RV College of Engineering®

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Academic Year 2023-2024 (Odd Semester)

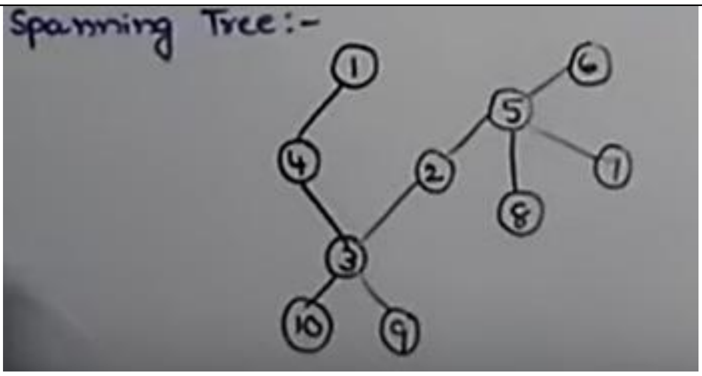
USN:

Department of Artificial Intelligence and Machine Learning

Course Code:21AI52 **Date:**
Sem: V **Duration:** 90 Minutes

CIE-II
Artificial Intelligence and Machine Learning

Answer all Questions

SL. No		Questions	M	BT	CO
1	a)	**States:** Location (airport) and current time. **Initial state:** users query **Actions**: flight from current location, seat class, leaving after the current time, leaving enough time for within airport transfer. **Goal test** destination arrived? **Path cost** monetary cost, waiting time, flight time, customs and immigration procedure, seat quality, time of day, type of airplane, frequent flyer mileage, and so on.	05	L4	CO2
	b)	 9 7 6 5 2 9 10 3 4 1 DFS(G) = 1 4 3 10 9 2 5 6 7 8	05	L3	CO1
2	a)	**Solution-** **Step-01:** We start with node A. Node B and Node F can be reached from node A. A* Algorithm calculates f(B) and f(F). • f(B) = 6 + 8 = 14, f(F) = 3 + 6 = 9 Since f(F) < f(B), so it decides to go to node F. **Path- A → F** **Step-02:** Node G and Node H can be reached from node F. A* Algorithm calculates f(G) and f(H). f(G) = (3+1) + 5 = 9, f(H) = (3+7) + 3 = 13 Since f(G) < f(H), so it decides to go to node G. Path- A → F → G **Step-03:** Node I can be reached from node G. A* Algorithm calculates f(I). f(I) = (3+1+3) + 1 = 8 It decides to go to node I. Path- A → F → G → I **Step-04:** Node E, Node H and Node J can be reached from node I. A* Algorithm calculates f(E), f(H) and f(J). f(E) = (3+1+3+5) + 3 = 15, f(H) = (3+1+3+2) + 3 = 12 f(J) = (3+1+3+3) + 0 = 10 Since f(J) is least, so it decides to go to node J. Path- A → F → G → I → J This is the required shortest path from node A to node J.	06	L3	CO2

	b)	BFS: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 DLS (depth limit 3): 1, 2, 4, 5, 3, 6, 7 IDS: first iteration: 1 second iteration: 1, 2, 3 third iteration: 1, 2, 4, 5, 3, 6, 7 fourth iteration: 1, 2, 4, 8, 9, 5, 10, 11	04	L2	CO2
3	a)		6	2	2

Algorithm :

```
Let $k$ be the number of nearest neighbors and $D$ be the set of training examples.
for each test instance $z = (\mathbf{x}', y')$ do
    Compute $d(\mathbf{x}', \mathbf{x})$, the distance between $z$ and every example, $(\mathbf{x}, y) \in D$.
    Select $D_z \subseteq D$, the set of $k$ closest training examples to $z$.
    $y' = \underset{v}{\operatorname{argmax}} \sum_{(\mathbf{x}_i, y_i) \in D_z} I(v = y_i)$
end for
```

Solution:

BMI	Age	Sugar	Distance
33.6	50	1	14.14
26.6	30	O	19.72
23.4	40	O	20.20
43.1	67	O	27.00
35.3	23	1	18.92
35.9	67	1	28.08
36.7	45	1	8.52
25.7	46	O	18.88
23.3	29	O	23.09
31	56	1	20.37

Pseudo code : 02 Marks
Solving the Problem : 03 marks
Final answer : 01 marks

Test Example BMI=43.6, Age=40, Sugar=1

	b)	Discuss the characteristics of KNN Algorithm	4	1	1

- Instance based learning
- Does not build global model
- Uses training examples to make predictions on test
- Require a proximity measure to determine the similarity or distance between instances
- Requires classification function that returns the predicted class of a test instance based on its proximity to other instances
- Classifying a test instance can be quite expensive because we need to compute the proximity values individually between the test and training examples.
- Nearest neighbor classifiers make their predictions based on local information
- Produces decision boundaries of arbitrary shape.
- The decision boundaries have high variability because they depend on the composition of training examples in the local neighborhood.
- Increasing the number of nearest neighbors may reduce such variability.

		• Have difficulty handling missing values in both the training and test sets since proximity computations normally require the presence of all attributes			
4		**Explanation : 03 marks** Consider each attribute and class label as random variables Given a record with attributes ($X_1, X_2,\ldots, X_d$), the goal is to predict class Y • Specifically, we want to find the value of Y that maximizes $P(Y\| X_1, X_2,\ldots, X_d)$ • Can we estimate $P(Y\| X_1, X_2,\ldots, X_d)$ directly from data? • For the purpose of classification, we are interested in computing the probability of observing a class label y for a data instance given its set of attribute values x. • This can be represented as P(y|x), which is known as the posterior probability of the target class. • Using the Bayes Theorem, we can represent the posterior probability as • The first term P(x|y) is known as the class-conditional probability of the attributes given the class label. • The second term in the numerator is the prior probability P(y). • The denominator is the probability of evidence, P(x). • P(x|y) measures the likelihood of observing x from the distribution of instances belonging to y. • If x indeed belongs to class y, then we should expect P(x|y) to be high. Calculate the probability of the species being M or H in total. – **01 marks** P(Species=M)=4/8=0.5 P(Species=H)=4/8=0.5 Next, we will calculate the conditional probability of each attribute value for each class label. – **03 marks** P(Color=White/Species=M)=2/4=0.5 P(Color=White/Species=H)=¾=0.75 P(Color=Green/Species=M)=2/4=0.5 P(Color=Green/Species=H)=¼=0.25 P(Legs=2/Species=M)=1/4=0.25 P(Legs=2/Species=H)=4/4=1 P(Legs=3/Species=M)=3/4=0.75 P(Legs=3/Species=H)=0/4=0 P(Height=Tall/Species=M)=3/4=0.75 P(Height=Tall/Species=H)=2/4=0.5 P(Height=Short/Species=M)=1/4=0.25 P(Height=Short/Species=H)=2/4=0.5 P(Smelly=Yes/Species=M)=3/4=0.75 P(Smelly=Yes/Species=H)=1/4=0.25 P(Smelly=No/Species=M)=1/4=0.25 P(Smelly=No/Species=H)=3/4=0.75 The probability of X belonging to Species M will be as follows. – **01 marks** P(M/X)=P(Species=M)*P(Color=Green/Species=M)*P(Legs=2/Species=M)*P(Height=Tall/Species=M)*P(Smelly=No/Species=M) =0.5*0.5*0.25*0.75*0.25 =0.0117	10	3	2

		Probability of X belonging to Species H will be calculated as follows. – **01 marks** P(H/X)=P(Species=H)*P(Color=Green/Species=H)*P(Legs=2/Species=H)*P(Height =Tall/Species=H)*P(Smelly=No/Species=H) =0.5*0.25*1*0.5*0.75 =0.0468 So, the probability of X belonging to Species M is 0.0117 and that to Species H is 0.0468. Hence, we will assign the entity X with attributes {Color=Green, Legs=2, Height=Tall, Smelly=No} to species H. – **01 Mark**			
5	a)	Discuss Logistic regression as generalized linear model? ➢ Logistic regression belongs to a broader family of statistical regression models, known as generalized linear models (GLM). ➢ In these models, the target variable y is considered to be generated from a probability distribution P(y|x), whose mean μ can be estimated using a link function g(.) as follows: $g(\mu) = z = \mathbf{w}^T\mathbf{x} + b.$ ➢ The parameters of logistic regression, (w, b), are estimated during training using a statistical approach known as the maximum likelihood estimation (MLE) method. ➢ This method involves computing the likelihood of observing the training data given (w, b), and then determining the model parameters (w∗, b∗) that yield maximum likelihood	5	2	1
	b)	List the characteristics of Logistic Regression? ➢ Discriminative model for classification. ➢ The learned parameters of logistic regression can be analyzed to understand the relationships between attributes and class labels. ➢ Can work more robustly even in high-dimensional settings ➢ Can handle irrelevant attributes ➢ Cannot handle data instances with missing values	5	4	2

Course Outcome	
CO1	Understand and apply Information Retrieval principles to extract relevant information from the given problem
CO2	Analyze the different Information Retrieval techniques, retrieval models and search engines appropriate for a given problem by engaging in lifelong learning for emerging technology
CO3	Exhibit effective communication to solve open problems using Information Retrieval principles to extract the information from different models
CO4	Demonstrate solutions using concepts of Information Retrieval by exhibiting team work and effective communication
CO5	Examine the applications of Information Retrieval principles using modern engineering tools for technological change

M-Marks, BT-Blooms Taxonomy Levels, CO-Course Outcomes

Marks Distribution	**Particulars**	**CO1**	**CO2**	**CO3**	**CO4**	**CO5**	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**
	Max Marks	19	31	--	--	--	8	22	15	5	--	--