta_{h2} x_{i1} = 0.249$$

$$w_4^+ = w_4 + \eta \delta_{h2} x_{i2} = 0.299$$

$$b_2^+ = b_2 + \eta \times \delta_{h2} \times 1 = 0.375$$

for the second observation, values ~~of~~
⑥ will be

$$i_1 = \cancel{0.25} 0.25$$

$$i_2 = 0.18$$

$$T_1 = 0.23$$

$$T_2 = 0.79.$$

For these values steps ① - ④
will be repeated for a single
iteration.