

Sl. No.	PART B – Max Marks (20)	Marks	L1-L6	CO																									
2	<p>Given the below confusion matrix for 3-class classification problem</p> <table><tr><th>Actual \ Predicted</th><th>Apple</th><th>Orange</th><th>Banana</th></tr><tr><th>Apple</th><td>254</td><td>74</td><td>96</td></tr><tr><th>Orange</th><td>28</td><td>317</td><td>33</td></tr><tr><th>Banana</th><td>12</td><td>46</td><td>280</td></tr></table> <p>Find</p> <p>a. False positives for Orange - 1 Mark</p> <p>b. Recall for Banana - 2 Marks</p> <p>c. Accuracy for Apple - 2 Marks</p> <p>Answer:</p> <p>False positives for orange = 28+33 = 61 ----- 1 Mark</p> <p>Recall for Banana ----- 2 Marks</p> <p>TPs for banana = 280</p> <p>FNs for banana = 96+33 = 129</p> <p>Recall = TP/(TP+FN) = 0.6845</p> <p>Accuracy for Apple ----- 2 Marks</p> <p>TPs for Apple = 254</p> <p>FPs for Apple = 74+96 = 170</p> <p>FNs for Apple = 28+12 = 40</p> <p>TNs for Apple = 317+33+46+280 = 676</p> <p>Accuracy = (TP+TN)/(TP+FP+FN+TN) = 0.8157</p>	Actual \ Predicted	Apple	Orange	Banana	Apple	254	74	96	Orange	28	317	33	Banana	12	46	280	5	L3	CO2									
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3	<p>Consider the dataset the below dataset in which last variable is dependant variable. Find the best splitting attribute (feature) at level-0 (root node) using Gini Index criterion. You are required to specify Gini index of each attribute (feature) explicitly.</p> <table><tr><th>Weather</th><th>Temperature</th><th>Humidity</th><th>Wind</th><th>Play?</th></tr><tr><td>Rainy</td><td>Cool</td><td>Normal</td><td>Strong</td><td>No</td></tr><tr><td>Sunny</td><td>Mild</td><td>High</td><td>Weak</td><td>No</td></tr><tr><td>Sunny</td><td>Hot</td><td>High</td><td>Strong</td><td>Yes</td></tr><tr><td>Cloudy</td><td>Hot</td><td>High</td><td>Strong</td><td>Yes</td></tr></table> <p>Answer:</p> $\text{Gini index} = 1 - \sum_{i=1}^C (P_i)^2$ <p>Gini index for Weather (Students are required to provide the three splits) ----- 1 Mark</p> <p>Gini(Weather=Rainy) = 0</p> <p>Gini(Weather=Sunny) = 0.5</p> <p>Gini(Weather=Cloudy) = 0</p> <p>Gini(Weather) = 0.25</p> <p>Gini index for Temperature (Students are required to provide the three splits) ----- 1 Mark</p> <p>Gini(Temperature=Cool) = 0</p>	Weather	Temperature	Humidity	Wind	Play?	Rainy	Cool	Normal	Strong	No	Sunny	Mild	High	Weak	No	Sunny	Hot	High	Strong	Yes	Cloudy	Hot	High	Strong	Yes	5	L3	CO2
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	<p>Gini(Temperature =Mild) = 0</p> <p>Gini(Temperature =Hot) = 0</p> <p>Gini(Temperature) = 0</p> <p>Gini index for Humidity (Students are required to provide the two splits) ----- 1 Mark</p> <p>Gini(Humidity=Normal) = 0</p> <p>Gini(Humidity =High) = 0.4444</p> <p>Gini(Humidity) = 0.333</p> <p>Gini index for Wind (Students are required to provide the two splits) - ----- 1 Mark</p> <p>Gini(Wind=Strong) = 0.4444</p> <p>Gini(Wind =Weak) =0</p> <p>Gini(Wind) = 0.333</p> <p>Choose Temperature as a best splitting attribute a level-0 since it has lowest Gini index value. ----- 1 Mark</p>																																																			
4	<p>Cluster the data points (with (x, y) representing locations) into two clusters {(2, 10), (2, 5), (8, 4), (5, 8), (7, 5))}. Employ the k-means clustering method by taking the seed mean points (i.e., the initial centroids) as the first two points, i.e., (2, 10) and (5, 8). At each stage (iteration) of the method give the centroids. Find the final centroids of the clusters and cluster members. Euclidian distance can be used for finding distance.</p> <p>Iteration 1: 2 Marks</p> <table><tr><th>Samples</th><th>Distance from C1 (2,10)</th><th>Distance from C2 (5,8)</th><th>Cluster Assignment</th></tr><tr><td>(2,10)</td><td>0</td><td>$\sqrt{13}$</td><td>C1</td></tr><tr><td>(2,5)</td><td>5</td><td>$\sqrt{18}$</td><td>C2</td></tr><tr><td>(8,4)</td><td>$\sqrt{64}$</td><td>$\sqrt{25}$</td><td>C2</td></tr><tr><td>(5,8)</td><td>$\sqrt{13}$</td><td>0</td><td>C2</td></tr><tr><td>(7,5)</td><td>$\sqrt{50}$</td><td>$\sqrt{13}$</td><td>C2</td></tr></table> <p>Updated cluster centres:</p> <p>C1 = (2,10)</p> <p>C2 = (5.5,5.5)</p> <p>Iteration 2: 2 Marks</p> <table><tr><th>Samples</th><th>Distance from C1 (2,10)</th><th>Distance from C2 (5.5,5.5)</th><th>Cluster Assignment</th></tr><tr><td>(2,10)</td><td>0</td><td>$\sqrt{32.5}$</td><td>C1</td></tr><tr><td>(2,5)</td><td>5</td><td>$\sqrt{12.5}$</td><td>C2</td></tr><tr><td>(8,4)</td><td>$\sqrt{64}$</td><td>$\sqrt{8.5}$</td><td>C2</td></tr><tr><td>(5,8)</td><td>$\sqrt{13}$</td><td>$\sqrt{6.5}$</td><td>C2</td></tr><tr><td>(7,5)</td><td>$\sqrt{50}$</td><td>$\sqrt{2.5}$</td><td>C2</td></tr></table>	Samples	Distance from C1 (2,10)	Distance from C2 (5,8)	Cluster Assignment	(2,10)	0	$\sqrt{13}$	C1	(2,5)	5	$\sqrt{18}$	C2	(8,4)	$\sqrt{64}$	$\sqrt{25}$	C2	(5,8)	$\sqrt{13}$	0	C2	(7,5)	$\sqrt{50}$	$\sqrt{13}$	C2	Samples	Distance from C1 (2,10)	Distance from C2 (5.5,5.5)	Cluster Assignment	(2,10)	0	$\sqrt{32.5}$	C1	(2,5)	5	$\sqrt{12.5}$	C2	(8,4)	$\sqrt{64}$	$\sqrt{8.5}$	C2	(5,8)	$\sqrt{13}$	$\sqrt{6.5}$	C2	(7,5)	$\sqrt{50}$	$\sqrt{2.5}$	C2	5	L3	CO3
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	<p>We can stop K-means clustering algorithm since there is no change in the cluster reassignment.</p> <p>Final Cluster centroids $C1 = (2,10)$ and $C2 = (5.5,5.5)$ ----- 1 Mark</p>																		
5	<p>Consider two class classification problem. Let the training set be $D = \{(X_1, t_1), (X_2, t_2), (X_3, t_3), (X_4, t_4)\}$ where each element (X, t) consists of the feature vector $X = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$, along with its given class-label t. Let $(X_1, X_2, X_3, X_4) = \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix}\right)$, and $(t_1, t_2, t_3, t_4) = (+1, +1, +1, -1)$.</p> <p>We want to learn the Perceptron classifier. Let the solution we are trying to get be $f(X)$ such that $f(X) = w_0 + w_1x_1 + w_2x_2$. If $f(X) \geq 0$, we classify X to the +1 class, otherwise we classify X to the -1 class.</p> <p>Consider the solution in parametric form be $W = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix}$ and let the initial solution be $W_{init} = \begin{bmatrix} -2 \\ 0 \\ 0 \end{bmatrix}$. Let the objective function that we are trying to minimize be $J(W) = \frac{1}{2} \sum_{i=1}^4 (t_i - o_i)^2$ where t_i is the given class label of X_i and $o_i = f(X_i)$.</p> <p>a. Find $J(W_{init})$ b. Find $\nabla J(W_{init})$</p> <p>Note: o_i represents predicted value not predicted label.</p> <p>Answer Scheme:</p> <p>Find predicted value for each sample</p> <table border="1"> <thead> <tr> <th>Sample</th> <th>Actual Label (t_i)</th> <th>Predicted value (o_i)</th> </tr> </thead> <tbody> <tr> <td>$\begin{bmatrix} 0 \\ 0 \end{bmatrix}$</td> <td>+1</td> <td>-2</td> </tr> <tr> <td>$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$</td> <td>+1</td> <td>-2</td> </tr> <tr> <td>$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$</td> <td>+1</td> <td>-2</td> </tr> <tr> <td>$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$</td> <td>-1</td> <td>-2</td> </tr> </tbody> </table> <p>a. $J(W_{init}) = 14$ ----- 2 Marks</p> <p>b. $\nabla J(W) = \begin{bmatrix} -\sum_{i=1}^4 \{t_i - (w_0 + w_1x_1 + w_2x_2)\} \\ -\sum_{i=1}^4 \{t_i - (w_0 + w_1x_1 + w_2x_2)\}x_1 \\ -\sum_{i=1}^4 \{t_i - (w_0 + w_1x_1 + w_2x_2)\}x_2 \end{bmatrix}$</p> <p>$\nabla J(W_{init}) = \begin{bmatrix} -10 \\ -4 \\ -4 \end{bmatrix}$ ----- 3 Marks</p>	Sample	Actual Label (t_i)	Predicted value (o_i)	$\begin{bmatrix} 0 \\ 0 \end{bmatrix}$	+1	-2	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	+1	-2	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	+1	-2	$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$	-1	-2	5	L3	CO4
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$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$	-1	-2																	

Course Outcomes

1. Understand various types of machine learning algorithms and the role of data preprocessing in machine learning
2. Evaluate regression and classification model's performance on real-time datasets
3. Apply unsupervised learning algorithms for pattern discovery and structural analysis in datasets
4. Build Multilayer Perceptron to perform classification
5. Perform image classification using Convolutional Neural Networks
6. Design and implement machine learning solutions to solve a real-world problem through a guided or open-ended project.

Marks Distribution										
L1	L2	L3	L4	L5	L6	CO1	CO2	CO3	CO4	CO5
	5	20					11	6	8	