EECS 395, 495 and Data_Science 423: Machine Learning: Foundations, Applications, and Algorithms

(the course will number 375/475)

Spring 2018: MWF 10-10:50; Ryan Auditorium
Prof. A. K. Katsaggelos; aggk@eecs.northwestern.edu; M468
Office hours: W 2:00p-3:30p
TAs: Yin Xia, Hao Zhou, Hao Ge
Office hours: Wed and Fri 5:00p-6:30p in Room L361

Prerequisites

A basic understanding of Linear Algebra and Vector Calculus (e.g., students should be able to easily compute gradients/Hessians of a multivariate function), as well as basic understanding of the Python or MATLAB/OCTAVE programming environments.

- This course counts towards the AI breadth requirement for both undergraduate and graduate students. Students may receive credit for both this course and **EECS 349**.
- **Course is crosslisted with Data_Sci 423**

REQUIRED TEXT: J. Watt, R. Borhani, and A. K. Katsaggelos, *Machine Learning Refined: Foundations, Algorithms, and Applications*, Cambridge University Press, 2016.

COURSE OUTLINE:

1. Introduction
    1. What kinds of things can you build with machine learning tools?
    2. How does machine learning work? The 5 minute elevator pitch edition
    3. Predictive models – our basic building blocks
    4. Feature design and learning – what makes things distinct?
    5. Numerical optimization – the workhorse of machine learning
2. Fundamentals of numerical optimization
    1. Calculus defined optimality
    2. Using calculus to build useful algorithms
    3. Gradient descent
    4. Newton's method
3. Regression
    1. Linear regression - applications in climate science, feature selection, compression, neuroscience, and marketing
    2. Knowledge-driven feature design for regression
    3. Nonlinear regression
    4. The L-2 regularizer
4. Classification
    1. The perceptron

    2. Logistic regression/Support Vector Machines
    3. Multiclass classification
    4. Knowledge driven feature design for classification– examples from computer vision (object/face detection and recognition), text mining, and speech recognition
5. Probabilistic Formulation
    1. Regression
        1. Bayesian linear regression
        2. Non-linear regression
        3. Sparse linear regression
    2. Classification
        1. Bayesian logistic regression
        2. Non-linear logistic regression
        3. Boosting
6. Feature learning
    1. Function approximation and bases of features
    2. Feed-forward neural network bases, deep learning, and kernels
    3. Cross-validation
7. Special topics
    1. Step length determination for gradient methods
    2. Advanced gradient descent schemes: stochastic gradient descent and momentum
    3. Dimension reduction: K-means clustering and Principal Component Analysis

PROBLEM SETS:

Weekly pencil-and-paper and computer problems will be assigned and graded. A few small computer projects will also be assigned. The graduate students in the class will be given an extra open-ended assignment. Homeworks will be assigned on Fridays and will be due on Saturdays a week later at midnight. **No late homeworks will be accepted.**

EXAMS:

There will be one midterm exam in this course on Monday May 7, 2018.

COURSE GRADE:

Final grades for the course will be based on the midterm exam (35%) and the homework assignment grades (65%).

EXTRA CREDIT OPPORTUNTIES:

Up to 1 percentage point of extra credit can be earned by the first student to report a particular error found in the class text. Additional extra credit points will be considered for constructive suggestions for improving the text.