Programme Name: M.Sc(IT-Artificial Intelligence)

Course Code: 601 [Mandatory] **Total Credits:** 04 (60 Lecture Hrs) **University assessment:** 50 marks	**Course Name:** Machine Learning (Theory) **Total Marks:** 100 marks **College/Department assessment:** 50 marks

Pre requisite:

1. Sound knowledge of Python
2. Sound knowledge of concepts in probability, statistics & mathematics

Course Objectives (COs)

To enable the students to:

CO1: Understand the foundational concepts and terminology of machine learning, including supervised and unsupervised learning techniques.

CO2: Grasp the theoretical underpinnings of various machine learning algorithms and methods, such as decision trees, Bayesian estimation, and reinforcement learning.

CO3: Implement and apply machine learning algorithms to solve real-world problems, demonstrating proficiency in data pre-processing, model selection, and evaluation techniques.

CO4: Evaluate and compare the performance of different machine learning models and techniques through rigorous experimentation and analysis of results.

CO5: Design and develop advanced machine learning systems and solutions, incorporating ensemble methods, reinforcement learning, and experimental design principles.

MODULE I: Machine Learning Basics & Supervised Learning	**(2 CREDITS)**
Unit 1: Machine Learning Basics a. **Introduction to Machine Learning & Supervised Learning**: Introduction to Machine Learning, Types of Machine Learning (Chapter 1), VC dimension, PAC Learning, Noise, Learning Multiple Classes, Regression, Model Selection and Generalization, Dimensions of a Supervised Machine Learning Algorithm – (Chapter 2) b. **Bayesian Decision Theory & Parametric Methods**: Classification, Losses and Risks, Discriminant Functions, Utility Theory, Association Rules (Chapter 3), Maximum Likelihood Estimation, Bias and Variance, The Bayes' Estimator, Parametric Classification, Regression, Bias/Variance Dilemma, Model Selection Procedures (Chapter 4) c. **Multivariate Methods & Nonparametric Methods**: Multivariate Data, Parameter Estimation, Estimation of Missing Values, Multivariate Normal Distribution, Multivariate Classification, Tuning Complexity, Discrete Features, Multivariate Regression(Chapter 5), Nonparametric Density Estimation, Generalization to Multivariate Data, Nonparametric Classification, Condensed Nearest Neighbor, Nonparametric Regression: Smoothing Models, How to Choose the Smoothing Parameter **Chapter 8**	18 Hrs [OC1, OC2]
Unit 2: Supervised Learning Techniques a. **Decision Trees**: Univariate Trees, Classification Trees, Regression Trees, Pruning, Rule Extraction from Trees, Learning Rules from Data, Multivariate Trees Chapter 9 b. **Linear Discrimination & Kernel Machines**: Generalizing the Linear Model, Geometry of the Linear Discriminant, Pairwise Separation, Parametric Discrimination Revisited, Gradient Descent, Logistic Discrimination, Discrimination by Regression (Chapter 10), Optimal Separating Hyperplane, The Nonseparable Case: Soft Margin Hyperplane, ν-SVM, Kernel Trick, Vectorial Kernels, Defining Kernels, Multiple Kernel Learning, Multiclass Kernel Machines, Kernel Machines for Regression, One-Class Kernel Machines (Chapter 13) c. **Bayesian Estimation**: Estimating the Parameter of a Distribution, Bayesian Estimation of the Parameters of a Function, Gaussian Processes (chapter 14)	15 Hrs [OC3]
MODULE II : Unsupervised Learning, Ensemble Model Reinforcement Learning	**(2 CREDITS)**
Unit 3: Unsupervised Learning a. **Dimensionality Reduction**: Subset Selection, Principal Components Analysis, Factor Analysis, Multidimensional Scaling, Linear Discriminant Analysis, Isomap, Locally Linear Embedding (chapter 6)	12 Hrs [OC4, OC5]

b. **Clustering**: Mixture Densities, k-Means Clustering ,Expectation-Maximization Algorithm, Mixtures of Latent Variable Models, Supervised Learning after Clustering, Hierarchical Clustering, Choosing the Number of Clusters (chapter 7) c. **Hidden Markov Models**: Discrete Markov Processes, Hidden Markov Models, Three Basic Problems of HMMs, Evaluation Problem, Finding the State Sequence, Learning Model Parameters, Continuous Observations, The HMM with Input, Model Selection (chapter 15)	
Unit 4: Ensemble Models and Reinforcement Learning a. **Combining Multiple Learners**: Generating Diverse Learners, Model Combination Schemes, Voting, Error-Correcting Output Codes, Bagging, Boosting, Mixture of Experts Revisited, Stacked Generalization, Fine-Tuning an Ensemble, Cascading (chapter 17) b. **Reinforcement Learning**: Single State Case: K-Armed Bandit, Elements of Reinforcement Learning, Model-Based Learning - Value Iteration & Policy Iteration, Temporal Difference Learning, Generalization, Partially Observable States, The Setting, Example: The Tiger Problem (chapter 18) c. **Design and Analysis of Machine Learning Experiments**: Factors, Response, and Strategy of Experimentation, Response Surface Design, Randomization, Replication, and Blocking, Guidelines for Machine Learning Experiments, Cross-Validation and Resampling Methods, Measuring Classifier Performance, Interval Estimation, Hypothesis Testing, Assessing a Classification Algorithm's Performance, Comparing Two Classification Algorithms, Comparing Multiple Algorithms: Analysis of Variance, Comparison over Multiple Datasets, Comparing Two Algorithms, Multiple Algorithms (chapter 19)	15 Hrs [OC6,OC7, OC8]

Sr. No.	Title	Author/s	Publisher	Edition	Year
1.	Introduction to Machine Learning	Ethem Alpaydın	The MIT Press Cambridge	Third	2014
2.	Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow	Aurélien Géron	O'Reilly	Second	2019
3.	Introduction to Machine Learning with Python	Andreas C. Müller, Sarah Guido	O'Reilly	First	2017
4.	Machine Learning: The Art and Science of Algorithms that Make Sense of Data	Peter Flach	Cambridge University Press		2012
5.	Introduction to Statistical Machine Learning with Applications in R	Hastie, Tibshirani, Friedman	Springer	Second	2012

Course Outcomes (OCs)

Upon completion of this course, student will be able to:

1. Demonstrate a deep understanding of the foundational concepts and terminology of machine learning, including supervised and unsupervised learning paradigms.
2. Apply theoretical principles behind Bayesian decision theory, parametric, and nonparametric methods to solve classification and regression problems.
3. Implement decision tree algorithms, linear discrimination techniques, and kernel machines for supervised learning tasks.
4. Utilize dimensionality reduction and clustering techniques to analyse and interpret complex datasets in unsupervised learning scenarios.
5. Understand the theoretical foundations of Hidden Markov Models and their applications in machine learning.
6. Apply ensemble learning techniques such as bagging and boosting to improve model performance and robustness in prediction tasks.
7. Implement and analyse reinforcement learning algorithms, including value iteration and policy iteration, to solve sequential decision-making problems.
8. Evaluate the performance and generalization of machine learning models through rigorous experimentation and cross-validation techniques.

9. Critically assess and compare the performance of multiple machine learning algorithms using appropriate evaluation metrics and statistical techniques.