Applied Machine Learning

EX852-Co1

Lecture : (4 hr. per week) **Year: I**
Practical : (1.5 hr. per week) **Part: II**

Course Objectives:

The objective of this course is to give an introduction to machine learning techniques and theory with a focus on its use in practical applications. During the course, a selection of topics will be covered in dimensionality reduction and feature extraction, regression and classification techniques will be discussed under supervised learning, clustering and mixture models will be taught within the realm of unsupervised learning, machine learning will be observed from a probabilistic perspective, and an overview of reinforcement learning will be provided.

Course Contents:

1. **Machine Learning Preliminaries** **[8 hrs.]**
   - 1.1 Traditional Programming vs. Machine Learning
   - 1.2 Well-Posed Learning Problems
   - 1.3 Design Principles of Learning Systems
   - 1.4 Origin of Machine Learning, Adversarial Games and Intelligent Machines
   - 1.5 Scenarios Suitable for Machine Learning
   - 1.6 Styles of Machine Learning
   - 1.7 Challenges in Machine Learning
   - 1.8 No Free Lunch Theorem, Bias-Variance Decomposition
2. **Feature Engineering and High Dimensional Data** **[10 hrs.]**
   - 2.1 Data and Features, Numerical and Categorical Data
   - 2.2 Feature Normalization and Discretization, Dealing with Outliers
   - 2.3 Computable Features, Imputing Missing Data
   - 2.4 Encoding Categorical Variables, Transforming Numerical Variables
   - 2.5 Feature Selection, Filter Method, Wrapper Method, Embedded Method
   - 2.6 Feature Utility Metrics
   - 2.7 Balanced and Imbalanced Datasets, Handling Imbalanced Datasets
   - 2.8 Blessings and Curse of Dimensionality
   - 2.9 Feature Extraction, Dimensionality Reduction, PCA, SVD

3. Regression and Classification Models **[11 hrs.]**

3.1 Linear, Logistic, and Polynomial Regression Models

3.2 Regularization Methods, Ridge and Lasso Regression

3.3 LDA and QDA Classifiers

3.4 Naïve Bayes Classifier, K-Nearest Neighbor Classifier

3.5 Decision Trees, Classification and Regression Trees (CART)

3.6 Ensemble Models, Bagging, Boosting, Stacking, Random Forests

3.7 Hyperplanes and Optimal Separation, Support Vector Machine Algorithm

3.8 Kernel Functions, Kernel Trick

3.9 Performance Metrics for Supervised Learning Models

4. Clustering Methods and Mixture Models **[10 hrs.]**

4.1 Hierarchical Clustering, Agglomerative and Divisive Clustering

4.2 K-Means Algorithm and K-Medoids Clustering

4.3 Density-based Clustering, DBSCAN Algorithm, OPTICS Algorithm

4.4 Kernel Density Estimation, Mean-Shift Clustering

4.6 Mixture Models, Mixtures of Gaussians

4.7 Expectation Maximization Algorithm, EM for GMM

4.8 Evaluating Unsupervised Learning Models

5. Probabilistic Graphical Models and Inference **[10 hrs.]**

5.1 Nodes and Edges of Graphs, Subgraphs, Paths, Trails, Cycles and Loops

5.2 Directed and Undirected Graphs, Clique Trees

5.3 Bayesian Belief Networks, Hidden Markov Models, Markov Random Field

5.4 Monte Carlo Inference, Markov Chain Mote Carlo Inference

5.5 Gibbs Sampling, Metropolis-Hastings Algorithm

5.6 Exact and MAP Inference, Belief Propagation

5.7 Inference in HMM, Forward-Backward Algorithm, Viterbi Algorithm

6. Reinforcement Learning **[11 hrs.]**

6.1 Elements of Reinforcement Learning, Limitations and Scope

6.2 K-armed Bandit Problem, Gradient Bandit Algorithm

6.3 Deterministic and Stochastic Environments, Agent Objective and Behavior

6.4 Markov Decision Processes (MDP), Partially Observable MDP (POMDP)

6.5 Policy-based Learning, Proximal Policy Optimization, Actor-Critic Models

6.7 Q-Learning, SARSA, Temporal Difference Learning

6.8 Monte Carlo Learning, Monte Carlo Tree Search

Assignments

1. Solving selected numerical problems and derivations from reference books
2. Reviewing a paper related to applied machine learning published within the last five years in a reputed journal
3. Performing a case study of a recent technological trend that implements machine learning
4. Implementing and presenting some latest machine learning algorithms as directed by the course instructor

Practical

1. Feature Selection and Dimensionality Reduction
2. Regression and Classification based Algorithms
3. Clustering Algorithms
4. Algorithms belonging to Graphical Models
5. Reinforcement Learning Algorithms

Evaluation Schemes

a. Internal Examination

Type	Weightage
Minor tests	70%
Assignments	30%

b. Final Examination

There will be five units of questions carrying 12 marks each. The question will cover all chapters of the syllabus. The evaluation scheme will be as indicated in the table:

Units	Chapters	Marks *
1	1, 2, 3, 4, 5, 6	12
2	1, 2, 3, 4, 5, 6	12
3	1, 2, 3, 4, 5, 6	12
4	1, 2, 3, 4, 5, 6	12
5	1, 2, 3, 4, 5, 6	12
Total		**60**
* There may be minor variation in distribution of marks		

References:

1. Pablo Duboue, "The Art of Feature Engineering: Essentials for Machine Learning, Cambridge University Press, First Edition, 2020
2. Ethem Alpaydun, "Introduction to Machine Learning", MIT Press, Third Edition, 2015
3. Mehryar Mohri, Afshin Rostamizadeh, Ameet Talwalkar, "Foundations of Machine Learning", MIT Press, Second Edition, 2018
4. Christopher M. Bishop, "Pattern Recognition and Machine Learning", Springer, First Edition, 2011
5. Kevin P. Murphy, "Machine Learning: A Probabilistic Perspective", MIT Press, First Edition, 2012
6. Richard S. Sutton and Andrew G. Burto, "Reinforcement Learning: An Introduction", Second Edition, 2018