Name of the Programme: MCA
Course Code: CSA-509
Title of the Course: Machine Learning
Number of Credits: 4 (4L+0T-0P)
Effective from AY: 2022-23

Prerequisites for the course	Basic concepts of Linear Algebra, Probability theory	
Objectives:	This course provides students with an in-depth introduction to three main areas of Machine Learning: supervised and unsupervised and reinforcement learning. This course will cover some of the main models and algorithms for regression, classification, clustering and Markov decision processes. Topics will include linear and logistic regression, regularisation, SVMs and kernel methods, ANNs, clustering, and dimensionality reduction ,sequential learning Like HMM and reinforcement learning.	
Content:	1. Introduction:- well posed learning problem – designing a learning system-perspectives and issues in machine learning.	4 hours
	2. Concept learning – concept learning task –notation –inductive learning hypothesis-concept learning as search- version space and candidate elimination algorithm-decision tree –random forest.	6 hours
	3. Linear regression - logistic regression-Support vector machine kernel- Model selection and feature selection-Ensemble methods: Bagging, boosting. Evaluating and debugging learning algorithms.	7 hours
	4. Continuous Latent Variables-Revision of Principal Component Analysis -Maximum variance formulation - Minimum-error formulation - Applications of PCA - PCA for high-dimensional data.	7 hours
	5. Neural Networks -Feed-forward Network Functions –perceptron - Weight-space symmetries -Network Training - Parameter optimization -Local quadratic approximation - Use of gradient information - Gradient descent optimization - Error Backpropagation - Evaluation of error-function derivatives - A simple example - Efficiency of backpropagation .	10 hours
	6. Probabilistic model – The normal distribution and its geometric interpretation-probabilistic models for categorical data -using naïve Bayes model for classification, training a naïve Bayes model - discriminative learning by optimizing conditional likelihood - probability models with hidden variables: Expectation-Maximization, Gaussian mixture model	9 hours
	7. Distance-based models – neighbour and exemplers -nearest-neighbour classification -distance based clustering -K means algorithm, clustering around medoids , silhouetees-hierarchical clustering -from kernels to distances	5 hours
	8. Sequential Data - Markov Models - Hidden Markov Models - Maximum likelihood for the HMM -The forward-backward algorithm - The sum-product algorithm for the HMM -Scaling factors - The Viterbi algorithm.	7 hours
	9. Reinforcement learning – Introduction- learning task-Q learing-non deterministic rewards and actions-temporal difference learning.	5 hours
Pedagogy:	Lectures/ tutorials/assignments/self-study	
References/Readings	Main Reading :- 1.Introduction to Statistical Learning, Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani, Springer, 2013. 2. EthemAlpaydin, Introduction to Machine Learning, MIT Press. 3. Richard O. Duda, Peter E. Hart, David G. Stork Pattern Classification,.	

	4. Peter Flach , Machine Learning , Cambridge 5.Christopher M. Bishop,Pattern recognition and machine Learning, springer. 6.Deep Learning, Ian Good fellow, MIT press 7.Tom Michele, Machine Learning, McGraw-Hill.	
Course Outcomes	By the end of the course , students should: ● Develop an appreciation for what is involved in learning from data. ● Understand a wide variety of learning algorithms. ● Understand how to apply a variety of learning algorithms to data. ● Understand how to perform evaluation of learning algorithms and model selection. ● Equips them with a general understanding of deep learning.	

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