2018 Scheme

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NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

An Autonomous Institution Approved by UGC/AICTE/Govt. of Karnataka
Accredited by NBA (Tier – I) and NAAC 'A+' Grade
Affiliated to Visveswaraya Technological University, Belagavi
Post Box No. 6429, Yelahanka, Bengaluru – 560 064, Karnataka, India

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

MID SEMESTER EXAMINATION-II

Course Title with code	Introduction to Machine Learning, 18CSE751	**Maximum Marks**	**30 Marks**
Date and Time	24-12-21, 2:30pm to 3:30pm	**No. of Hours**	1.0
Course Instructor(s)	Dr. Vani V		

Instructions to Students

1. Answer any **two full questions.**
2. Any missing data may assume suitably.

Q. No	Question	MAX MARKS	CO	BL	PO/PSO
1. a	For the following 2 test instances, determine the class using **Naïve Bayes Classifier** with the training instances as given in **Table 1.a.**	8	3	3	1,2, 3/2

Y1 = [eyecolour = brown, married = yes, sex = female, hairlength = long]

Y2 = [eyecolour = blue, married = no, sex = male, hairlength = short]

Table 1.a Sports Club Dataset

eyecolour	married	sex	hairlength	class
brown	yes	male	long	football
blue	yes	male	short	football
brown	yes	male	long	football
brown	no	female	long	netball
brown	no	female	long	netball
blue	no	male	long	football
brown	no	female	long	netball
brown	no	male	short	football
brown	yes	female	short	netball
brown	no	female	long	netball
blue	no	male	long	football
blue	no	male	short	football

Solution:

P(eyecolour = brown|class=football)= 0.43
P(eyecolour = blue|class=football)= 0.57
P(eyecolour = brown|class=netball)=1
P(eyecolour = blue|class=netball)=0

P(married = yes | class = football) =0.43
P(married =no| class = football) =0.57
P(married = yes |class = netball)=0.2
P(married=no|class=netball)=0.8

P(sex=male|class = football)= 1
P(sex=female|class = football)= 0
P(sex=female|class=netball)= 1
P(sex=male|class=netball)= 0

P(hairlength=long|class=football) =0.57
P(hairlength=short|class=football) =0.43
P(hairlength=long|class=netball) =0.8
P(hairlength=short|class=netball) =0.2

P(Y1|Class=football) = 0
P(Y1|Class = netball) = 0.16 * 0.42= 0.067
Y1 = [eyecolour = brown, married = yes, sex = female, hairlength = long] => netball

P(Y2|Class = football) = 0.14 * 0.58 =0.0812
P(Y2|Class = netball) =0
Y2 = [eyecolour = blue, married = no, sex = male, hairlength = short] => football

Marking Scheme:
For each object classification :4 marks 4x 2 = 8 marks

1. b Determine the class for the following objects

1. y = [1,22] &
2. y = [1,3]

using the 3-NN classifier and the 5-NN classifier, both using training samples from the **Table 1.c** . Justify, why the two classifiers differ in their classification behavior.

7 3 3 1,2, 3/2

Table 1.c Training Samples

X1	1	1	1	2	3	3	3	4	5
X2	1	2	4	3	0	2	5	4	3
Class	+	-	-	+	+	+	-	-	-

Solution:

X1	1	1	1	2	3	3	3	4	5
X2	1	2	4	3	0	2	5	4	3
Class	+	-	-	+	+	+	-	-	-
Distance y1	21	20	18	19.03	22.09	20.099	17.12	18.25	19.42
Distance y2	2	1	1	1	3.61	2.24	2.83	3.16	4

y1=[1,22] y2=[1,3]

1NN	y2 => -/+	3NN	y2 => -	5NN	y2=>+
1NN	y1 => -	3NN	y1=> -	5NN	y1=> -

KNN -> lazy learning algorithm, Change the value from low to high as a process of parameter tuning to achieve best performance. According to the research history, K = Sqrt(n) could be perfect number of nearest neighbors that can be considered for classification. However, in the given problem for classification of y2 sample, the prediction differs when we consider larger K. To avoid these problems, we can use Weighted KNN.

Marking Scheme:

<table>
<tr><td></td><td>For each classification :1.5 marks 4x 1.5 = 6 marks

1 mark for justification</td><td></td><td></td><td></td><td></td></tr>
<tr><td>2. a</td><td>Generate the decision rules for the decision tree in Figure 2.a

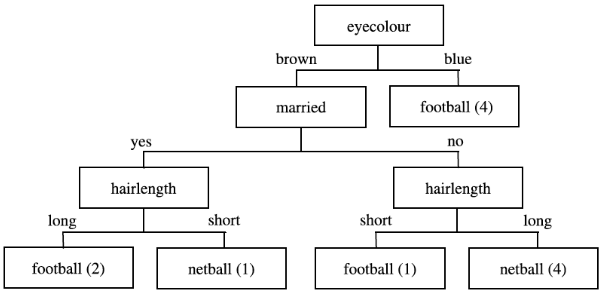


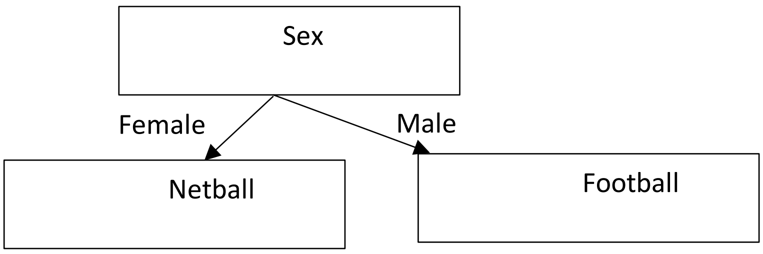
Figure 2.a Decision Tree

<u>Solution:</u>

R1 : If eyecolour = blue then class=football
R2: If eyecolour = brown AND married = yes AND hairlength = long then class=football
R3: If eyecolour = brown AND married = yes AND hairlength = short then class=netball
R4: If eyecolour = brown AND married = no AND hairlength = long then class=netball
R5: If eyecolour = brown AND married = no AND hairlength = short then class=football</td><td>5

Each rule 1 mark</td><td>4</td><td>3</td><td>1,2, 3/2</td></tr>
<tr><td>2. b</td><td>Can another decision tree with a smaller number of predictors be identified for the given dataset in Table 1.a on determining who joins which club? If so, draw that decision tree with necessary reasoning.

<u>Solution:</u>


</td><td>3</td><td>4</td><td>3</td><td>1,2, 3/2</td></tr>
<tr><td>2. c</td><td>Determine the best attribute split by calculating the information gain of sex, eyecolour, married, and hairlength attributes with the given dataset in Table 1.a
<u>Solution:</u>

<table>
<tr><td></td><td colspan="2"><u>Sex</u></td></tr>
<tr><td><u>Class</u></td><td><u>Male</u></td><td><u>Female</u></td></tr>
<tr><td>Football</td><td>7</td><td>0</td></tr>
<tr><td>Netball</td><td>0</td><td>5</td></tr>
</table>

<table>
<tr><td></td><td colspan="2"><u>Eyecolour</u></td></tr>
<tr><td><u>Class</u></td><td><u>Brown</u></td><td><u>Blue</u></td></tr>
<tr><td>Football</td><td>3</td><td>4</td></tr>
</table>
</td><td>7</td><td>4</td><td>3</td><td>1,2, 3/2</td></tr>
</table>

Netball	5	0

	Married	
Class	**Yes**	**No**
Football	3	4
Netball	1	4

	HairLength	
Class	**Short**	**Long**
Football	3	4
Netball	1	4

E(Class) = Entropy(5,7)
=Entropy(5/12,7/12)
= -7/12 log(7/12) – 5/12 log(5/12)
= -0.5833*-0.777-0.4167*(-1.263)
= 0.45357 + 0.52625
= 0.9798

E(Sex) = 7/12 * E(Sex = male) +5/12 * E(Sex = female)
= 7/12 * 0 +5/12 * 0 = 0

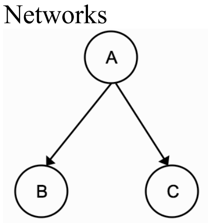
E(EyeColour) = 8/12 * E(eyecolour=brown) +4/12 * E(eyecolour = blue)
=8/12 * (-3/8 * log(3/8) – 5/8 * log(5/8) +4/12 * (-4/4 *log(4/4) -0/4*log(0/4))
= 0.63627

E(married) = 4/12* E(married=yes) + 8/12 * E(married = no)
= 4/12 *(-3/4*log(3/4) -1/4 * log(1/4))+8/12(-4/8*log(4/8)-4/8*log(4/8))
= 4/12 * (-0.75 * -0.415 – 0.25 * -2) +8/12(-.5*-1-0.5*-1)
= 4/12*0.811 _ 8/12 * 1 = 0.9370
E(hairlength) = E(married) = 0.9370
Infogain(Sex) = E(Class) – E(Sex) = 0.9798 – 0 = 0.9798
Infogain(eyecolour) = 0.9798-0.63627 = 0.34353
Infogain(married) =Infogain(hairlength) = 0.0428

0.9799 3 sex
0.3436 1 eyecolour
0.0428 2 married
0.0428 4 hairlength

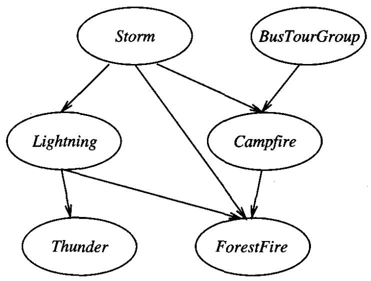
Marking Scheme:
Overall Entropy Calculation:1 Mark
Each info gain 1.5 x 4 = 6 marks

3. a	Illustrate with suitable example the term “conditional independence” in Bayesian Networks	3	3	3	1,2, 3/2



where C is not directly linked to B, but there is a link through A.

<table>
<tr>
<td></td>
<td>
C is conditionally independent of B, given A.



In the above Bayesian Belief Network, **Thunder is conditionally independent of other variables given Lightning.**

In contrast to the naive Bayes classifier, which assumes that all the variables are conditionally independent given the value of the target variable, Bayesian belief networks allow stating conditional independence assumptions that apply to subsets of the variables. Thus, Bayesian belief networks provide an intermediate approach that is less constraining than the global assumption of conditional independence made by the naive Bayes classifier, but more tractable than avoiding conditional independence assumptions altogether
</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>3. b</td>
<td>
Given the Bayesian network shown in **Figure 3.b**, compute the following probabilities.
(a) P(B = good, F = empty, G = empty, S = yes).
(b) P(B = bad, F = empty, G = not empty, S = no).
(c) Given that the battery is bad, compute the probability that the car will start.

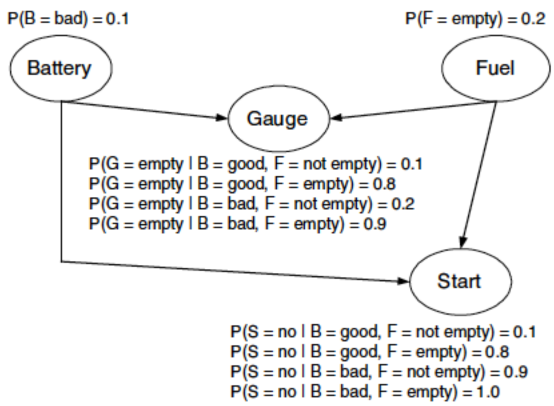

Figure 3.b Bayesian Belief Network

$$\begin{aligned} & P(B = good, F = empty, G = empty, S = yes) \\ = & P(B = good) \times P(F = empty) \times P(G = empty \mid B = good, F = empty) \\ & \times P(S = yes \mid B = good, F = empty) \\ = & 0.9 \times 0.2 \times 0.8 \times 0.2 = 0.0288. \end{aligned}$$

$$\begin{aligned} & P(B = bad, F = empty, G = not\ empty, S = no) \\ = & P(B = bad) \times P(F = empty) \times P(G = not\ empty \mid B = bad, F = empty) \\ & \times P(S = no \mid B = bad, F = empty) \\ = & 0.1 \times 0.2 \times 0.1 \times 1.0 = 0.002. \end{aligned}$$

$$\begin{aligned} & P(S = yes \mid B = bad) \\ = & \sum_{\alpha} P(S = yes \mid B = bad, F = \alpha) P(B = bad) P(F = \alpha) \\ = & 0.1 \times 0.1 \times 0.8 \\ = & 0.008 \end{aligned}$$

<u>**Marking Scheme:**</u>
For each question :2 marks 3x 2 = 6 marks   P(F=α) = 1-0.2 = 0.8
</td>
<td>6</td>
<td>3</td>
<td>3</td>
<td>1,2, 3/2</td>
</tr>
<tr>
<td>3. c</td>
<td>Consider the dataset in Table 1.a. Use the Modified Value Difference Metrics (MVDM) measure to compute the distance between every pair of attribute values for the sex, eyecolour, married, and hairlength attributes.</td>
<td>6</td>
<td>4</td>
<td>3</td>
<td>1,2, 3/2</td>
</tr>
</table>

	d(sex=female, sex=male) = 2 d(eyecolour=blue, eyecolour=brown) = 1.25 d(married=yes,married=no) =0.5 d(hairlength=long,hairlength=short)=0.625 **Marking Scheme:** For each pair :1.5 marks 4x 1.5 = 6 marks				

Faculty Signature	Course Co-Ordinator/Mentor Signature	HoD Signature