



## CT2 set B - Nothing much

Data Mining And Analytics (SRM Institute of Science and Technology)



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**Test: CLA-T2**

**Course Code & Title: 18CSC355T Data Mining and Analytics**

**Year & Sem: III Year / V Sem**

**Date: 26-09-2023**

**Duration: 2 Hour**

**Max. Marks: 50**

**Course Articulation Matrix: (to be placed)**

S.No.	Course Outcome	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
1	CO1	L	H		H	L				L	L		H
2	CO2	M	H		H	L				M	L		H
3	CO3	M	H		H	L				M	L		H
4	CO4	M	H		H	L				M	L		H
5	CO5	H	H		H	L				M	L		H

**Part - A**  
**(10 x 1 = 10 Marks)**

**Instructions: Answer all**

Q. No	Question	Marks	BL	CO	PO	PI Code
1	Which algorithm is used for frequent itemset mining? a) Decision tree algorithm b) K-nearest neighbors algorithm c) <b>Apriori algorithm</b> d) Naive Bayes algorithm	1	L1	2	1	1.7.1
2	Frequency of occurrence of an item set is called as _____ a) Support b) Confidence c) <b>Support Count</b> d) Rules	1	L1	2	1	1.7.1
3	In a supermarket there were 100 transactions. In that 20 transactions have bread, out of 20 transactions butter occurs in 8 transactions. So what is the confidence percentage for butter? a) 20 Percentage b) <b>40 Percentage</b> c) 45 Percentage d) 8 Percentage	1	L2	2	2	2.6.3
4	When do you consider an association rule interesting ? a) If it only satisfies min_support b) If it only satisfies min_confidence c) <b>If it satisfies both min_support and min_confidence</b> d) There are other measures to check so	1	L1	2	2	2.6.3
5	How do you calculate Confidence (A -> B)? a) <b>Support(A ∩ B) / Support (A)</b> b) Support(A ∩ B) / Support (B) c) Support(A ∪ B) / Support (A) d) Support(A ∪ B) / Support (B)	1	L2	2	1	1.7.1
6	You are given data about seismic activity in the United States, and you want to predict the magnitude of the upcoming earthquake. This can be considered as an example of which of	1	L2	3	1	1.7.1

	the following methods? a) <b>Supervised learning</b> b) Unsupervised learning c) Serration d) Dimensionality reduction					
7	In some cases, telecommunication companies desire to segment their clients into distinct groups in order to send suitable and related subscription offer. This can be considered as an example of which of the following methods? a) Supervised learning <b>b)Unsupervised learning</b> c) Serration d). Data extraction	1	L2	3	5	5.4.1
8	Suppose your classification model predicted true for a class which actual value was false. Then this is a- <b>a) False positive</b> b) False negative c) True positive d) True negative	1	L2	3	1	1.7.1
9	The true positive value is 10 and the false positive value is 15. Calculate the value of precision a) 0.6 <b>b). 0.4</b> c) 0.5 d). None	1	L3	3	1	1.7.1
10	Which one of the following is the main reason for pruning a Decision Tree? a).to save computing time during testing b).to save space for storing the decision tree c).to make the training set error smaller <b>d).to avoid overfitting the training set</b>	1	L2	1	1	1.7.1

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2	CO2	M	H		H	L				M	L		H
3	CO3	M	H		H	L				M	L		H
4	CO4	M	H		H	L				M	L		H
5	CO5	H	H		H	L				M	L		H

**PART B (5x 4 = 20 Marks)**

Q. No	Question	Marks	BL	CO	PO	PI Code
11	<p>What are the limitations of the Apriori algorithm and how may it be made more efficient?</p> <p>Limitations of the Apriori algorithm  The main limitation is the costly wasting of time to hold many candidates sets with frequent itemsets, low minimum support, or large itemsets.  A large amount of data needs to be stored in memory for processing, so large transaction items require much more resources.</p> <p>Improving the Efficiency of Apriori</p> <ul style="list-style-type: none"> <li>Transaction Reduction(reducing the number of transactions scanned in future iterations</li> <li>Partitioning(partitioning the data to find candidate itemsets):</li> <li>Sampling(mining on a subset of the given data):</li> <li>Dynamic itemset counting (adding candidate itemsets at different points during a scan):</li> <li>Hash-based technique (hashing itemsets into corresponding buckets):</li> </ul>	5	L2	2	2	2.8.2
12	<p>Explain about multilevel association rules and their purpose. Also, list and brief the many forms of multilevel association rules.</p>	5	L1	2	1	1.2.2

	<div><div>Multilevel Association Rules</div><div><ul style="list-style-type: none"><li>When transactions data is taken for link analysis. It is present at the low level of abstraction that is detail form.</li><li>It is very difficult to form association rules at the low level of abstraction as data scarcity is there. Also resultant rules can not efficiently used.</li><li>Using concept hierarchies, transaction data can be represented at various levels of abstraction.</li><li>In Multilevel Association Rules, association rules are generated at multiple levels of abstraction</li><li>Instead of going at lower level of abstraction, association rules are generated from higher level of abstraction which represents common sense knowledge and be use used efficiently.</li></ul></div><div>Need of Multiple-Level Association Rules?<ul style="list-style-type: none"><li>Sometimes at low data level, data does not show any significant pattern. But there are useful information hiding behind.</li><li>Aim is to find the hidden information in or between levels of abstraction</li></ul></div><div>Three ways<ul style="list-style-type: none"><li>1) Uniform Support (Using uniform minimum support for all levels)</li><li>2) Reduced support (Using reduced minimum support at lower levels)</li><li>3) Group-based support (Using item or group based minimum support)</li></ul></div></div>																					
13	<div><div>Brief about the Metrics for Evaluating classifier Performance</div><div><table><tr><th>Measure</th><th>Formula</th></tr><tr><td>accuracy, recognition rate</td><td><math>\frac{TP + TN}{P + N}</math></td></tr><tr><td>error rate, misclassification rate</td><td><math>\frac{FP + FN}{P + N}</math></td></tr><tr><td>sensitivity, true positive rate, recall</td><td><math>\frac{TP}{P}</math></td></tr><tr><td>specificity, true negative rate</td><td><math>\frac{TN}{N}</math></td></tr><tr><td>precision</td><td><math>\frac{TP}{TP + FP}</math></td></tr><tr><td><math>F_1</math>, <math>F_1</math>, F-score, harmonic mean of precision and recall</td><td><math>\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}</math></td></tr><tr><td><math>F_\beta</math>, where <math>\beta</math> is a non-negative real number</td><td><math>\frac{(1 + \beta^2) \times \text{precision} \times \text{recall}}{\beta^2 \times \text{precision} + \text{recall}}</math></td></tr></table></div></div>	Measure	Formula	accuracy, recognition rate	$\frac{TP + TN}{P + N}$	error rate, misclassification rate	$\frac{FP + FN}{P + N}$	sensitivity, true positive rate, recall	$\frac{TP}{P}$	specificity, true negative rate	$\frac{TN}{N}$	precision	$\frac{TP}{TP + FP}$	$F_1$ , $F_1$ , F-score, harmonic mean of precision and recall	$\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$	$F_\beta$ , where $\beta$ is a non-negative real number	$\frac{(1 + \beta^2) \times \text{precision} \times \text{recall}}{\beta^2 \times \text{precision} + \text{recall}}$	5	L1	3	2	2.8.2
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14	<div><div>Explain about decision tree and write all the possible rules from the following Decision tree.</div><div><div><div><div>Running Nose</div><div><div><div>+</div><div>Coughing</div><div><div><div>+</div><div>healthy</div></div><div><div>-</div><div>Unhealthy</div></div></div><div><div>-</div><div>Unhealthy</div></div></div></div></div></div></div></div>	5	L2	3	2	2.6.4																

	<p>the result of the algorithm. It is a versatile supervised machine-learning algorithm, which is used for both classification and regression problems</p> <p>Root Node: It is the topmost node in the tree, which represents the complete dataset. It is the starting point of the decision-making process.</p> <p>Decision/Internal Node: A node that symbolizes a choice regarding an input feature. Branching off of internal nodes connects them to leaf nodes or other internal nodes.</p> <p>Leaf/Terminal Node: A node without any child nodes that indicates a class label or a numerical value.</p> <p>Splitting: The process of splitting a node into two or more sub-nodes using a split criterion and a selected feature.</p> <p>Branch/Sub-Tree: A subsection of the decision tree starts at an internal node and ends at the leaf nodes.</p> <p>Parent Node: The node that divides into one or more child nodes.</p> <p>Child Node: The nodes that emerge when a parent node is split.</p> <pre> R1:    If(Running    Nose=-)    then Status=Unhealthy  R2: If(Running Nose=+) AND (Coughing=+) then Status=Healthy  R2: If(Running Nose=+) AND (Coughing=-) then Status=Unhealthy </pre>					
15	<p>Is clustering unsupervised or supervised classification? Give the reason for your answer.</p> <p>Clustering can be considered the most important unsupervised learning problem; so, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data. A loose definition of clustering could be “the process of organizing objects into groups whose members are similar in some way”. A cluster is therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters.</p>	5	L2	3	2	2.6.4

**PART C (2 x 10 = 20 Marks)**

16	<p>i.Built the FP tree for the given transactions , Find all frequent item sets from conditional pattern base of each node using Fp growth algorithm and the minimum support is 30% (7 marks)</p> <table><tr><td>TID</td><td>List of Items</td></tr><tr><td>T1</td><td>E,A,D,B</td></tr><tr><td>T2</td><td>D,A,C,E,B</td></tr><tr><td>T3</td><td>C,A,B,E</td></tr><tr><td>T4</td><td>B,A,D</td></tr><tr><td>T5</td><td>D</td></tr><tr><td>T6</td><td>D,B</td></tr><tr><td>T7</td><td>A,D, E</td></tr><tr><td>T8</td><td>B,C</td></tr></table> <p>ii .Explain the support and confidence (3 marks )</p> <div><div><p>Frequent pattern are</p><p><b>C:3,CB:3</b></p><p><b>E:4, DE:3, AE:4, BE:3, ADE:3, ABE:3</b></p><p><b>A:5, AD:5, AB:4, ABD:3</b></p><p><b>D:6, BD:4</b></p><p><b>B:6</b></p></div><table><tr><td>TID</td><td>List of Items</td></tr><tr><td>T1</td><td>B, D, A, E</td></tr><tr><td>T2</td><td>B, D, A, E, C</td></tr><tr><td>T3</td><td>B, A, E, C</td></tr><tr><td>T4</td><td>B, D, A</td></tr><tr><td>T5</td><td>D</td></tr><tr><td>T6</td><td>B, D</td></tr><tr><td>T7</td><td>D, A, E</td></tr><tr><td>T8</td><td>B, C</td></tr></table></div>	TID	List of Items	T1	E,A,D,B	T2	D,A,C,E,B	T3	C,A,B,E	T4	B,A,D	T5	D	T6	D,B	T7	A,D, E	T8	B,C	TID	List of Items	T1	B, D, A, E	T2	B, D, A, E, C	T3	B, A, E, C	T4	B, D, A	T5	D	T6	B, D	T7	D, A, E	T8	B, C	10	L3	2	2	2.8.2
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17	<p>Consider the Dataset for finding frequency pattern using Apriori Algorithm Find the frequent item sets and generate association rules on this. Assume that minimum support threshold (s = 30%) and minimum confident threshold (c = 70%)</p> <table><tr><td>TID</td><td>List of Items</td></tr><tr><td>T1</td><td>E,A,D,B</td></tr><tr><td>T2</td><td>D,A,C,E,B</td></tr><tr><td>T3</td><td>C,A,B,E</td></tr></table>	TID	List of Items	T1	E,A,D,B	T2	D,A,C,E,B	T3	C,A,B,E	10	L3	3	4	4.4.2																												
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18	<p>Construct Decision tree and Rules for the given dataset using Information Gain.</p> <table><tr><th>Age</th><th>Income</th><th>Student</th><th>Credit Rating</th><th>Buys_Computer</th></tr><tr><td>&lt;=30</td><td>High</td><td>No</td><td>Fair</td><td>No</td></tr><tr><td>&lt;=30</td><td>High</td><td>No</td><td>Excellent</td><td>No</td></tr><tr><td>31..40</td><td>High</td><td>No</td><td>Fair</td><td>Yes</td></tr><tr><td>&gt;40</td><td>Medium</td><td>No</td><td>Fair</td><td>Yes</td></tr><tr><td>&gt;40</td><td>Low</td><td>Yes</td><td>Fair</td><td>Yes</td></tr><tr><td>&gt;40</td><td>Low</td><td>Yes</td><td>Excellent</td><td>No</td></tr><tr><td>31..40</td><td>Low</td><td>Yes</td><td>Excellent</td><td>Yes</td></tr><tr><td>&lt;=30</td><td>Medium</td><td>No</td><td>Fair</td><td>No</td></tr><tr><td>&lt;=30</td><td>Low</td><td>Yes</td><td>Fair</td><td>Yes</td></tr><tr><td>&gt;40</td><td>Medium</td><td>Yes</td><td>Fair</td><td>Yes</td></tr><tr><td>&lt;=30</td><td>Medium</td><td>Yes</td><td>Excellent</td><td>Yes</td></tr><tr><td>31..40</td><td>Medium</td><td>No</td><td>Excellent</td><td>Yes</td></tr><tr><td>31..40</td><td>High</td><td>Yes</td><td>Fair</td><td>Yes</td></tr><tr><td>&gt;40</td><td>Medium</td><td>No</td><td>Excellent</td><td>No</td></tr></table>	Age	Income	Student	Credit Rating	Buys_Computer	<=30	High	No	Fair	No	<=30	High	No	Excellent	No	31..40	High	No	Fair	Yes	>40	Medium	No	Fair	Yes	>40	Low	Yes	Fair	Yes	>40	Low	Yes	Excellent	No	31..40	Low	Yes	Excellent	Yes	<=30	Medium	No	Fair	No	<=30	Low	Yes	Fair	Yes	>40	Medium	Yes	Fair	Yes	<=30	Medium	Yes	Excellent	Yes	31..40	Medium	No	Excellent	Yes	31..40	High	Yes	Fair	Yes	>40	Medium	No	Excellent	No	10	L3	3	8	8.4.1
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	Information gain for root node						
	Attributes	Gain					
	Age	0.25					
	Income	0.03					
	Student	0.15					
	Credit rating	0.05					
	Information gain for second left node						
	Attributes	Gain					
	Income	0.57					
	student	0.97					
	Credit rating	0.02					
	Information gain for second Right node						
Attributes	Gain						
Income	0.02						
student	0.02						
Credit rating	0.97						

	<div><p><b>Decision Tree</b></p><p><b>Decision Tree Rules</b></p><p><b>R1:</b> If(Age=31...40) then Buys_Computer=Yes</p><p><b>R2:</b> If(Age&lt;=30) AND (Student=Yes) then Buys_Computer=Yes</p><p><b>R3:</b> If(Age&lt;=30) AND (Student=No) then Buys_Computer=No</p><p><b>R4:</b> If(Age=&gt;40) AND (Credit Rating=Fair) then Buys_Computer=Yes</p><p><b>R5:</b> If(Age=&gt;40) AND (Credit Rating=Excellent) then Buys Computer=No</p></div>																																																												
(OR)																																																													
19	<div><p>i. Create the naive bayes model from the given dataset and the target class is stolen</p><p>ii. find the target class (stolen) for the unseen data x= (red ,Sports and Domestic)</p><p>iii. find the target class (stolen) for the unseen data x= (yellow ,SUV and imported)</p><table><tr><th>Car no.</th><th>Color</th><th>Type</th><th>Origin</th><th>Stolen</th></tr><tr><td>1</td><td>Red</td><td>Sports</td><td>Domestic</td><td>Yes</td></tr><tr><td>2</td><td>Red</td><td>Sports</td><td>Domestic</td><td>No</td></tr><tr><td>3</td><td>Red</td><td>Sports</td><td>Domestic</td><td>Yes</td></tr><tr><td>4</td><td>Yellow</td><td>Sports</td><td>Domestic</td><td>No</td></tr><tr><td>5</td><td>Yellow</td><td>Sports</td><td>Imported</td><td>Yes</td></tr><tr><td>6</td><td>Yellow</td><td>SUV</td><td>Imported</td><td>No</td></tr><tr><td>7</td><td>Yellow</td><td>SUV</td><td>Imported</td><td>Yes</td></tr><tr><td>8</td><td>Yellow</td><td>SUV</td><td>Domestic</td><td>No</td></tr><tr><td>9</td><td>Red</td><td>SUV</td><td>Imported</td><td>No</td></tr><tr><td>10</td><td>Red</td><td>Sports</td><td>Imported</td><td>Yes</td></tr></table></div>	Car no.	Color	Type	Origin	Stolen	1	Red	Sports	Domestic	Yes	2	Red	Sports	Domestic	No	3	Red	Sports	Domestic	Yes	4	Yellow	Sports	Domestic	No	5	Yellow	Sports	Imported	Yes	6	Yellow	SUV	Imported	No	7	Yellow	SUV	Imported	Yes	8	Yellow	SUV	Domestic	No	9	Red	SUV	Imported	No	10	Red	Sports	Imported	Yes	10	L3	3	8	8.4.1
Car no.	Color	Type	Origin	Stolen																																																									
1	Red	Sports	Domestic	Yes																																																									
2	Red	Sports	Domestic	No																																																									
3	Red	Sports	Domestic	Yes																																																									
4	Yellow	Sports	Domestic	No																																																									
5	Yellow	Sports	Imported	Yes																																																									
6	Yellow	SUV	Imported	No																																																									
7	Yellow	SUV	Imported	Yes																																																									
8	Yellow	SUV	Domestic	No																																																									
9	Red	SUV	Imported	No																																																									
10	Red	Sports	Imported	Yes																																																									

Prior Probability

P(Yes)=5/10

P(No)=5/10

Likelihood

Classification→	Yes (5)	No(5)
Color		
Red (5)	3/5	2/5
Yellow (5)	2/5	3/5

Classification→	Yes(5)	No(5)
Type		
Sports(6)	4/5	2/5
SUV (4)	1/5	3/5

Classification→	Yes(5)	No(5)
Origin		
Domestic(5)	2/5	3/5
Imported(5)	3/5	2/5

Testing Model

Unseen Sample (X)=<Red , Sports, Domestic>

P(Yes | X) = P(X | Yes) × P(YES)

= P(Red | Yes) × P(Sports | Yes) × P(Domestic | Yes) × P(Yes)

=  $\frac{3}{5} \times \frac{4}{5} \times \frac{2}{5} \times \frac{5}{10} = 0.0960$

P(No | X) = P(X | No) × P(No)

= P(Red | No) × P(Sports | No) × P(Domestic | No) × P(No)

=  $\frac{2}{5} \times \frac{2}{5} \times \frac{3}{5} \times \frac{5}{10} = 0.0480$

P(Yes)>P(No)

Unseen sample(X) is classified as yes. That is prediction for car stolen is yes.

Testing Model

Unseen Sample (X)=<Yellow , SUV, Imported>

P(Yes | X) = P(X | Yes) × P(YES)

= P(Yellow | Yes) × P(SUV | Yes) × P(Imported | Yes) × P(Yes)

=  $\frac{2}{5} \times \frac{1}{5} \times \frac{3}{5} \times \frac{5}{10} = 0.0240$

P(No | X) = P(X | No) × P(No)

= P(Yellow | No) × P(SUV | No) × P(Imported | No) × P(No)

=  $\frac{3}{5} \times \frac{3}{5} \times \frac{2}{5} \times \frac{5}{10} = 0.0720$

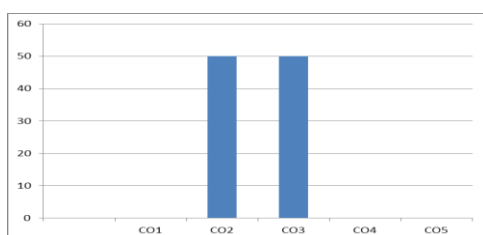
P(No)>P(Yes)

Unseen sample(X) is classified as no. That is prediction of car stolen is no.

**\*Program Indicators are available separately for Computer Science and Engineering in AICTE examination reforms policy.**

### Course Outcome (CO) and Bloom's level (BL) Coverage in Questions

**CO Coverage in %**



**BL Coverage in %**

