جـــامـــعـــة مـحـــمـــد بـــن زايـــد
لـلــذكـــاء الاصـطــنـــاعـــي
MOHAMED BIN ZAYED UNIVERSITY
OF ARTIFICIAL INTELLIGENCE

Core Courses Syllabi

ML701 - Machine Learning

Title	Machine Learning
Code	ML701
Loading	4 Credit-hours
Prerequisites	Basic Concepts in Calculus, Linear Algebra and Programming
Catalog Description	This course provides a comprehensive introduction to Machine Learning. It builds upon fundamental concepts in Mathematics, specifically probability and statistics, linear algebra, and calculus. Students will learn about supervised and unsupervised learning, various learning algorithms, and basics of learning theory, graphical models, and reinforcement learning.
Goal	This graduate level course aims to familiarize students with foundations of core machine learning algorithms. This course aims to instill in students a strong grasp of supervised and unsupervised as well as the variants of learning algorithms. In addition, this course aims to expose students to the basics of learning theory, graphical models, and reinforcement learning.
Content	This course covers the following major module: **(I)** supervised learning, **(II)** unsupervised learning, **(III)** learning theory **(IV)** graphical models and reinforcement learning
Recommended Textbooks	Tom M. Mitchell, *Machine Learning*, McGraw-Hill Science/Engineering/Math publishing, ISBN: 0070428077
Recommended References & Supplemental Material	The following textbooks may be useful: 1. C. Bishop, *Pattern Recognition and Machine Learning*, Berlin: Springer-Verlag, 2006, ISBN: 0387310738 2. K. Murphy, *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012, ISBN-10: 0262018020

<table>
<tr><th>Teaching Week</th><th>Topics</th></tr>
<tr><td>1</td><td>Machine Learning Basics
Lectures
• Recap on probability theory and linear algebra
• Introduction to optimization
• Overview of libraries and programming recap
Lab
• Demonstration of programming environment and libraries
• Practice problems to get started with Python, Matlab, Jupyter Notebook, Numpy arrays etc.</td></tr>
<tr><td>2</td><td>Introduction to Supervised Learning
Lecture
• Regression vs classifier,
• Discriminative vs generative model
• General concepts: hypothesis, loss function (types of loss functions), cost function
• Gradient descent: stochastic vs batch
• Likelihood
• Newton’s algorithm
Lab
• Problem solving related to regression and fundamental optimization methods
• Implementation of regression
• Data preprocessing lab – handling missing data, noisy labels etc.</td></tr>
<tr><td>3</td><td>Linear Models
Lecture
• Linear regression: LMS algorithm, locally weighted regression
• Classification and logistic regression: sigmoid function, logistic regression, softmax regression,
• Classification and regression metrics
• Generalized linear models: exponential family, assumption of GLMs
Lab
• Instructor-led walk-through of examples to demonstrate concepts
• Data visualization lab</td></tr>
</table>

Teaching Week	Topics
4	**Support Vector Machines** **Lecture** • Optimal margin classifier • Lagrange duality • Support vectors, max-margin learning • Hinge loss, kernels, Lagrangian **Lab** • Implement basic variant of SVM classifier from scratch without using any publicly available library
5	**Generative Learning** **Lecture** • Gaussian discriminant analysis • Mixture models • Naïve Bayes model **Lab** • Implementation of Naïve Bayes algorithm
6	**Tree-based and Ensemble Models:** **Lecture** • Decision tree • Random forest • Boosting (adaptive boosting and gradient boosting) **Lab** • Instructor-led demonstrations of random forest for classification
7	**Learning Theory** **Lecture** • Union bound • Hoeffding inequality • Empirical risk • Probably approximately correct framework • Shattering • Upper bound theorem • Vapnik-Chervonenkis (VC) dimension and theorem **Lab** • Mathematical Proofs and problem solving related to learning theory

Teaching Week	Topics
8	**Introduction to Unsupervised Learning** **Lecture** • Introduction to unsupervised learning • Gaussian Mixture Model • Expectation-Maximization • k-means clustering **Lab** • Instructor-led walkthrough of concepts taught in class
9	**Clustering** **Lecture** • Hierarchical clustering • DB scan algorithm • Clustering assessment metrics (Silhouette coefficient, Calinski-Harabasz index) • Density estimation **Lab** • Implement basic version of K-means clustering algorithm without help from any public library
10	**Dimensionality Reduction** **Lecture** • Principal component analysis (Eigenvalues/vectors, Spectral theorem, PCA algorithm) • Independent component analysis (Bell and Sejnowski ICA algorithm) • Linear discriminant analysis • Factor analysis **Lab** • Implement PCA and ICA from scratch, without using any library
11	**Neural Networks:** **Lecture** • Basic architecture: multi-layer perceptron • Activation functions (Sigmoid, tanh, relu, lrelu etc.) • Losses (cross-entropy, l1/l2 loss, binary cross entropy, focal loss, hinge-loss etc.) • Back propagation, learning rate • Regularization (dropout, batch normalization) **Lab** • Demonstration and familiarization with deep learning libraries

Teaching Week	Topics
12	**Convolutional Neural Networks:** **Lecture** • Convolution operation • Normalization operations, novel layers • Training and inference **Lab** • Train Neural Networks using standard libraries for basic problems
13	**Recurrent Neural Networks:** **Lecture** • Recurrent networks • Backpropagation through time • Long short term memory • Gated recurrent units **Lab** • Instructor-led walkthrough of concepts taught in class
14	**Reinforcement Learning:** **Lecture** • Markov decision processes • Policy function • Value function • Bellman equation • Value iteration algorithm • Q-learning **Lab** • Instructor-led demonstrations related to reinforcement learning
15	**Graphical Models:** **Lecture** • Bayesian networks • Markov models **Lab** • Instructor-led demonstrations related to graphical models