MACHINE LEARNING (IT523PE)
(PROFESSIONAL ELECTIVE-III)
COURSE PLANNER

I. COURSE OVERVIEW:

Because of the increasing need for intelligent and accurate decision making, there is an exponential growth in the adoption of Machine Learning (ML) technologies. Hence these are poised to remain the most important technologies in the years to come. This covers the concepts and techniques from the various fields of Machine learning, the concepts of statistics and other advanced algorithms. The core of machine learning algorithms and theory used for learning performance are elaborated. Machine learning tools used to predict future trends and behaviors, allowing businesses to make proactive and knowledge- driven decisions. The course addresses the state-of-the-art machine learning techniques and how to apply them in business related problems. The first, and biggest, part of the course will focus on supervised learning through decision trees, and advanced techniques like neural networks and naive bayes. In the second part, about instance-based learning, genetic algorithms, reinforcement learning and analytical learning.

II. PRE-REQUISITES:

- Data Structures
- Knowledge on statistical methods

III. COURSE OBJECTIVIES:

1. Explains machine learning techniques such as decision tree learning, Bayesian learning etc.
2. To understand computational learning theory.
3. To study the pattern comparison techniques.

IV.COURSE LEARNING COUCOMES (CLOs):

CLO Code	CLO's	At the end of the course, the student will have the ability to:	Bloom's Taxonomy Levels	POs / PSOs mapped
CS733PE.01	CLO1	*Understand* the concepts of computational intelligence like machine learning	L2: UNDERSTAND	PO1, PO2, PO3, PSO1, PSO2
CS733PE.02	CLO2	Explore the skills to apply machine learning techniques to address the real time problems in different areas	L4: ANALYZE	PO1, PO2, PO3, PO4, PSO1, PSO2
CS733PE.03	CLO3	*Understand* the concept of learning and candidate elimination algorithms	L2: UNDERSTAND	PO1, PO2, PO3, PO4, PSO1, PSO2
CS733PE.04	CLO4	*Explore* on tree based decision tree learning algorithm and its applications	L4: ANALYZE	PO1, PO2, PO3, PO4, PO5, PSO1, PSO2
CS733PE.05	CLO5	*Understand* the Artificial Neural Networks and its usage in machine	L2: UNDERSTAND	PO1, PO2, PO3, PO4,

		learning application.		PO5, PSO1, PSO2
CS733PE.06	CLO6	*Understand* the concepts of Bayesian learning, computational learning and instance-based learning and their usage in machine learning application.	L2: UNDERSTAND	PO1, PO2, PO3, PO4, PO5, PSO1, PSO2

V. HOW PROGRAM OUTCOMES ARE ASSESSED:

Program Outcomes (POs)		Level	Proficiency assessed by
PO1	**Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.	3	Presentation on real-world problems
PO2	**Problem analysis**: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.	3	Assignments
PO3	**Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.	2	Assignments
PO4	**Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.	2	Mini/Major Projects
PO5	**Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.	2	Mini/Major Projects
PO6	**The engineer and society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.	-	--
PO7	**Environment and sustainability**: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.	-	--
PO8	**Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.	-	--
PO9	**Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.	-	--
PO10	**Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.	-	-

Program Outcomes (POs)		Level	Proficiency assessed by
PO11	**Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	-	--
PO12	**Life-long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.	-	-

VI.HOW PROGRAM SPECIFIC OUTCOMES ARE ASSESSED:

Program Specific Outcomes (PSOs)		Level	Proficiency assessed by
PSO1	**Foundation of mathematical concepts:** To use mathematical methodologies to crack problem using suitable mathematical analysis, data structure and suitable algorithm.	2	Assignments
PSO2	**Foundation of Computer System:** The ability to interpret the fundamental concepts and methodology of computer systems. Students can understand the functionality of hardware and software aspects of computer systems.	2	Mini/Major Projects
PSO3	**Foundations of Software development:** The ability to grasp the software development lifecycle and methodologies of software systems. Possess competent skills and knowledge of software design process. Familiarity and practical proficiency with a broad area of programming concepts and provide new ideas and innovations towards research.	-	-

1: Slight (Low) 2: Moderate (Medium) 3: Substantial (High) - : None

VII. MAPPING COURSE OUTCOMES LEADING TO THE ACHIEVEMENT OF PROGRAM OUTCOMES AND PROGRAM SPECIFIC OUTCOMES:

Course Learning Outcomes	Program Outcomes (PO)												Program Specific Outcomes (PSO)		
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO 3
CLO1	3	2	2	-	-	-	-	-	-	-	-	-	2	2	-
CLO2	3	3	2	2	-	-	-	-	-	-	-	-	2	2	-
CLO3	2	2	2	2	-	-	-	-	-	-	-	-	2	1	-
CLO4	3	3	3	3	3	-	-	-	-	-	-	-	1	2	-
CLO5	2	2	2	2	2	-	-	-	-	-	-	-	2	2	-
CLO6	2	2	2	2	2	-	-	-	-	-	-	-	1	2	-
AVG	**2.5**	**2.33**	**2.16**	**2.2**	**2.33**	-	-	-	-	-	-	-	**1.83**	**1.83**	**--**

1: Slight (Low) 2: Moderate (Medium) 3: Substantial (High) - : None

VIII. SYLLABUS:

UNIT-I

Introduction: Well-posed learning problems, designing a learning system, Perspectives and issues in machine learning.

Concept learning and the general to specific ordering: Introduction, a concept learning task, concept learning as search, find-S: finding a maximally specific hypothesis, version spaces and the candidate elimination algorithm, remarks on version spaces and candidate elimination, inductive bias.

Decision Tree Learning: Introduction, decision tree representation, appropriate problems for decision tree learning, the basic decision tree learning algorithm, hypothesis space search in decision tree learning, inductive bias in decision tree learning, issues in decision tree learning.

UNIT-II

Artificial Neural Networks-1: Introduction, neural network representation, appropriate problems for neural network learning, perceptions, multilayer networks and the backpropagation algorithm.

Artificial Neural Networks-2: Remarks on the Back-Propagation algorithm, An illustrative example: face recognition, advanced topics in artificial neural networks.

Evaluation Hypotheses: Motivation, estimation hypothesis accuracy, basics of sampling theory, a general approach for deriving confidence intervals, difference in error of two hypotheses, comparing learning algorithms.

UNIT-III

Bayesian learning: Introduction, Bayes theorem, Bayes theorem and concept learning, Maximum Likelihood and least squared error hypotheses, maximum likelihood hypotheses for predicting probabilities, minimum description length principle, Bayes optimal classifier, Gibs algorithm, Naïve Bayes classifier, an example: learning to classify text, Bayesian belief networks, the EM algorithm.

Computational learning theory: Introduction, probably learning an approximately correct hypothesis, sample complexity for finite hypothesis space, sample complexity for infinite hypothesis spaces, the mistake bound model of learning.

Instance-Based Learning: Introduction, k-nearest neighbour algorithm, locally weighted regression, radial basis functions, case-based reasoning, remarks on lazy and eager learning.

UNIT-IV

Genetic Algorithms: Motivation, Genetic algorithms, an illustrative example, hypothesis space search, genetic programming, models of evolution and learning, parallelizing genetic algorithms.

Learning Sets of Rules: Introduction, sequential covering algorithms, learning rule sets: summary, learning First-Order rules, learning sets of First-Order rules: FOIL, Induction as inverted deduction, inverting resolution.

Reinforcement Learning: Introduction, the learning task, Q–learning, non-deterministic, rewards and actions, temporal difference learning, generalizing from examples, relationship to dynamic programming.

UNIT-V

Analytical Learning-1: Introduction, learning with perfect domain theories: PROLOG-EBG, remarks on explanation-based learning, explanation-based learning of search control knowledge.

Analytical Learning-2: Using prior knowledge to alter the search objective, using prior knowledge to augment search operators.

Combining Inductive and Analytical Learning: Motivation, inductive-analytical approaches to learning, using prior knowledge to initialize the hypothesis.

TEXT BOOK:

1. Machine Learning – Tom M. Mitchell, - Mc Graw Hill Education

REFERENCE BOOK:

1. Machine Learning: An Algorithmic Perspective, Stephen Marshland, Taylor & Francis

NPTEL RESOURCES:

1. NOC: Machine Learning, ML (Video): https://nptel.ac.in/courses/106106202/
1. NOC: Introduction to Machine Learning (Video): https://nptel.ac.in/courses/106105152/
2. NOC: Introduction to Machine Learning(Course sponsored by Aricent) (Video): https://nptel.ac.in/courses/106106139/

GATE SYLLABUS: NOT APPLICABLE

IES SYLLABUS: NOT APPLICABLE

I. LESSON PLAN:

S.No	UNIT	Week	Topics	Topics To be Covered	Link for PPT	Link for PDF	Course Learning Outcome	Teaching Aids	References
1	I	1	Introduction - Well-posed learning problems, designing a	• Introduction, • Why is Machine Learning • Important,	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	**Explain:** Learning Task	CHALK &BOARD / PPT Presentation	
2			Concept learning and the general to specific ordering , a	• Supervised, •unsupervised, •reinforcement learning, • Well-posed			**Explain:** Learning Task		
3			Concept learning as search, find-S: finding a maximally	• finding a maximally specific hypothesis • instance			**Explain:** finding a maximally specific hypothesis		

4		**2**	Version spaces elimination algorithm, remarks on version spaces	• The key idea in the candidate elimination algorithm			**Understand:** Inductive bias		
			inductive bias	• The LIST-THEN-ELIMINATE Algorithm • A More			**Understand:** General to Specific Ordering		
5			Decision Tree Learning – Introduction, decision tree representation,	• Inductive bias-Definition • Effect of incomplete			**Describe:** Decision Tree		
6			The basic decision tree learning algorithm, hypothesis	• the basic decision tree learning algorithm • ID3			**Describe:** hypothesis space search in decision		T1,R1
7		**3**	Inductive bias in decision tree learning, issues in decision tree learning.	• ID3 search strategy • Approximate inductive bias			**Define:** issues in decision tree learning.		
8			Applications of DT	• Avoiding Over fitting the Data Reduced error pruning Rule			**Understand:** DT		
9			Artificial Neural Networks-1– Introduction, neural network	• Introduction, • Biological Motivation • Properties of Neural					
1	**I**	**4**	appropriate problems for neural network learning, perceptions	• Appropriate problems for neural network learning		https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	**Understand:** ANN	CHALK &BOARD / PPT Presentation	T1,R1
1			multilayer networks and the back-propagation algorithm.	Back Propagation algorithm explanantion			**Define**: Multylayer Networks		

1		5	Artificial Neural Networks-2-Remarks on the Back-	• Remarks on the BACKPROPAGATION Algorithms	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing		**Describe:** ANN **Back Propogation**		
1			An illustrative example:face recognition, advanced topics in artificial	• An illustrative example: face recognition • Advanced			**Understand:** Examples		
1			Evaluation Hypotheses – Motivation, estimation hypothesis	• Evaluation Hypotheses: Motivation • Difficulties in Evaluating			**Describe**: Evaluation Hypothesis		
1		6	a general approach for deriving confidence intervals	• sampling theory - Definition • Error Estimation			**Describe**: a general approach for deriving		
1			difference in error of two hypotheses	• Difference in error of two Hypotheses, Comparing learning			**Describe:** difference in error of two hypothese		
1			comparing learning algorithms.	Comparision of learning algorithms			**Understand:**comparing learning algorithms		
1	I	7	Bayesian learning – Introduction, Bayes theorem, Bayes theorem	• Introduction, • Features of Bayesian Learning Methods	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	**Understand: :** Bayesian Learning	CHALK &BOARD / PPT Presentation	T1
1			Maximum Likelihood and least squared error hypotheses	• Bayes theorem and concept learning • Maximum a			Understand: : Maximum Likelihood		T1
2			maximum likelihood hypotheses for predicting probabilities,	• The Evolution of Probabilities Associated with			**Understand:** minimum description length		T1

2			Bayes optimal classifier, Gibs algorithm	• Minimum description length principle • Introduction			**Understand:** Gibs algorithm		T1
2		**8**	Naïve Bayes classifier, an example: learning to classify text	• Naïve Bayes classifier; An example: learning to classify text • Bayesian			**Examine:** Naïve Bayes classifier		T1
2			Bayesian belief networks, the EM algorithm.	• Explanation of EM algorithm with example			**Examine:** EM algorithm		T1
				11/8/2021-11/13/2021 MID TERM-I					
2	**I**	**1**	Computational learning theory – Introduction, probably learning an	• What are learning systems? • Computationa	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	**Motive: Computational learning theory**	CHALK &BOARD / PPT Presentation	T1
2			sample complexity for finite hypothesis space, sample	• Sample Complexity of PAC Learning • Sample Complexity			**Analyze:** Sample Complexity		T1
			k-nearest neighbour algorithm, locally weighted	• k-nearest neighbor algorithm with example • Locally			**Describe: KNN**		T1
2			Bridge Class II						
2	**I**	**1**	Genetic Algorithms – Motivation, Genetic algorithms, an	• Introduction, Motivation • Genetic Algorithms • An			**Understand:** Genetic Algorithms	CHALK &BOARD / PPT Presentation	T1
2			hypothesis space search, genetic programming, models of	• Models of evolution and learning; I. Lamarckian Evolution			**Describe**: Models of evolution and learning,		T1

2			parallelizing genetic algorithms.	• Parallelizing genetic algorithms			**Describe**: PGA.		T1
3			Learning Sets of Rules – Introduction,	• Learning rule • Learn-One-Rule I. General to			**Describe**: Pros And Cons Of learning sets of		T1
3		**1**	sequential covering algorithms, learning rule sets: summary,	• Learning Disjunctive Sets of Rules I. Learn Decision Tree			**Understand:** sequential covering algorithms		T1
3			learning First-Order rules,	• Learning First-Order rules;			**Describe**: First Order Rule		T1
3			learning sets of First-Order rules: FOIL,	Learning sets of First-Order rules: FOIL Algorithm with Example			**Describe**: FOIL		T1
3		**1**	Induction as inverted deduction,inverting resolution.	• Induction as inverted deduction with example • Inverted			**Summarize:** Learning Rules		T1
3		**MOCK Test-II,Bridge Class-III**							
3			Reinforcement Learning – Introduction, the learning task, Q–	• Reinforcement Learning I. RL model II. Model			**Model :RL**		T1
3		**1**	rewards andactions, temporal difference learning,	• Adaptive dynamic programming(ADP) in passive			**Understand :** temporal difference learning	CHALK &BOARD / PPT Presentation	T1
3			relationship to dynamic programming.	Relationship to dynamic programming			**Make Use Of :** Dynamic Programming		T1

3			**Case Study on Reinforcement Learning		https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	https://drive.google.com/drive/folders/194Lsjtspv5pM7G2tZL-nuwJOhxrff0ou?usp=sharing	**Understand**		T1
4		1	Analytical Learning-1-Introduction, learning with perfect domain	• Introduction, Analytical Learning-1 • Inductive vs. Analytical			**Utilize :** PROLOG		T1
4			remarks on explanation-based learning, explanation-based learning	• Each learned Horn clause corresponds to a sufficient condition for			**Make Use Of :** Explanation based Learning		T1
4			Analytical Learning-2-Using prior knowledge to alter the search	• Detail explanation about EBNN Algorithm with example			**Make Use Of :** Analytic Learning		T1
4		1	using prior knowledge to augment search operators.	• Detail explanation about FOCL Algorithm with example			**Understand :** using prior knowledge to		T1
4			Combining Inductive and Analytical Learning – Motivation	• Combining Inductive and Analytical Learning I. The			**Apply :** Combining Inductive and		T1
4			inductive-analytical approaches to learning,	Inductive and analatical approaches in learning			**Apply:** inductive-analytical approaches to		T1
		1	using prior knowledge to initialize the hypothesis.	• Detail explanation about FOCL Algorithm with example			**Apply** :using prior knowledge to		T1, R1
4			**Case Study of Analytics Learning				**Utilize**		T1
4		1	**01/10/2022-01/18/2022 MID TERM-II**						

IX. DESCRIPTIVE QUESTIONS

UNIT-1

Short Answer Questions

QUESTIONS	Blooms taxonomy level	Course Learning Outcomes
What is Machine learning? What is the need of it?	Remember	CLO1
Give the structure of learning problem.	Remember	CLO2, CLO3
What is concept learning?	Remember	CLO3
Give example for General-to-Specific Ordering of Hypotheses.	Remember	CLO3
List the appropriate problems for decision tree learning.	Understand	CLO4
List the issues in decision tree learning.	Understand	CLO4

Long Answer Questions

QUESTIONS	Blooms taxonomy level	Course Learning Outcomes
Describe the *EnjoySport* concept learning *task*. Explain Find-S algorithm.	Understand	CLO3
Explain Candidate-Elimination Algorithm. Explain LIST-THEN-ELIMINATE Algorithm	Understand	CLO3
Explain version space with representation theorem and Define general boundary and specific boundary.	Understand	CLO3
Let consider designing a program to learn play checkers, with the goal of entering it in the world checkers tournament. Propose a target function to be learned and a target representation.	Understand	CLO3
Describe A decision tree for classification on the concept *Play Tennis*	Understand	CLO4

UNIT-2

Short Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
What is a perceptron?	Remember	CLO5
Draw the representational power of perceptron.	Understand	CLO5
Show the feed forward representation of the multilayer networks	Understand	CLO5
List the representational power of feedforward networks	Remember	CLO5
Define the binomial distribution	Remember	CLO5

Long Answer Questions

QUESTIONS	Blooms taxonomy level	Course Learning Outcomes
Explain the stochastic gradient version of the Backpropagation algorithm for feedforward networks.	Understand	CLO5
Describe the appropriate problems for neural network learning	Understand	CLO5
Describe the general approach for deriving confidence intervals	Understand	CLO5
Explain the remarks on the backpropagation algorithm	Understand	CLO5
Describe various advanced areas in artificial neural networks	Understand	CLO5

UNIT-3

Short Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
State Bayes theorem	Remember	CLO5
Discuss Maximum Likelihood and Least Square Error Hypothesis.	Understand	CLO5
Describe Maximum Likelihood Hypothesis for predicting probabilities.	Understand	CLO5
Define Gibbs algorithm	Remember	CLO5
What are the merits and demerits of lazy learners	Remember	CLO5

Long Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
Explain Naïve Bayes Classifier with an Example.	Understand	CLO5
Explain Bayesian belief network with an example	Understand	CLO5
Illustrate the EM algorithm	Apply	CLO5
What are the applications of probably learning an approximately correct model	Remember	CLO5
Demonstrate k-nearest neighbour algorithm for classification	Apply	CLO5
Discuss the significance of locally weighted regression	Understand	CLO5

UNIT-4

Short Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
List the factors motivated the popularity of genetic algorithms	Remember	CLO6
State Baldwin Effect	Remember	CLO6
Give an example for fitness function in genetic algorithms	Understand	CLO6
Write the Sequential Covering algorithm for learning a disjunctive set of rules.	Understand	CLO5
Define Q-learning	Remember	CLO5

Long Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
Create or generate new offspring from the given population for genetic algorithm? Illustrate.	Create	CLO6
Write the genetic Algorithm	Understand	CLO6
Illustrate general-to-specific beam search algorithm for Learn-One-Rule.	Apply	CLO6
Illustrate the basic FOIL algorithm	Apply	CLO5
Demonstrate Q-learning algorithm with an example.	Apply	CLO5
Illustrate to handle nondeterministic MDPs (Markov Decision Process)?	Apply	CLO6

UNIT-5

Short Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
Describe Analytical Learning	Understand	CLO6
Define the weakest preimage of a conclusion	Remember	CLO6
Define *Approximate inductive bias of PROLOG-EBG*	Remember	CLO6
Explain the FOCL algorithm	Understand	CLO5
Compare and contrast purely analytical and purely inductive learning	Analyze	CLO5

Long Answer Questions

QUESTIONS	Blooms taxonomy level	Course outcomes
List the main properties of PROLOG-EBG algorithm? Is it deductive or inductive? Justify your answer.	Remember	CLO6
Illustrate Inductive-Analytical approaches to learning	Apply	CLO6
Demonstrate the EBNN algorithm	Apply	CLO6
"Explanation determines feature relevance." Substantiate this statement with respect to explanation based learning.	Understand	CLO5
Write KBANN algorithm to explain usage of prior knowledge to reduce complexity.	Understand	CLO5

XI. OBJECTIVE QUESTIONS

UNIT-1

1. A computer program is said to *learn* from _____ E with respect to some class of tasks T and performance P, if its performance at tasks in T, as measured by P, improves with E.
   A) Training
   B) Experience
   C) Database
   D) Algorithm
   Answer: B
2. Which of the following are classification tasks? (Mark all that apply)
   A) Find the gender of a person by analyzing his writing style
   B) Predict the price of a house based on floor area, number of rooms etc.
   C) Predict whether there will be abnormally heavy rainfall next year
   D) Predict the number of copies of a book that will be sold this month
   Answer: A, C
3. Which of the following are examples of unsupervised learning?
   A) Group news articles based on text similarity
   B) Make clusters of books on similar topics in a library
   C) Filter out spam emails
   D) Segment online customers into two classes based on their age group – below 25 or above 25
   Answer: A, B
4. Validation set is used for testing the generalization performance of a learning algorithm:
   A) T
   B) F
   Answer: A

5. Which one of the following functions has the highest bias?
A. Linear model
B. Quadratic model
C. Decision tree
Answer: A
6. Find-S:
A) Finding a maximally specific hypothesis
B) finding a minimally specific hypothesis
C) both A & B
D) none of the above
Answer: A
7. The CANDIDATE-ELIMINATION algorithm utilizes the general-to-specific ordering to compute the __________ by incrementally computing the sets of maximally specific (S) and general (G) hypothesis.
A) Version Space
B) Hypothesis space
C) both A & B
D) none of the above
Answer: A
8. Which of the following is true for a decision tree?
A) Decision tree is an example of linear classifier.
B) The entropy of a node typically decreases as we go down a decision tree.
C) Entropy is a measure of purity
D) An attribute with lower mutual information should be preferred to other attributes.
Answer: B
9. ID3 searches a _________space
A) Complete hypothesis
B) Version Space
C) Partial hypothesis
D) none of the above
Answer: A
10. ______ the training data is an important issue in decision tree learning.
A) Version Space
B) Overfitting
C) ID3
D) None of the above
Answer: B

UNIT-2

1. ANN stands for ________________
A) Artificial Neural Networks
B) Artificial Natural Network
C) Artificial Neutral Network
D) None of the above
Answer: A

2. One type of ANN system is based on a unit called a ______
A) Neuron
B) Perceptron
C) Hypothesis
D) Gradient descent
Answer: B

3. A 4-input neuron has bias of 0 and weights 1, 2, 3 and 4. The transfer function is given by f(v)= max (0,v). The inputs are 4, 10, 5 and 20 respectively. The output will be
A) 238
B) 76
C) 119
D) 121
Answer: C

4. The back-propagation learning algorithm applied to a two layer neural network
A) always finds the globally optimal solution.
B) finds a locally optimal solution which may be globally optimal.
C) never finds the globally optimal solution.
D) finds a locally optimal solution which is never globally optimal
Answer: B

5. The _______ algorithm is the most common network learning method.
A) ID3
B) Backpropagation
C) ANN
D) All of the above
Answer: B

6. The _____ is considered by the Backpropagation algorithm is the space of all functions that can be represented by assigning weights to the given, fixed network of interconnected units.
A) Hypothesis space
B) Version Space
C) both A & B
D) none of the above
Answer: A

7. Backpropagation searches the space of possible hypothesis using _______ to iteratively reduce the error in the network to fit to the training examples.
A) Gradient descent
B) Inductive bias
C) Perceptron
D) none of the above
Answer: A

8. The _____ gives the probability of observing *r* heads in a series of *n* independent coin tosses, if the probability of heads in a single toss is *p*.
A) Normal distribution
B) Binomial distribution
C) Probability distribution
D) Estimation bias
Answer: B

9. Statistical theory provides a bias for estimating the ____error of a hypothesis h, based on its observed error over a sample S of data.
A) False

B) True
C) Observed
D) none of the above
Answer: B

10. Possible cause of errors in estimating hypothesis accuracy is _____
A) Inductive bias
B) estimation bias
C) variance
D) B & C
Answer: D

UNIT-3

1. Which of the following properties is false in the case of a Bayesian Network:
A) The edges are directed
B) Contains cycles
C) Represents conditional independence relations among random variables
D) All of the above
Answer: B
2. A and B are Boolean random variables. Given: P(A=True) = 0.3, P(A=False) = 0.7, P(B=True|A=True) = 0.4, P(B=False|A=True) = 0.6, P(B=True|A=False) = 0.6, P(B=False|A=False) = 0.4 . Calculate P(A=True|B=False) by Bayes rule.
A) 0.49
B) 0.39
C) 0.37
D) 0.28
Answer: B
3. The Bayes optimal classifier
A) is an ensemble of some selected hypothesis in the hypothesis space
B) is an ensembles of all hypothesis in the hypothesis space
C) is the hypothesis that gives best result on test instances
D) none of the above
Answer: B
4. A straight forward Bayesian analysis will show that under certain assumptions any learning algorithm that _____the squared error between the output hypothesis predictions and the training data will output a ______hypothesis.
A) minimizes & maximum likelihood
B) maximum likelihood & minimizes
C) Both A & B
D) None of the above
Answer: A
5. *PAC* stands for ________________
A) Probably Approximately Correct
B) Probabilistic Approximation Core
C) Probabilistic Association Concept
D) None of the above
Answer: A
6. The *Vapnik-Chervonenkis dimension*, VC(H), of ____________ H defined over instance space X is the size of the largest finite subset of X shattered by H.
A) Hypothesis space

B) Version space
C) Instance space
D) None of the above
Answer: A

7. The ____ algorithm combines the weighted votes of multiple prediction algorithms to classify new instances.
A) PAC
B) VC
C) *WEIGHTED-MAJORITY*
D) *MISTAKE BOUND MODEL*
Answer: C

8. In *k*-NN algorithm, given a set of training examples and the value of *k* < size of training set (n), the algorithm predicts the class of a test example to be the
A) most frequent class among the classes of *k* closest training examples.
B) least frequent class among the classes of *k* closest training examples.
C) class of the closest point.
D) most frequent class among the classes of the *k* farthest training examples.
Answer: A

9. ____ means approximating a real-valued target function.
A) Residual
B) Regression
C) Kernel function
D) None of the above
Answer: B

10. RBS stands for ______________________ and CBR stands for __________________________
Answer: ***RBS: Radial Basis Function; CBR: Case-Based Reasoning***

UNIT-4

1. ___ provides an approach to learning that is based loosely on simulated evolution.
A) Genetic Algorithms (GA)
B) k-NN
C) Genetic Programming (GP)
D) ANN
Answer: A

2. Genetic Algorithms (GA) operations are ________
A) Crossover
B) Mutation
C) Both A & B
D) none of the above
Answer: C

3. _______ is a form of evolutionary computation in which the individuals in the evolving population are computer programs rather than bit strings.
A) Genetic Algorithms (GA)
B) Genetic Programming (GP)
C) k-NN
D) none of the above
Answer: B

4. Genetic Algorithms (GAs) conduct a _________ search for hypothesis that optimizes a predefined fitness function.
A) Randomized

B) Parallel
C) Hill-climbing
D) All the above
Answer: D

5. FOIL stands for ____________________
Answer: First-Order Inductive Learner

6. The sequential covering algorithm learns a ______ set of rules by first learning a single accurate rule.
A) Conjunctive
B) Disjunctive
C) Reflexive
D) All
Answer: B

7. Sets of first-order rules provide a ____ expressive representation.
A) Highly
B) Low
C) Medium
D) None of the above
Answer: A

8. _____ addresses the question of how an autonomous agent that senses and acts in its environment can learn to choose optimal actions to achieve its goals.
A) Case-based reasoning
B) Reinforcement learning
C) Analytical learning
D) Concept learning
Answer: B

9. Reinforcement learning algorithms are related to _______algorithms frequently used to solve optimization problems.
A) Dynamic programming
B) Static programming
C) Greedy methods
D) Branch and bound
Answer: A

10. _____ learning that can acquire optimal control strategies from delayed rewards, even when the agent has no prior knowledge of the effects of its actions on the environment.
A) Reinforcement learning
B) Q-learning
C) Concept learning
D) Analytical learning
Answer: B

UNIT-5

1. _____ learning uses prior knowledge and deductive reasoning to augment the information provided by the training examples.
A) Inductive learning
B) Analytical learning
C) Concept learning
D) Q-learning
Answer: B

2. EBL stands for _____
   Answer: Explanation-Based Learning
3. PROLOG-EBG stands for _____
   Answer: Logic Programming - Explanation-Based Generalization
4. PROLOG-EBG is a _____, rather than inductive, learning process.
   A) Deductive
   B) Analytical
   C) Disjunctive
   D) Conjunctive
   Answer: A
5. Purely analytical methods use prior knowledge to derive general hypothesis deductively.
   A) True
   B) False
   Answer: A
6. KBANN stands for ______________________
   Answer: Knowledge-Based Artificial Neural Network
7. EBNN stands for _____________
   Answer: Explanation-Based Neural Network learning
8. ___ uses the domain theory to expand the set of candidates considered at each step in the search.
   A) FOIL
   B) FOCL
   C) PROLOG-EBG
   D) TANGENTPROP
   Answer: B
9. ____ uses prior knowledge represented by desired derivatives of the target function.
   A) FOIL
   B) FOCL
   C) EBNN
   D) TANGENTPROP
   Answer: D
10. ____ uses the domain theory to alter the objective in searching the hypotheses space of possible weights for an artificial neural network.
   A) FOIL
   B) FOCL
   C) EBNN
   D) TANGENTPROP
   Answer: C

XII. WEBSITES:

- *Machine Learning, Tom Mitchell, McGraw Hill, 1997*
  http://www.cs.cmu.edu/~tom/mlbook.html
- *NPTEL Resources:*

NOC: Machine Learning, ML (Video):
https://nptel.ac.in/courses/106106202/

NOC: Introduction to Machine Learning (Video):
https://nptel.ac.in/courses/106105152/

NOC: Introduction to Machine Learning (Course sponsored by Aricent) (Video):
https://nptel.ac.in/courses/106106139/

XIII. EXPERT DETAILS:

- Tom Mitchell, E. Fredkin University Professor, Machine Learning Department, School of Computer Science, Carnegie Mellon University, USA. *(visit: http://www.cs.cmu.edu/~tom/)*
- Prof. S. Sarkar, IIT Kharagpur *(https://nptel.ac.in/syllabus/106105152/)*
- Dr. Balaraman Ravindran, IIT Madras *(https://nptel.ac.in/syllabus/106106139/)*
- Prof. Balaji Srinivasan, IIT Madras *(https://nptel.ac.in/syllabus/106106198/)*
- Prof. Ganapathy, IIT Madras *(https://nptel.ac.in/syllabus/106106198/)*

XIV. JOURNALS:

- IEEE Transactions on Pattern Analysis and Machine Intelligence
- IEEE Transactions on Knowledge and Data Engineering
- Machine Learning Journal, Springer Publications (https://www.springer.com/computer/ai/journal/10994)
- Journal of Machine Learning Research (http://www.jmlr.org/)

XV. LIST OF TOPICS FOR STUDENT SEMINARS:

- Candidate elimination algorithm
- Decision tree learning algorithm
- Backpropagation algorithm
- Naïve Bayes classifier
- Bayesian belief networks
- k-nearest neighbour algorithm
- Genetic algorithms
- Q-learning
- PROLOG-EBG

XVI. CASE STUDIES / SMALL PROJECTS:

Following are potential course projects for 15-781, Machine Learning:

PROJECT-1:

TITLE: Text Classification with Bayesian Methods

DESCRIPTION: Given the growing volume of online text, automatic document classification is of great practical value, and an increasingly important area for research. Naive Bayes has been applied to this problem with considerable success, however, naive Bayes makes many assumptions about data distribution that are clearly not true of real-world text. This project will aim to improve upon naive Bayes by selectively removing some of these assumptions. I imagine beginning the project by removing the assumption that document length is independent of class---thus, designing a new version of naive Bayes that uses document length in order to help classify more accurately. If we finish this, we'll move on to other assumptions, such as the word independence assumption, and experiment with methods that capture some dependencies between words. The paper at http://www.cs.cmu.edu/~mccallum/papers/multinomial-aaai98w.ps is a good place to start some reading. You should be highly proficient in C programming, since you'll be modifying rainbow (http://www.cs.cmu.edu/~mccallum/bow/rainbow).

PROJECT-2:

TITLE: Using a repository of old text to answer new questions

DESCRIPTION: Consider a repository of email messages in which discussion center around living with a disease, such as celiac, heart disease or diabetes. Frequently new people become diagnosed and join the list, resulting in a good number of questions being asked repeatedly. Unfortunately, messages do not adhere to a restricted vocabulary and so traditional web-based keyword searching is often ineffective. In this project, you will use and evaluate algorithms to generate responses to new email messages based on the repository of old email messages. You can begin with a Bayesian text classifier [as discussed in class: Lewis, 1991; Lang, 1995; Joachims, 1996] and a semantic generalization algorithm I have constructed and based on your analysis, explore interesting variants to determine the effectiveness of this new approach.