

## **Assignment 02**

## **CSE422: Artificial Intelligence**

Reshad Ul Karim

Student ID: 22201594

Section: 16

Submitted to

Dr. Swakkhar Shatabda

Professor, Department of Computer Science and Engineering

**BRAC** University



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			Approximation of the contract	
Age (A)	Grender	Smartphone(s)	Count	P(A,G.S)
Young	Male	Nokia	14	0.14
Young	Male	Sameung	8	0.08
Young	Male	Apple	14	0.14
Young	Female	Nokia.	8	0.08
Young	Female	Barnsung	12	0.12
Young	female	Apple .	9	0.09
Old	Male	Napia	チ	0.07
old	Male	Samung	5	0.05
Old	Male	Apple	11	0.11
old	Female	Nokia	1	0.01
Old	Female	Samsung	3	0.03
old	Fernale	Apple	8	0.08
7-21 73	De la maria	LVE IE	100	1
		-	-	

(1) P (not Apple Old Age) = P(not Apple 1) Old Age)
P(Old Age)

= 0.07+0.05+0.01+0.03 0.07+0.05+0.11+0.01+0.03

... P (not Apple ) 01d Age) = 16 = 0.457 [Am]

 $\frac{8}{41} = \frac{9}{41} \times \frac{29}{41}$ but \frac{8}{41} + \frac{261}{1681}

$$P(s = Samsung, A = young | G = female) = \frac{12}{41}$$
  
 $P(s = Samsung | G = female) = \frac{15}{41}$ 

P (A= young | G= female) = 
$$\frac{29}{41}$$
  
but,  $\frac{12}{41} + \frac{15}{41} \times \frac{29}{41}$ 

$$= \frac{12}{41} + \frac{435}{1681}$$

Again,

but, 
$$\frac{9}{41} \neq \frac{17}{41} \times \frac{29}{41}$$

$$\frac{9}{41} \neq \frac{493}{1681}$$

but, 
$$\frac{1}{41} \neq \frac{9}{41} \times \frac{12}{41}$$

but, 
$$\frac{3}{41} + \frac{15}{41} \times \frac{12}{41}$$

$$\Rightarrow \frac{3}{41} \neq \frac{180}{1681}$$

$$P(S = Apple), A = old | G_1 = female) = \frac{8}{41}$$
but  $\frac{8}{41} + \frac{17}{41} \times \frac{12}{41}$ 

$$\therefore \frac{8}{41} \neq \frac{204}{1681}$$

So, we can see for each condition of age and smartphone

so smartphone is not conditionally independent to age given gender is female.

(1) 
$$p(s = samsung | A = old) = \frac{8}{35}$$
  
So expected number =  $\frac{8}{35} \times 30$   
= 6.857  
 $\times 6$  wers.

$$P(A|B,C) = P(B|A,C)$$

$$P(A|C) = P(B|C)$$

$$P(A|B,C) = \frac{P(A,B,C)/P(C)}{P(B,C)/P(C)} = \frac{P(A,B|C)}{P(B|C)}$$

$$P(B|A,C) = \frac{P(A,B,C)/P(C)}{P(A,B,C)/P(C)} = \frac{P(A,B|C)}{P(A|C)}$$

We know,

$$P(A|C) = P(B|C)$$

$$So, \quad P(A,B|C) = \frac{P(A,B|C)}{P(A|C)}$$

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

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

H = HMPV positive H=HMPV negotive T = Test Positive T = Tested Negotive P(T H) =0.07 P(T/H)=0.88 P(H) = 0.86, P(H) = 0.14 P(T) = 0.07 1 X0.14 +0.88 X0.86 =0.766 P(TH) = 0.93) P(T|H = 0.12) @ P(H|T) = P(T|H).P(H) = 0.07 X0.14 P(F) = 0.07 X0.14 = 0.0128 [Am] (B) P (H) T. T. T. T) = P(T.T. T. T) H) . P(H) P(T.T.T.T) PP (T.T.T.T H)= 0.07x[0.93]3=0.0563 · P (T.T. T.T | H) = 0.88×[0.12]3 = 0.00152 . . P (T.T.T.T) = 0.0563 X0.14 + 0.00 152 X0.86 =0.00919

## Answer to the question. 3

Exam Score Range	Pars	Fail	Total
Above 80%	8	2	10
Between 50% and 80%.	5	5	10
Below 50%.	1	9	.10
El Kurting to a ser	14	16	30

@ Entropy=0.918

Entrapy for above 80%

Entropy for between 50% and 80%.

$$E_{2} = -\frac{5}{10}\log_{2}\frac{5}{10} - \frac{5}{10}\log_{2}\frac{5}{10} = 1$$

Bos information gain = 0.918-0.730=0.188

· Sulfrag

(b)

Attendance	Pass	Fail	Total
tigh Attendance	1	2	3
Moderate	D <sub>1</sub> .	7	ナ
Total	1	9	10

For High Attendomce,  

$$E_1 = -\frac{1}{3}\log_{\frac{1}{2}} - \frac{0}{7}\log_{\frac{1}{2}} = 0.9183$$
  
For Moderate Attendance  
 $E_2 = \frac{0}{7}\log_{\frac{1}{2}} - \frac{7}{7}\log_{\frac{1}{2}} = 0$ 

So, weighted entropy  $E_{after} = \frac{3}{10} \times 0.9183 + 0 = 0.2755$ 

Entropy for below 50% = 0.469

Intropy for below 50% = 0.469

Into 2mation gain = 0.469-0.2755

= 0.1935

- (a) (i) false. It can be used for regression tanks as well.
  - 1 True. This ensures we get the most information from the split.
  - (11) False. Enthapy measures the impurity and disorder of the dataset. The higher the impurity, the more uncertain the split is.

## Answer to the question. 4

- @ Weight is a continuous variable, therefore it is a regression problem.
- Dearning rate helps us control the size of the step taken by the algorithm. A learning rate that decreases over time lets a model take larger steps toward the aptimum when training begins—helping it quickly escape flat regions or shallow traps—and then gradually switches to smaller, more cautious



updates as it approaches a minimum. Early an, the higher rate encourages fast progress across the loss surfaces while later the reduced rate prevents overshooting and dampens ascillation around aptimum, allowing finer adjustments. This "leig then small approach not only speeds up convergence in the initial phases but also improves stability and precision at end, making it more likely that model will settle into a good solution exather than becurring indefinitely or stagneting too soon.

As we can see at point 1, the gradient of the everor function JO) is positive. But according to the



equation of gradient dissent we have to add the megative of the gradient. Bo, we sulctract digradient from the old parameter which takes to point 2, as it is closer to maxima. The negative in the favorable ensure we move in the correct direction for example, towards the minima.

(a) 
$$d = 0.4$$
  
 $m_1 = 0.4$ ,  $m_2 = 0.5$ ,  $c = 0.6$   
 $\hat{y} = m_1 x_1 + m_2 x_2 + c$  ...  $\hat{y} = 0.4 x_1 + 0.5 x_2 + 0.6$   
Naw, for  $(2,3,4)$   
 $\hat{y} = 0.4 \times 2 + 0.5 \times 3 + 0.6 = 2.9$   
... Emmor =  $y - \hat{y} = 4 - 2.9 = 1.1$   
 $for (3,4,5)$   
 $\hat{y} = 0.4 \times 3 + 0.5 \times 4 + 0.6 = 3.8$   
... Error =  $y - \hat{y} = 5 - 3.8 = 1.2$   
 $far (4,5,6)$   
 $\hat{y} = 0.4 \times 4 + 0.5 \times 5 + 0.6 = 4.7$   
... Error =  $6 - 4.7 = 1.3$ 

Lass function: 
$$\frac{1}{m} \sum_{i=1}^{m} (y-\hat{y})^{2}$$

$$\frac{\partial J}{\partial W_{0}} = -\frac{2}{m} \sum_{i=1}^{m} (y-\hat{y})$$

$$\frac{\partial J}{\partial W_{1}} = -\frac{2}{m} \sum_{i=1}^{m} (y-\hat{y})^{\alpha_{1}}$$

$$\frac{\partial J}{\partial W} = -\frac{2}{m} \sum_{i=1}^{m} (y-\hat{y})^{\alpha_{2}}$$

$x^{1}$	22	ennor	errorx x1	error#x2
2	3	1.1	2.2	3.3
3	4	1.2	3.6	4.8
4	5	1.3	5.2	6.5

3.6 11.0

14.6

$$\nabla J(c) = -\frac{2}{3} \times 3.6 = -2.4$$
  
 $\forall J(m_1) = -\frac{2}{3} \times 11 = -\frac{22}{3}$   
 $\nabla J(m_2) = -\frac{2}{3} \times 14.6 = -\frac{146}{15}$   
 $m_{1}_{rew} = 0.4 - 0.1 \times (-\frac{22}{3}) = 1.133$   
 $m_{2}_{rew} = 0.5 - 0.1 \times (-\frac{146}{15}) = 1.4733$   
 $e_{rew} = 6.6 - 0.1 \times (-2.4) = 0.84$ 

: 
$$c = 0.84$$
,  
 $m_1 = 1.133$   
 $m_2 = 1.473$  [Am]