

(1)

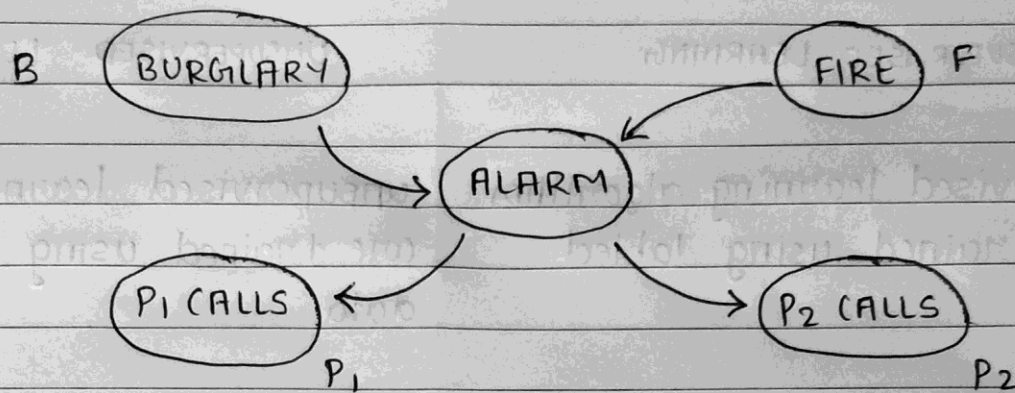
Q4.	SUPERVISED LEARNING	UNSUPERVISED LEARNING
→	supervised learning algorithm are trained using labeled data	unsupervised learning algo. are trained using unlabeled data.
→	It takes direct feedback to check if it is predicting correct output or not.	It does not take any feedback
→	In this input data is provided to model along with output	In this only input data is provided to the model
→	It includes algo such as linear regression, logistic regression, etc.	It includes algo such as clustering, KNN, and apriori algorithm.

BAYESIAN BELIEF NETWORK

It is a graphical representation of different probabilistic relationships among random variable in a particular set.

It is a classifier with no dependency on attributes i.e. it is condition independent

Due to its feature of joint probability, the probability in bayesian belief network is derived based on condition - $P(\text{attribute} \& \text{percent})$.



- In figure, we have an alarm 'A' a node, say installed in house of person 'Rudra' which signs upon 2 probabilities i.e. burglary 'B' & fire 'F' which are parent nodes of the alarm node. The alarm is parent node of 2 probability. 'P1' calls 'P1' & 'P2' calls 'P2' person nodes.
- Upon the instance of burglary & fire 'P1' & 'P2' call person 'Rudra'. But those are few drawbacks
- As sometimes 'P1' may forget to call person 'Rudra', even after having the alarm.
- Similarly 'P2' sometimes fails to call the person 'Rudra' as he is only able to hear the alarm, from a certain distance.

Q3 (a) sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$

The derivative of sigmoid is

$$\begin{aligned}\frac{d\sigma(x)}{dx} &= \frac{d}{dx} \left[\frac{1}{1+e^{-x}} \right] \\&= \frac{d}{dx} (1+e^{-x})^{-1} \\&= -(1+e^{-x})^{-2} (-e^{-x}) \\&= \frac{e^{-x}}{(1+e^{-x})^2} \\&= \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}} \\&= \frac{1}{1+e^{-x}} \cdot \frac{(1+e^{-x})-1}{1+e^{-x}} \\&= \frac{1}{1+e^{-x}} \left(\frac{1+e^{-x}}{1+e^{-x}} - \frac{1}{1+e^{-x}} \right) \\&= \frac{1}{1+e^{-x}} \left(\frac{1-1}{1+e^{-x}} \right) \\&= \sigma(x) \cdot (1-\sigma(x))\end{aligned}$$

GIVEN $\sigma(x) = 0.5 \rightarrow 0.5 = \frac{1}{1+e^{-x}}$

$$\rightarrow 1+e^{-x} = 2$$

$$\rightarrow e^{-x} = 1$$

$$\rightarrow (-x) = \log_e 1$$

$$\rightarrow \boxed{x = -\log_e 1}$$

$$x = 0$$

(b) A decision tree has many analysis in real life and turns out, it has influential a wide area of machine learning, covering both classification and regression.

As the name goes, it uses tree-like model of decisions. They can be used either to drive informal discussions or to map out an algorithm that predicts the best chance mathematically.

A decision tree typically starts with a single node, which branches into possible outcomes. Each of those outcomes leads to additional nodes, which branch off into other possibilities. This gives it a tree-like shape.

Q1.	X	Y	x = unit test marks y = final exam marks
	72	84	
	50	63	
	81	77	
	74	78	
	94	90	
	86	75	
	59	49	

→ We know that linear regression hypothesis is:

$$h_0(x) = \theta_0 + \theta_1 x$$

Let's suppose it is $y = a + bx$

Using the method of least square:

$$\sum y = a \sum 1 + b \sum x \quad \text{--- (1)}$$

$$\sum xy = a \sum x + b \sum x^2 \quad \text{--- (2) multiply 1 by } x$$

Calculating the parameters :-

$$\sum x = 516$$

$$\sum x^2 = 39434$$

$$\sum y = 516$$

$$\sum xy = 39008$$

$$\therefore 7a + 516b = 516$$

$$516a + 39434b = 39008$$

(we get this by substituting parameters in above eqⁿ)

(6)

(a) On solving equations, we get

$$a = 22.47 \quad b = 0.695$$

(b) Predicted final exam marks of the student who scored 85 in unit test can be calculated as:-

$$y(x) = 22.47 + 0.695x$$

$$[a/0.0] \quad [b/0.1]$$

$$\begin{aligned} y(85) &= 22.47 + (0.695 \times 85) \\ &= 81.5 \end{aligned}$$

$$\underline{\underline{y(85) = 82}}$$