

#### **Department of Artificial Intelligence and Machine Learning**

Course Code:21AI52
Sem: V
Date: 08.01.2024
Duration: 90 Minutes

### CIE-I Artificial Intelligence and Machine Learning

**Scheme and Solutions** 

SL	. No	Questions		M	BT	CO	
1	(a)				06	L3	CO1
			True/False	Support			
		An agent that senses only	False	The vacuum cleaning is rational,			
		partial information about the		despite having no information			
		state cannot be perfectly		about the other square			
		rational.					
				If every action results in the same			
		environment in which every		result.			
		agent is rational.	7.1				
		The input to an agent program	False	The agent program and function			
		is the same as the input to the		are different entities, the program			
		agent function.		contains history percepts and the			
				function is only the current			
		Cumpos on count calcate its	Tours	percept.			
		Suppose an agent selects its	True	Eventually one of the random selections will be the correct one.			
		action uniformly at random from the set of possible		selections will be the correct one.			
		actions. There exists a					
		deterministic task					
		environment in which this					
		agent is rational.					
		Every agent is rational in an	False	A GPS mapping system that			
		unobservable environment.		doesn't record its findings.			
		A perfectly rational poker-	False	There is always a chance that its			
		playing agent never loses.		opponent will be dealt with better			
				cards.			
		6*1 = <b>6 Marks</b>					
	b)		lence a rational a	gent should select an action that is	04	L2	CO1
	0)			e, given the evidence provided by	0-	22	COI
		1					
		the percept sequence and whatever built-in knowledge the agent possesses.					
		a. <b>Healthcare:</b> Rational agents make medical diagnoses, plan treatment, and monitor patients' progress. They can analyze medical data, predict the					
		progression of diseases, an					
		<b>b. Transportation:</b> Rational					
		_	irces. Self-driving cars, drones, and				
		robots use rational agents to r					
		•	safely transporting passengers or				
		completing a task.	<i>6</i> , <i>5</i> , <i>6</i>	manay and arming published of			
		Definition – <b>02 Marks</b>					
		Applications – <b>02 marks</b>					



# **Department of Artificial Intelligence and Machine Learning**

2   a	ı)						06	L3	CO2
	<i></i>	Task	Performance Measure	Environment	Actuators	Sensors			
		Robot soccer	Score of the	Ball, team	The robot	Video camera,			
		player	team or the	members,	devices, such	communication			
			competitor, winning	competitors, a sport	as legs for running and	links among team members,			
			game	ground	kicking	orientation			
						sensors, touch			
		Internet	Minimizing	The Internet,	Add a new	web pages,			
		book-shopping	cost,	browsers	order, retrieve	buttons or			
		agent	information about		existing order information,	hyperlinks clicked by			
			interesting		display	users			
			books		information to				
		Autonomous Mars	Collect,	Mars, vehicle	Collection,	Video camera,			
		rover	analyze and	iviais, veineie	analysis, and	audio			
			explore		motion	receivers,			
			samples on Mars		devices, radio transmitter	communication links			
		Theorem-proving	Time	The theorem	Accept the	Input device			
		assistant	requirement,	to prove,	right theorem,	that reads the			
			degree of	existing	reject the	theorem to			
			correction	axioms	wrong theorem, infer	prove			
					based on				
					axioms and				
					facts				
		Each Carries – 1.5							
b		TI4:1:4 1	.4 E14.	1 1'	. 02 M 1		04	1.0	CO1
0	"	Utility based ager	us: Explanation	on and diagram	1 – UZ Marks		04	L2	CO1
		( <b>*</b>	Se	nsors					
		State		<u> </u>					
				he world					
		State How the world eve		he world te now					
		How the world evo	blves is lik	te now	En				
			blves is lik		Envir				
		How the world evo	blves is lik	will be like	Environ				
		How the world evo	blves is lik	will be like	Environm				
		How the world evo	blves is lik	will be like	Environment				
		How the world evo	do What it v if I do	will be like action A	Environment				
		How the world evo	do What it v if I do	will be like action A	Environment				
		What my actions  Goals	do What it v if I do	will be like action A	Environment				
		How the world evo	do What it vif I do	will be like action A	Environment				
		What my actions  Goals	do What it vif I do	will be like action A action I	Environment				
		How the world evo	do What it if I do What should	will be like action A action I	Environment				
		What my actions  Goals	do What it if I do What should	will be like action A action I	Environment				
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		How the world every What my actions  Goals  Agent  Model-based refle	What it vif I do  What it vif I do  Actu	action I do now	Environment				
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		How the world every What my actions  Goals  Agent  Model-based refle	What it vif I do  What it vif I do  Actu	will be like action I do now actors	Environment				
		How the world every What my actions  Goals  Agent  Model-based refle Explanation and di	What it vif I do  What it vif I do  Actu	will be like action I do now actors					
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# **Department of Artificial Intelligence and Machine Learning**

	10	1.4	CO3
Algorithm 3.1 A skeleton decision tree induction algorithm.  TreeGrowth $(E, F)$ 1: if stopping_cond $(E, F) = true$ then  2: $leaf = \text{createNode}()$ .  3: $leaf.label = \text{Classify}(E)$ .  4: return $leaf$ .  5: else  6: $root = \text{createNode}()$ .  7: $root.test\_cond = \text{find\_best\_split}(E, F)$ .  8: $let V = \{v v \text{ is a possible outcome of } root.test\_cond \}$ .  9: for each $v \in V$ do  10: $E_v = \{e \mid root.test\_cond(e) = v \text{ and } e \in E\}$ .  11: $child = \text{TreeGrowth}(E_v, F)$ .  12: add $child$ as descendent of $root$ and label the edge $(root \rightarrow child)$ as $v$ .  13: end for  14: end if  15: return $root$ .	10	L4	COS
Pseudo code – <b>05 Marks</b>			
For the given data, calculate (a) Entropy (b) Information Gain for the Outlook Feature Entropy can be calucated for one attribute (Play Volleyball) $Entropy(S) = -\frac{9}{14}log_2\left(\frac{9}{14}\right)\frac{5}{14}log_2\left(\frac{5}{14}\right) = 0.94$ - 02 Marks Information Gain – Outlook Feature $Entropy(S_{Sunny}) = -\frac{2}{5}log_2\left(\frac{2}{5}\right)\frac{3}{5}log_2\left(\frac{3}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Overcast}) = -\frac{4}{4}log_2\left(\frac{4}{4}\right)\frac{0}{4}log_2\left(\frac{0}{4}\right) = 0$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right)\frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right)\frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Rain}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$	10	L3	CO5
Using Validation Set - 1.5 marks  - Divide training data into two parts: - Training set: - use for model building - Validation set: - use for estimating generalization error - Note: validation set is not the same as test set - Drawback: - Less data available for training Incorporating Model Complexity - 1.5 marks - Rationale: Occam's Razor	05	L3	CO2
	Treestrowth $(E,F)$ = true then  2: leaf = createlode(). 2: leaf = createlode(). 3: leaf   screatelode(). 4: return leaf. 5: else 6: root = createlode(). 7: root.test.comd = find.best.split( $E,F$ ). 8: let $V = \{v v \text{ is a possible outcome of root.test.cond}}$ . 9: for each $v \in V$ do 10: $E_v = \{v \mid v \text{ is a possible outcome of root.test.cond}}$ . 11: chid = Treestrowth( $E_v, F$ ). 12: add child as descendent of root and label the edge (root $\rightarrow$ child) as $v$ . 13: end for 14: end if 15: return root.  Pseudo code $-$ 05 Marks  Illustrating with the given features and constructing the tree $-$ 05 marks  For the given data, calculate (a) Entropy (b) Information Gain for the Outlook Feature  Entropy can be calucated for one attribute (Play Volleyball) $Entropy(S) = -\frac{9}{14}log_2\left(\frac{9}{14}\right) - \frac{5}{14}log_2\left(\frac{5}{14}\right) = 0.94$ Information Gain $-$ Outlook Feature $Entropy(S_{Sunny}) = -\frac{2}{5}log_2\left(\frac{2}{5}\right) - \frac{3}{5}log_2\left(\frac{3}{5}\right) = 0.97$ $-02 \text{ Marks}$ $Entropy(S_{Overcast}) = -\frac{4}{4}log_2\left(\frac{4}{4}\right) - \frac{0}{4}log_2\left(\frac{0}{4}\right) = 0$ $-02 \text{ Marks}$ Information Gain(Outlook) = $0.94 - [(5/14) * 0.97 + (4/14) * 0 + (5/14) * 0.97]$ $\approx 0.246 - 02 \text{ marks}$ Using Validation Set $-1.5$ marks  Divide training data into two parts:  Training set:  use for model building  Validation set:  use for estimating generalization error  Note: validation set is not the same as test set  Drawback:  Less data available for training  Incorporating Model Complexity $-1.5$ marks	Treedrowth $(E,F)$ = true then 2: leaf = createlode(). 2: leaf = createlode(). 4: return leaf. 5: else 8: root = createlode(). 4: return leaf. 5: else 8: root = createlode(). 7: root.lest.cond = flab.bet.split(E,F). 7: root.lest.cond = flab.bet.split(E,F). 8: let $V = \{v v \text{ is a possible outcome of root.test.cond}\}$ . 9: for each $v \in V$ do 10: $E_v = \{v v \text{ is a possible outcome of root.test.cond}\}$ . 9: for each $v \in V$ do 10: $E_v = \{v v \text{ is a possible outcome of root.test.cond}\}$ . 9: add child as descendent of root and label the edge $(root - child)$ as $v$ . 11: $child = TreeGrowth(E_v,F)$ . 12: $child = TreeGrowth(E_v,F)$ . 13: $child = TreeGrowth(E_v,F)$ . 13: $child = TreeGrowth(E_v,F)$ . 14: end If 11: $child = TreeGrowth(E_v,F)$ . 15: $child = TreeGrowth(E_v,F)$ . 16: $child = TreeGrowth(E_v,F)$ . 17: $child = TreeGrowth(E_v,F)$ . 18: $child = TreeGrowth(E_v,F)$ . 19: $child = TreeGrowth(E_v,F)$ . 10: $child$	Algorithm 3.1 A skeleton decision tree induction algorithm. Treesfront $(E, F)$ 1: If stopping_cond( $E, F$ ) = true then  2: leaf = createllode().  3: leaf lobel = Clasestry(E).  4: return leaf.  5: choost = createllode().  7: root(set.cond = finla best.split(E, F).  8: let $V = (u v v a possble outcome of root.test.cond)$ .  9: for each $v \in V$ do  10: $E_v = \{v v (test.cond(e)) = v and e \in E\}$ .  11: child = Treesfront( $E_v$ , $F$ ).  12: add child as descendent of root and label the edge (root - child) as $v$ .  13: end for  14: return root.  Pseudo code - 05 Marks  Illustrating with the given features and constructing the tree - 05 marks  For the given data, calculate  (a) Entropy (b) Information Gain for the Outlook Feature  Entropy can be calucated for one attribute (Play Volleyball) $Entropy(S) = -\frac{9}{14}log_2\left(\frac{9}{14}\right) - \frac{5}{14}log_2\left(\frac{5}{14}\right) = 0.94$ Information Gain - Outlook Feature $Entropy(S_{Sunny}) = -\frac{2}{5}log_2\left(\frac{2}{5}\right) - \frac{3}{5}log_2\left(\frac{3}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Sunny}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks $Entropy(S_{Ruin}) = -\frac{3}{5}log_2\left(\frac{3}{5}\right) - \frac{2}{5}log_2\left(\frac{2}{5}\right) = 0.97$ - 02 Marks  Information Gain (Outlook) = 0.94 - [ (5/14) * 0.97 + (4/14) * 0 + (5/14) * 0.97 ] $\approx 0.246 - 02$ marks  Using Validation Set - 1.5 marks  - Divide training data into two parts:  - Training set:  - use for model building  - Validation set is not the same as test set  - Drawback:  - use for estimating generalization error  - Note: validation set is not the same as test set  - Drawback:  - Less data available for training  Incorporating Model Complexity - 1.5 marks

# **Department of Artificial Intelligence and Machine Learning**

<ul> <li>Given two models of similar generalization errors, one should prefer to simpler model over the more complex model</li> <li>A complex model has a greater chance of being fitted accidentally</li> <li>Therefore, one should include model complexity when evaluating a model. Error(Model) = Train. Error(Model, Train. Data) + x Complexity(Model)</li> <li>where α is a hyper-parameter that strikes a balance between minimizing trainerror and reducing model complexity. A higher value of α gives more emphases the model complexity in the estimation of generalization performance.</li> <li>Pessimistic Error Estimate of decision tree T with k leaf nodes - 1.0 Marks</li> <li>err(T) = err(T) + Ω × k/Ntrain.</li> <li>err(T): error rate on all training records</li> <li>Ω: trade-off hyper-parameter (similar to)</li> <li>Relative cost of adding a leaf node</li> <li>k: number of leaf nodes</li> <li>Ntrain: total number of training records</li> <li>Minimum Description Length - 1.0 Marks</li> <li>Cost(Model,Data) = Cost(Data Model) + x Cost(Model)</li> <li>Cost is the number of bits needed for encoding.</li> <li>Search for the least costly model.</li> <li>Cost(Data Model) encodes the misclassification errors.</li> <li>Cost(Model) uses node encoding (number of children) plus split condition encoding</li> </ul>	odel ning is to		
<ul> <li>b) Explain the concept of k-fold cross-validation? Provide an example to illustratits application in Machine Learning?</li> <li>• K-fold cross-validation is a resampling technique used in machine learning assess the performance and generalization ability of a model.</li> <li>• The main idea is to divide the dataset into k subsets (or folds), train the makes k times, each time using k-1 folds for training and the remaining one fold validation.</li> <li>• This process is repeated k times, with each of the k folds used exactly one the validation data.</li> <li>• The k results from the folds can then be averaged to produce a single estimate of model performance.</li> <li>• The total test error rate, errors then computed as</li> </ul>	odel I for ee as	L3	CO5

#### **Department of Artificial Intelligence and Machine Learning**

	k-fold cross validation – <b>03 Marks</b>		
	Example – <b>02 Marks</b>		

Cours	Course Outcome							
CO1	Explain and apply AI and ML algorithms to address various requirements of real-world problems.							
CO2	Design and develop AI and ML solutions to benefit society, science, and industry.							
CO3	Use modern tools to create AI and ML solutions.							
CO4	Demonstrate effective communication through team presentations and reports to analyze the impact of AI							
	and ML solutions on society and nature.							
CO5	Conduct performance evaluation, modeling, and validation of AI and ML solutions benefiting lifelong							
	learning.							

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

Marks	Particulars	CO1	CO2	CO3	CO4	CO5	L1	L2	L3	L4	L5	L6
Distribution	Max Marks	14	11	10	1	15		08	32	10		