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| A2CIT414 | **SEMESTER – VII** | **L** | **T** | **P** | **C** |
| **Machine Learning** | **3** | **0** | **0** | **3** |
| **Total Contact Hours: 45** | | | | |
| **Prerequisites: Data Mining** | | | | |

**Course Objectives:**

1. Be able to formulate machine learning problems corresponding to different applications.
2. Understand a range of machine learning algorithms along with their strengths and weaknesses.
3. Understand the basic theory underlying machine learning.
4. Be able to apply machine learning algorithms to solve problems of moderate complexity.
5. Be able to read current research papers and understand the issues raised by current research.

**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 representation, The List-Then-Eliminate Algorithm, Compact representation for version spaces, Candidate elimination algorithm and example, Remarks on version spaces and candidate-elimination: Converge, Order of training examples, Usage of partially learned concepts, biased hypothesis space.

**UNIT II:**

**Decision Tree Learning:** Introduction, Decision Tree representation and Appropriate problems for decision tree learning, ID3 Algorithm with example, Hypothesis space search in decision tree learning, Inductive bias in decision tree learning, Issues in Decision tree learning: Avoiding Over fitting the Data, Incorporating Continuous-Valued attributes, Alternative measures for attributes,Handling training examples with Missing Attribute Values, Handling attributes with Different Costs.

**Unit - III**

**Part - I**

**Artificial Neural Networks:** Biological motivation, Neural Network representation , Appropriate problems for neural network learning , Perceptrons - Representational power of Perceptrons, The Perceptron Training Rule , Gradient Descent and the Delta Rule - Visualizing the Hypothesis Space , Multilayer networks and the back propagation algorithm - A Differentiable Threshold Unit , The Backpropagation Algorithm , Remarks on the Backpropagation Algorithm: Convergence and local minima. Representational power of feed forward networks, Hypothesis space search, inductive bias, Hidden layer representations, Generalizations, Overfitting, and Stopping criterion.

**Part - II**

**Bayesian Learning:** Introduction, Bayes Theorem and Concept Learning , Maximum Likelihood and Least-Squared Error Hypothesis , Maximum Likelihood hypothesis for predicting probabilities, Minimum Description Length principle, Bayes optimum Classifier, Gibbs Algorithm

**Bayesian Belief Networks:** Conditional Independence, Representation, Inference, Learning Bayesian Belief Networks, Gradient Ascent Training of Bayesian Networks, Learning the structure of Bayesian Networks, The EM Algorithm: Estimating means of k Gaussians, General Statement of EM Algorithm.

**UNIT IV:**

**Computational Learning Theory:** Introduction, Probability Learning an Approximately Correct Hypothesis: The problem setting, Error of a Hypothesis, PAC Learnability; Sample Complexity for Finite Hypothesis Spaces: Agnostic Learning and Inconsistent Hypotheses, Conjunctions of Boolean Literals are PAC-Learnable, PAC-Learnability of other Concept Classes; Sample Complexity for Infinite Hypothesis Space: Shattering a set of Instances, The VC Dimension, Sample complexity and the VC Dimension

**Instance Based Learning:** Introduction, k-Nearest Neighbor learning: Distance-Weighted NEREST NEIGHBOR Algorithm, Locally Weighted Regression: Locally Weighted Linear Regression; Radial Basis functions, Case based reasoning

**UNIT V:**

**Learning Sets of Rules:** Introduction, Sequential Covering Algorithms: General to Specific Beam Search, Variations; Learning First-order rules; Learning Sets of First-order rules

**Analytical Learning**: Inductive and Analytical Learning problem; Learning with Perfect Domain Theories: PROLOG-EBG; Remarks on Explanation-Based Learning: Discovering New Features, Deductive Learning, Inductive Bias in Explanation-Based Learning, Knowledge level training

**Text Books:**

1. Machine Learning by Tom M. Mitchell, Indian Edition.

**COURSE OUTCOMES**

1. **KO#1: Have the knowledge of Concept Learning and the General-to-specific Ordering, decision tree learning.**
2. **KO#2: Have the knowledge of Artificial Neural Networks, Bayesian Learning, Bayesian Belief Networks.**
3. **KO#3: Have the knowledge of Computational Learning Theory, Instance Based Learning, Learning Sets of Rules, Analytical Learning.**
4. **UO#1: Grasp the significance of Concept Learning and the General-to-specific Ordering, decision tree learning.**
5. **UO#2: Grasp the significance of Artificial Neural Networks, Bayesian Learning, Bayesian Belief Networks.**
6. **UO#3: Grasp the significance of Computational Learning Theory, Instance Based Learning, Learning Sets of Rules, Analytical Learning.**
7. **AO#1: Fully appreciate the Machine Learning techniques and its implementation.**

**Knowledge Concepts:**

Cluster 1:

**Introduction to Learning, Concept Learning and the General-to-specific Ordering**

KC1:Introduction**:** Well posed learning problems

KC2: Designing a learning system

KC3: Perspectives and issues in Machine learning

KC4: Introduction to Concept Learning, A Concept learning task, Concept learning as search

KC5: Find-S: Finding a Maximally Specific Hypothesis

KC6: Version spaces representation, The List-Then-Eliminate Algorithm, Compact representation for version spaces

KC7: Candidate elimination algorithm and example

KC8: Remarks on version spaces and candidate-elimination: Converge; Order of training examples, Usage of partially learned concepts, biased hypothesis space

Cluster 2:

**Decision Tree Learning**

KC1:Introduction, Decision Tree representation and Appropriate problems for decision tree learning

KC2: ID3 Algorithm with example

KC3: Hypothesis space search in decision tree learning

KC4: Inductive bias in decision tree learning

KC5: Issues in Decision tree learning: Avoiding Over fitting the Data

KC6: Incorporating Continuous-Valued attributes

KC7: Alternative measures for attributes

KC8: Handling training examples with Missing Attribute Values, Handling attributes with Different Costs

Cluster 3:

**Artificial Neural Networks**

KC1:Biological motivation, Neural Network representation

KC2: Appropriate problems for neural network learning

KC3: Perceptrons - Representational power of Perceptrons, The Perceptron Training Rule

KC4: Gradient Descent and the Delta Rule - Visualizing the Hypothesis Space

KC5: Multilayer networks and the back propagation algorithm - A Differentiable Threshold Unit

KC6: The Backpropagation Algorithm

KC7: Remarks on the Backpropagation Algorithm: Convergence and local minima. Representational power of feed forward networks, Hypothesis space search, inductive bias

KC8: Hidden layer representations, Generalizations, Overfitting, and Stopping criterion

Cluster 4:

**Bayesian Learning, Bayesian Belief Networks**

KC1: Bayesian Learning: Introduction, Bayes Theorem and Concept Learning

KC2: Maximum Likelihood and Least-Squared Error Hypothesis

KC3: Maximum Likelihood hypothesis for predicting probabilities, Minimum Description Length principle

KC4: Bayes optimum Classifier, Gibbs Algorithm

KC5: Bayesian Belief Networks: Conditional Independence, Representation, Inference

KC6: Learning Bayesian Belief Networks, Gradient Ascent Training of Bayesian Networks, Learning the structure of Bayesian Networks

KC7: The EM Algorithm: Estimating means of k Gaussians

KC8: General Statement of EM Algorithm

Cluster 5:

**Computational Learning Theory, Instance Based Learning**

KC1:Computational Learning Theory: Introduction, Probability Learning an Approximately Correct Hypothesis: The problem setting, Error of a Hypothesis, PAC Learnability

KC2: Sample Complexity for Finite Hypothesis Spaces: Agnostic Learning and Inconsistent Hypotheses

KC3: Conjunctions of Boolean Literals are PAC-Learnable

KC4: PAC-Learnability of other Concept Classes

KC5: Sample Complexity for Infinite Hypothesis Space: Shattering a set of Instances, The VC Dimension, Sample complexity and the VC Dimension

KC6: Instance Based Learning: Introduction, k-Nearest Neighbor learning: Distance-Weighted NEREST NEIGHBOR Algorithm

KC7: Locally Weighted Regression: Locally Weighted Linear Regression

KC8: Radial Basis functions, Case based reasoning

Cluster 6:

**Learning Sets of Rules, Analytical Learning**

KC1:Learning Sets of Rules: Introduction, Sequential Covering Algorithms: General to Specific Beam Search, Variations

KC2: Learning First-order rules

KC3: Learning Sets of First-order rules

KC4: Analytical Learning: Inductive and Analytical Learning problem

KC5: Learning with Perfect Domain Theories: PROLOG-EBG

KC6: Remarks on Explanation-Based Learning: Discovering New Features, Deductive Learning

KC7: Inductive Bias in Explanation-Based Learning

KC8: Knowledge level training