



# University of Asia Pacific

## Department of CSE

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Reg ID: 17201012

Year: 4th

Semester: 1st

Course Code: CSE 403

Course Title: Artificial Intelligence

Date: 25.04.2021

"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



Sl.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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2. No examinees shall be allowed to submit their answer scripts before 50% of the allocated time of examination has elapsed.

3. No examinees would be allowed to go to washroom within the first 60 minutes of final examinations.

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Answer to the Q. No. 1(a)

A back-propagation neural network is a multi-layer network and the layers are fully connected, that is every neuron in each layer is connected to every other neuron in the adjacent forward layer.

As it is a fully connected so we can refer to it as a sequential network.

Back-propagation is basically an algorithm of propagating the total loss back into the neural network to know how much of the loss every node is responsible for, and subsequently updating the weights.

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## Answer to the Q. NO. 1-(b)

Given,

$$x_i = 0$$

$$x_1 = 1$$

$$x_2 = 0$$

$$x_3 = 1$$

} inputs

$$y = 1 \rightarrow \text{output}$$

$$\theta = 0.2 \rightarrow \text{threshold}$$

$$\alpha = 0.1 \rightarrow \text{learning rate}$$

Now,

$$w_1 = 12\% \cdot 2 - 0.2 = -0.2$$

$$w_2 = 12\% \cdot 3 - 0.5 = -0.5$$

$$w_3 = 0.1$$

①

$$\hat{y} = \text{step} \left[ \sum_{i=1}^3 x_i w_i - \theta \right]$$

$$\Rightarrow \hat{y} = \text{step} [x_1 w_1 + x_2 w_2 + x_3 w_3 - \theta]$$

$$= \text{step} [1 \times (-0.2) + 0 \times (-0.5) + 1 \times 0.1 - 0.2]$$

$$= \text{step} [-0.2 + 0.1 - 0.2]$$

$$= \text{step} [-0.3]$$

$$\therefore \hat{y} = 0$$

$$\text{step}[x] = \begin{cases} 0; & \text{if } x < 0 \\ 1; & \text{if } x \geq 0 \end{cases}$$

(ii)

$$\text{error}, e = y - \hat{y} = 1 - 0 = 1$$

$$w_1 = w_1 + \cancel{2x_1} + e \Delta x_1$$

$$= \cancel{-0.2} + 0.1 \times 1 \times 1 = -0.1$$

$$= \cancel{-1 + 0.1} = 0.9$$

$$w_2 = w_2 + \cancel{2x_2} + e \Delta x_2$$

$$= -0.5 + \cancel{0.1 \times (-0.5)} + 0.1 \times 0 \times 1$$

$$= \cancel{-1 + 0.5} = -0.5$$

$$w_3 = w_3 + \cancel{2x_3} + e \Delta x_3$$

$$= 0.1 + 0.1 \times 1 \times 1 = 0.2$$

$$= \cancel{1 + 0.2} = 1.2$$

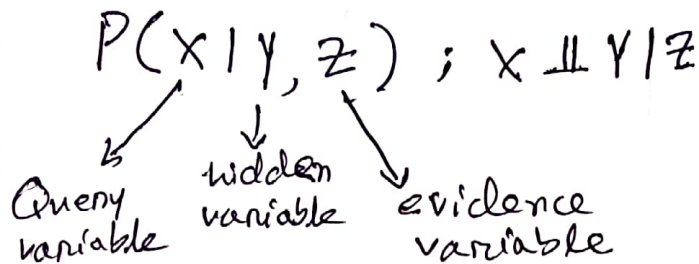
$$\therefore \text{New updated weights, } (w_1, w_2, w_3) = (\cancel{0.9}, \cancel{-0.5}, 1.2)$$

Ans

④

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## Answer to the Q. No. 2(a)



- i) Query variable: The variable which's probability is needed to know.
- ii) Hidden variable: The variable that is irrelevant to query variable and independent from it, thus can be excluded from the equation.
- iii) Evidence variable: The variable based on which we calculate the probability of query variable. It is a given event based on it query variable's probability is calculated.



## Answer to the Q.No. 2 (b)

Now,

$$q = 12 / 1000 =$$

$$q = 12 / 1000 = 0.012$$

$$p = \sqrt{12} / 100 = 0.035$$

$$u = 12 / 10000 = 0.0012$$

$$t = 1 - q = 1 - 0.012 = 0.988$$

$$R = 1 - p = 1 - 0.035 = 0.965$$

$$s = 1 - u = 1 - 0.0012 = 0.998$$

Transition matrix,  $A =$

$$X_{t-1} \begin{matrix} \text{Pizza} \\ \text{Burger} \\ \text{Hotdog} \end{matrix} \begin{bmatrix} 0.988 & 0.012 & 0 \\ 0.035 & 0 & 0.965 \\ 0.0012 & 0 & 0.998 \end{bmatrix} \begin{matrix} \text{pizza} \\ \text{burger} \\ \text{hotdog} \end{matrix} X_t$$

given  $p(X_1) = [0, 1, 0]$   
pizza burger hotdog

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$$\begin{aligned}
 P(X_2 = \text{pizza}) &= P(X_2 = \text{pizza} | X_1 = \text{pizza}) P(X_1 = \text{pizza}) \\
 &\quad + P(X_2 = \text{pizza} | X_1 = \text{burger}) P(X_1 = \text{burger}) \\
 &\quad + P(X_2 = \text{pizza} | X_1 = \text{hotdog}) P(X_1 = \text{hotdog}) \\
 &= 0.988 \times 0 + 0.035 \times 1 + 0.0012 \times 0 \\
 &= 0.035
 \end{aligned}$$

$$\begin{aligned}
 P(X_2 = \text{burger}) &= P(X_2 = \text{burger} | X_1 = \text{pizza}) P(X_1 = \text{pizza}) \\
 &\quad + P(X_2 = \text{burger} | X_1 = \text{burger}) P(X_1 = \text{burger}) \\
 &\quad + P(X_2 = \text{burger} | X_1 = \text{hotdog}) P(X_1 = \text{hotdog}) \\
 &= 0.012 \times 0 + 0 \times 1 + 0 \times 0 \\
 &= 0
 \end{aligned}$$

$$\begin{aligned}
 P(X_2 = \text{hotdog}) &= P(X_2 = \text{hotdog} | X_1 = \text{pizza}) P(X_1 = \text{pizza}) \\
 &\quad + P(X_2 = \text{hotdog} | X_1 = \text{burger}) P(X_1 = \text{burger}) \\
 &\quad + P(X_2 = \text{hotdog} | X_1 = \text{hotdog}) P(X_1 = \text{hotdog}) \\
 &= 0 \times 0 + 0.965 \times 1 + 0.998 \times 0 \\
 &= 0.965
 \end{aligned}$$

$$\therefore P(X_2) = \begin{bmatrix} 0.035, & 0, & 0.965 \\ \text{pizza} & \text{burger} & \text{hotdog} \end{bmatrix}$$

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$$\begin{aligned}\therefore P(X_3 = \text{pizza}) &= P(X_3 = \text{pizza} | X_2 = \text{pizza}) P(X_2 = \text{pizza}) \\ &\quad + P(X_3 = \text{pizza} | X_2 = \text{burger}) P(X_2 = \text{burger}) \\ &\quad + P(X_3 = \text{pizza} | X_2 = \text{hotdog}) P(X_2 = \text{hotdog})\end{aligned}$$

$$= 0.988 \times 0.035 + 0.035 \times 0 + 0.0012 \times 0.965$$

$$= \cancel{0.035} + 0.0346 + 0 + \cancel{0.00158} = 0.001158$$

$$= 0.0358$$

$\therefore$  The predicted probability that they will serve pizza on 3rd day is 0.0358 or 3.58%.

Ans.



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## Answer to the Q.No. 3(a)

A ~~by~~ linguistic hedge on modifier is an operation that modifies the meaning of a term on fuzzy set. Hedges are some word that modify the linguistic variable of a fuzzy set.

Hedges are basically modifiers that gives a degree of membership to a fuzzy set.

### Example:

If we consider pressure as a fuzzy set then hedges will be very pressure, ~~less~~ less pressure, ~~extem~~ extremely pressure.

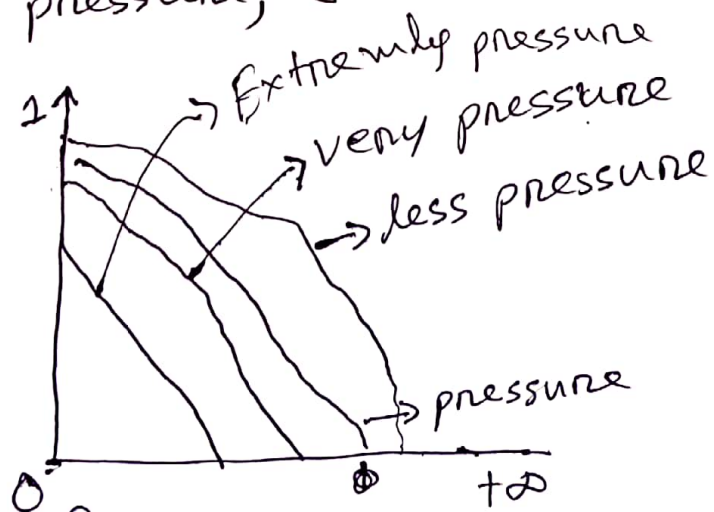


Fig: illustration of hedge with respect to fuzzy ~~so~~ values.

## Answer to the Q. No. 3(b)

Now,

$$A = 012/1000 = 0.012$$

$$B = 012/2000 = 0.006$$

$$C = 012/4000 = 0.003$$

$$D = 1 - A = 1 - 0.012 = 0.988$$

$$E = 1 - B = 1 - 0.006 = 0.994$$

very good programme membership =  $[0.012, 0.006, 0.003, 0.988, 0.994]$

we know,

$$\text{good} = \sqrt{\text{very good}}$$

$$\therefore \text{extremely good} = (\text{good})^3$$

$$\therefore \text{more or less good} = (\text{good})^{\frac{1}{2}}$$

So,

$$\text{good programme membership} = [\sqrt{0.012}, \sqrt{0.006}, \sqrt{0.003}, \sqrt{0.988}, \sqrt{0.994}]$$

$$= [\sqrt{0.012}, 0.11, 0.077, 0.994, 0.997]$$

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(i)

$$\text{extremely good membership} = [(0.11)^3, (0.077)^3, (0.055)^3, (0.994)^3, (0.997)^3]$$

$$= [0.001, 0.0005, 0.0001, 0.982, 0.991]$$

(ii)

$$\text{more or less good membership} = [(0.11)^{\frac{1}{2}}, (0.077)^{\frac{1}{2}}, (0.055)^{\frac{1}{2}}, (0.994)^{\frac{1}{2}}, (0.997)^{\frac{1}{2}}]$$

$$= [0.33, 0.28, 0.23, 0.997, 0.998]$$

Graphical representation:

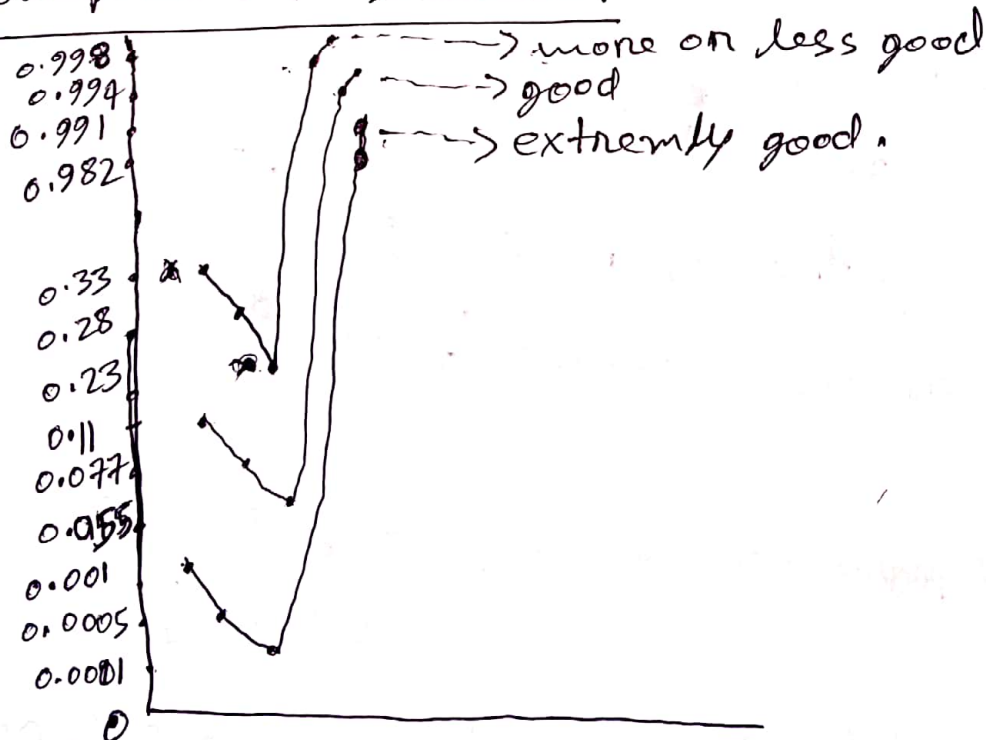


Fig. graphical representation.

# Answer to the Q No. 4

$$T_1 = 12 \times 3 + 2 = 2$$

$$T_2 = -7$$

$$T_3 = -2$$

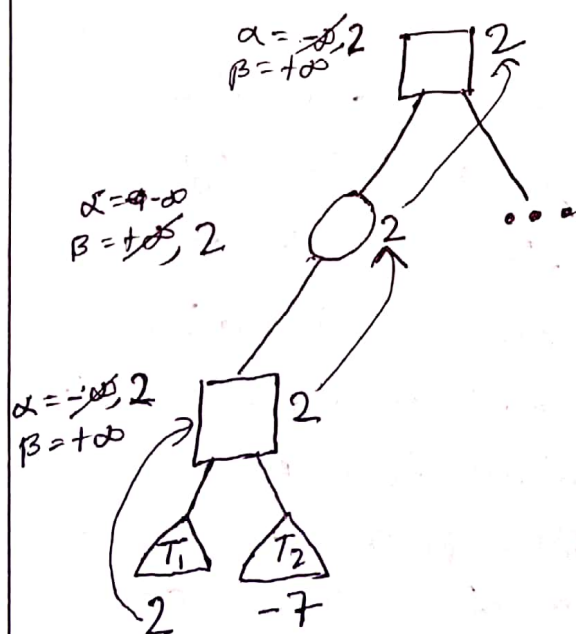
$$T_4 = T_1 + 3 = 2 + 3 = 5$$

Let,

$$\alpha = -\infty$$

$$\beta = +\infty$$

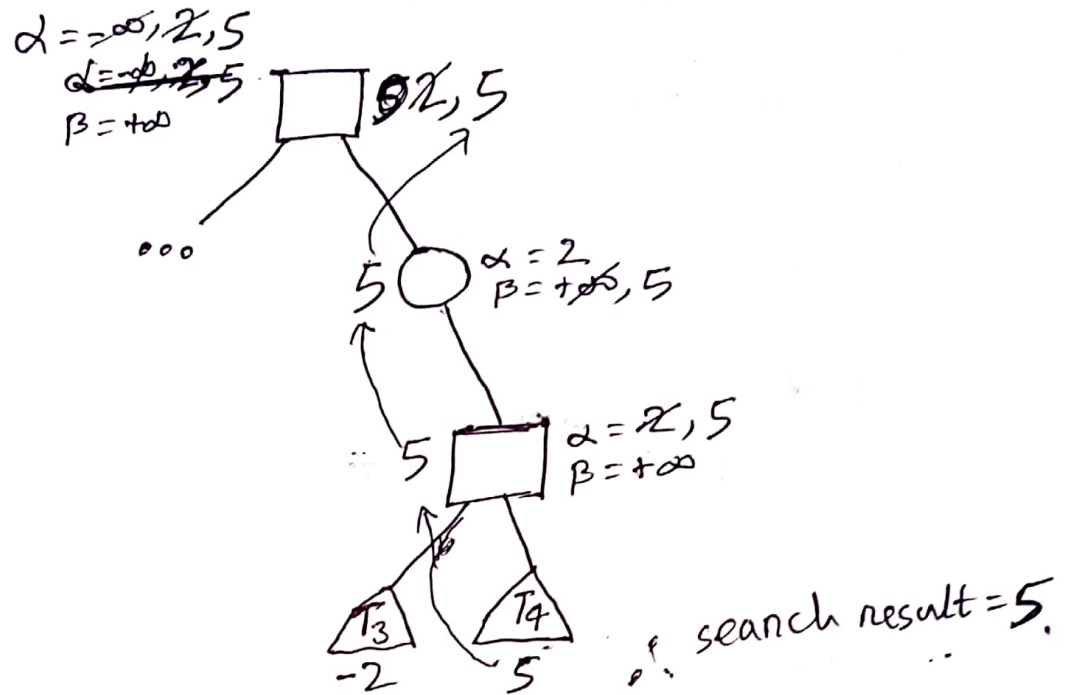
Left side:



(12)

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Right side:

Explanation:

search algorithm

The base Minimax ~~pruning~~ is very slow considering a complex problem. Because in complex problem branching factors are very high. This can be solved by ~~alpha-beta~~ pruning. It is an optimized technique that reduces the time complexity of Minimax pruning. It is basically a modified version of Minimax search in which we can eliminate or cut off a part of tree in such a way that the end result doesn't change. Here we take two parameters  $\alpha$  and  $\beta$  and the prune condition is  $\alpha \geq \beta$ .



The alpha-beta pruning to a standard minimax algorithm returns the ~~near~~ same move as the standard algorithm but it removes all the nodes which are <sup>not</sup> really ~~are~~ affecting the final decision but making algorithm slow.

So we can conclude alpha-beta pruning reduces the search space, time complexity ~~of~~ ~~the~~ of the search in game tree. Thus alpha-beta pruning makes the search very fast when compared to minimax algorithm.

~~The final tree stands~~

Ans