Worcester Polytechnic Institute
Department of Computer Science

FALL 2019 Term B
CS 4342 - Machine Learning

Course details:

Professor: Dr. Ali Yousefi

Office: FL 145

Email: ayousefi@wpi.edu please include **CS4342** in your subject line

Class time: Tuesday and Friday 3 – 4:50 pm

Office hours: Tuesday and Friday, 5 – 6 pm

Graduate teaching assistant (TA): Guanyi Mou, gmou@wpi.edu

TA office hours: Monday 4-6 pm, Thursday 4-6 pm – FL A22

Course objectives:

The main goal of this class is to introduce you to the ideas and techniques of machine learning, and the probabilistic models that underlie behind them. These ideas have their origins in classical results from statisticians such as Laplace, Bayes, and Fisher. However, modern computing techniques now permit applications of a scale and diversity that was barely conceivable only a few decades ago. As opposed to the traditional statistical focus on the analysis of experiments, most problems we'll discuss involve some form of a prediction. Classification algorithms predict a discrete value from a finite set of choices, while regression algorithms predict a continuous value. Supervised learning techniques can be used to design such predictors using training data that is labeled with the values you are trying to learn. Unsupervised learning techniques are instead used when such labels are unavailable, but you nevertheless hope to discover interesting structure within your data. These methods lead to effective algorithms for clustering and dimensionality reduction. This course will explore the conceptual relationships between these different learning problems and introduce some of the most practically effective statistical models and computational methods.

At the end of this course, you should have a basic understanding of how different ML methods work and be able to apply to many datasets collected from different scientific and research domains. With the explosion of "Big Data" problems, ML has become a very hot field in many scientific areas, and people with ML skills are in high demand!

We assume you are familiar with software packages like Matlab, Python, or R. Most of the course homework requires running different techniques in either of these software packages; thus, we strongly encourage you to familiarize yourself with either of these packages. We also assume every student has a full understanding of multivariate calculus, linear algebra, probability, and algorithms, which is the ket to have a full understanding of the practical, as well as the theoretical, aspects of each method taught during the course.

Multiple approaches we will cover in this course are new even in the machine learning and statistics community. Hence at the end of this course, you will have truly innovative and important applied skills to market and differentiate yourself with.

Prerequisites:

You should feel comfortable with the basics of probability: joint densities, conditional distributions, etc. An undergraduate level is fine — there will not be much measure theory and such background is not required. There will be some basic linear algebra, e.g., solving linear systems and thinking about eigenvalues/eigenvectors. We will regularly use multivariable calculus.

Course textbook:

"Machine Learning: a Probabilistic Perspective" by Kevin Patrick Murphy
A copy of the textbook can be found at https://www.cs.ubc.ca/~murphyk/MLbook/

Reference textbooks:

"Deep Learning" by Ian Goodfellow and Yoshua Bengio and Aaron Courville
A copy of the textbook can be found at http://www.deeplearningbook.org/

"Pattern Recognition and Machine Learning" by Christopher M. Bishop
A copy of this book can be found at https://www.microsoft.com/en-us/research/uploads/prod/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf

"The Elements of Statistical Learning" by Trevor Hastie, Robert Tibshirani, Jerome H. Friedman
A copy of this book can be found at https://web.stanford.edu/~hastie/Papers/ESLII.pdf

"An Introduction to Statistical Learning with Applications in R." by Trevor Hastie, Robert Tibshirani, Daniela Witten, Gareth James
A copy of the textbook can be found at http://faculty.marshall.usc.edu/gareth-james/ISL/

Software and tools:

Matlab
https://www.mathworks.com/products/matlab.html

Python
https://www.python.org/

R
http://www.r-project.org/

Evaluation (i.e. Grades):

In line with the applied nature of this class, a large portion of the assessment will be made through homework. There will be 5 homework assignments. The homework will contain some theory questions but the majority of the material will involve implementing the different methods that we cover in class. You can use different software packages, including Python, Matlab, and R, to solve the homework problems. There will multiple quizzes and a final exam which will be taken in the class. The breakdown of grades will be:

Homework	50%
Quick quizzes	10%
Final exam	30%
Term project (extra points)	10%

- The final exam has 20 extra bonus points; however, you can earn a maximum of 100 points out of 120 points.
- The quiz with the lowest grade will be dropped.
- The final exam will be taken in the class on Dec 13th, 2019.
- The project deadline is Sunday, Dec 15th, 2019. To submit the project, you need to provide a report describing the dataset, source code, reference papers, and result.
- The project description will be shared by Friday, Nov 1st.
- The projects with outstanding results will be supported for publications.
- Assignments' deadlines will be on Fridays beginning the second week of the class.

Students with disabilities:

Any student requesting academic accommodations based on a disability is required to register with the Office of Disability Services. A letter of verification for approved accommodations can be obtained from DSP. Please be sure the letter is delivered to me as early in the semester as possible. ODS is located at 124 Daniels Hall; the office hours are Monday-Friday from 8 am-12 pm, and 1 pm-5 pm. The office phone number is 508-831-4908, and the email address is disabilityservices@wpi.edu.

Helpful links:

Introduction to Machine Learning, Brown University
http://cs.brown.edu/courses/cs195-5/spring2012/index.html

Introduction to Machine Learning, UCI
https://canvas.eee.uci.edu/courses/3287/assignments/syllabus

Andrew W. Moore, CMU
http://www.cs.cmu.edu/~awm/tutorials.html

Advanced Machine Learning, Harvard
https://www.seas.harvard.edu/courses/cs281/

KAGGLE is an online community of data scientists and machine learners
https://www.kaggle.com/

Coursera, Online courses & credentials by top educators
https://www.coursera.org/learn/machine-learning

Major conferences:

NeurIPS
https://nips.cc/

ICML
https://icml.cc/

Machine learning experts you need to know:

Zoubin Ghahramani
Michael I Jordan
Trevor Hastie
Robert Tibshirani
Geoffrey Hinton
Terry Sejnowski
Yoshua Bengio
Yann LeCun
Andrew Ng
Jürgen Schmidhuber
David M. Blei
Yaser S. Abu-Mostafa
Andrej Karpathy
Ian Goodfellow
⋮
https://www.analyticsvidhya.com/blog/2019/07/heroes-of-machine-learning-experts-researchers/

Course outline:

This is a **tentative** view of the course outline.

Class 1. Course introduction, an overview of probability

Class 2. MLE, MAP, and naïve Bayes classifiers

Class 3. Gaussian models

Class 4. Bayesian statistics

Class 5. Frequentist statistics

Class 6. Linear regression

Class 7. Logistic regression

Class 8. Sparse linear models

Class 9. Kernels

Class 10. Clustering

Class 11. Decision trees

Class 12. Neural networks

Class 13. Deep learning

Class 14. Final Exam

Other topics that we might cover in the class:

1. Graphical models
2. Latent variables and EM algorithm
3. Markov and hidden Markov models