CS303: Machine Learning	**3**	**0**	**2**	**Engineering Mathematics**

Course Objective: The student should be able to understand the different supervised, unsupervised and reinforcement learning algorithms and choose the appropriate machine learning tool for different real world examples.

S. No	Course Outcomes (CO)
CO1	Design and implement supervised learning algorithms, including linear regression and classification models, and evaluate their performance using appropriate metrics.
CO2	Apply unsupervised learning techniques, such as k-means and hierarchical clustering, to real-world datasets and interpret the results.
CO3	Develop and train neural network models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for complex pattern recognition tasks.

CO4	Apply reinforcement learning algorithms, such as Q-learning and policy gradient methods, to create agents capable of solving decision-making problems in simulated environments.
CO5	Critically evaluate the ethical implications of AI technologies and apply principles of responsible AI in the development and deployment of machine learning models.

S. No	Contents	Contact Hours
UNIT 1	Review of Probability Theory: Definitions, independent events, joint probability, marginal probability, conditional probability, sum rule, product rule, Bayes' theorem, concept of probability distribution, likelihood. Random process and random variable: Definitions, continuous and discrete random variables, expectation, variance, covariance. Classification and Regression: curve fitting, model selection, curse of dimensionality, loss function. Evaluation of ML models: The train/test/validation split, under-fitting, overfitting, generalization, Bias vs Variance, validation curves. Metrics: Confusion matrix, Accuracy, Precision, Recall, Specificity, F1 score Precision-Recall or PR curve, ROC (Receiver Operating Characteristics) curve, PR vs ROC curve.	**8**
UNIT 2	Information Theory: Concept of information, Entropy, Information gain, relative and mutual information. Classification using Decision Trees: Iterative Dichotomiser 3 (ID3), Greedy decision tree learning, selecting best feature for split, classification error, prediction with decision trees. Decision trees with real valued features, threshold split in 1-D, threshold split in 2-D, finding optimal threshold split. Overfitting in decision tress: Principle of Occam's Razor, complex and simpler decision trees, early stopping, Decision tree pruning. CART, C4.5. Kn –nearest neighbor density estimation, K-nearest neighbor classifier (K-NN). Naïve-Bayes Classifier. Linear discriminant functions, logistic discrimination, Linear separability, generalized linear discriminants. Least-square techniques, gradient descent algorithms. Supervise Learning-Linear Regression, linear regression with one variable, Derivative of cost function, gradient descent algorithm. Logistic regression: Classification, learning parameters, cost function for logistic regression, gradient descent algorithm in logistic regression. Support Vector Machine (SVM).	**13**
UNIT 3	Artificial Neural Network (ANN): Introduction, Perceptron model, applications of linear model. Perceptron learning, perceptron convergence theorem, limitations of perceptron. Fisher's linear Discriminant-Linear discriminant analysis (LDA). Multi-layer perceptron: Error back-propagation	**7**
UNIT 4	Unsupervised Learning: similarity measures, k-means clustering, k-means as coordinate descent algorithm, k-mean++. Convergence of k-means algorithm, limitations: uncertainty in cluster assignment, failure modes of k-means, mixture models. Gaussian mixture models (GMM), Maximum likelihood estimation (MLE), Expectation Maximization, Inferring soft assignments with expectation maximization (EM), Convergence and overfitting of MLE. Hierarchal Clustering. Data representation and Dimension Reduction: change of basis vectors, principle component analysis (PCA). Factor analysis, Manifold Learning	**7**
UNIT 5	Reinforcement learning: Introduction, difference with supervised learning, Evaluative feedback: n-armed bandit problem, action-value methods, softmax action selection. The reinforcement learning problem: Agent-Environment interface, goals and rewards, returns, unified notation for episodic and continuing tasks, Markov property, Markov decision processes, value functions, optimal value functions. Dynamic programming: policy evaluation, policy improvement, policy iteration. Temporal-Difference Learning: TD prediction and advantages, Optimality of TD(0), Sarsa: On-Policy TD Control. Q-Learning: Off-Policy TD Control, Actor-Critic Methods.	**7**
	Total	**42**