Machine Learning (CS 6375)

Class Hours and Location: MW 11:30 AM - 12:45 PM ECSS 2.412

Office hrs: M 1:30 PM - 2:30 PM and by appointment

TA: TBA.

Course Description:

The main aim of the course is introduce the foundational ideas inside machine learning. Both mathematical concepts and hands-on skills required for algorithms will be provided. Students will learn the latest machine learning algorithms and models that are typically used in practice. The goal is to equip students to build learning systems, deploy and comprehend their performance.

Textbooks:

No required text book. Slides will be uploaded in elearning.

Recommended Books :

Machine Learning, Tom Mitchell McGraw-Hill (1997)
A Course in Machine Learning, Hal Daume III (preprint available online)
Machine Learning: a Probabilistic Perspective by Kevin Murphy
Pattern Recognition and Machine Learning by Christopher M. Bishop

Course Objective:

At the end of the course, I expect that the students will be able to:

- Understand and implement the most popular learning algorithms
- Understand the theoretical foundations of these algorithms
- Evaluate multiple learning algorithms across several tasks

Grading:

Final Project (20%)

Programming Assignments (30%)

Exams (50%)

Syllabus:

- Introduction to discriminative and generative methods
- Logistic Regression and Naive Bayaes
- Perceptron and Neural Networks
- Decision trees
- Support vector machines
- Computational Learning Theory, Bias-Variance Theory, Bayesian Learning Theory
- Ensemble methods
- Deep Learning
- Unsupervised learning - k-means, PCA, hierarchical clustering
- Introduction to Reinforcement Learning

Teaching and Learning Methods:

This course consists of a combination of readings, homeworks and programming projects. For the theory part of the course, the students will be required to read 2 algorithms every week and the instructor will present the lectures on the algorithms. The instructor's aim will be to enable the understanding of the algorithm in depth and the practical issues with implementing the algorithm. The students will be required to perform experimentation on several data sets either by programming or using an off-the-shelf package. The goal of the students will be to demonstrate that they understand the practical issues with applying many of the machine learning algorithms.

Tentative Schedule (subject to change):

Week	***Topic***	***Reading***
1	Introduction & Linear Threshold Units	Class Slides
2	LTUs (continued), Decision Trees	Mitchell Book chapter on decision trees
3	Naive Bayes and Logistic Regression	Chapter 3 of Mitchell Book
4	Nearest Neighbors & Perceptron	Lecture Slides
		Andrew Ng's class

5	Support Vector Machines	notes
6	Learning theory, Bias variance methods	Lecture Slides
7	Ensemble Methods	
8	**Exam 1**	
9	Deep Learning	
10	Introduction to RL	
11	RL Continued	
12	Unsupervised Learning	
13	Unsupervised Learning WrapUp(PA 3 due)	
14	Final Exam and Wrap Up	
XX	Spring break in between weeks 7 and 8	

Academic Integrity:

Everyone is responsible for reading the university statement on Academic Integrity before starting the first assignment. Homeworks, including programming projects, are to be completed individually. You may discuss the material with other students, but all written work must be your own. All forms of cheating, whether copying from another student or plagiarism from Internet sources, will result in a zero on the assignment and possible disciplinary action. Homework assignments are due by the start of class on the due date unless otherwise specified.

Attendance Policy:

2 consecutive absences, no penalty. 3 consecutive absences, 1 letter grade drop; 4 consecutive absences, an F grade. Absences due to medical reasons, death in family, etc., can be excused, but proof may be required. See Department attendance policy for graduate students.