EL-GY 6143: Introduction to Machine Learning
(Spring 2021, Updated 12/7/2020)

Overview

This course provides a hands-on approach to machine learning and statistical pattern recognition. The course will describe fundamental algorithms for linear regression, classification, model selection, support vector machines, neural networks, dimensionality reduction and clustering. The course includes demos and labs on real and synthetic data using Python. Applications will be demonstrated in audio and image processing, robotic control, gene expression data, neural decoding and text processing. No prior machine learning experience is required.

Students will learn to: Formulate problems using a variety of simple ML models. Use software packages to train and validate models. Analyze the performance of these methods using tools from optimization and probability. Pre-process data and visualize results from various sources (time series, audio, image, text, etc.).

Course instructor: Dr. Pei Liu (peiliu at nyu.edu)

TAs: TBD

Office Hour:

Instructor: Time TBD on Zoom

TA: Time TBD on Zoom

Lectures: Monday 11:00 AM - 1:30 PM.

Texts:

- Hastie, Tibshirani, Friedman, "Elements of Statistical Learning". http://statweb.stanford.edu/~tibs/ElemStatLearn/printings/ESLII_print10.pdf
- Raschka, "Python Machine Learning", 2015. http://file.allitebooks.com/20151017/Python%20Machine%20Learning.pdf

Supplementary texts and resources

- Bishop, "Pattern Recognition and Machine Learning"
- James, Witten, Hastie and Tibshirani, "An Introduction to Statistical Learning", http://www-bcf.usc.edu/~gareth/ISL/ISLR%20Seventh%20Printing.pdf
- Installing python (need to do this before first recitation): http://jupyter-notebook-beginner-guide.readthedocs.io/en/latest/index.html
- Python tutorial: https://docs.python.org/3/tutorial/

Grading:

- Midterm 30%, Final 30%, Labs and homework 20%, Project 20% (two people in one team)
- Labs will involve approximately nine python-based exercises developed by Prof. Sundeep Rangan.
- Midterm and final exams are closed book with cheat sheets. Students will need to be able to write simple python in the exams.
- HW and labs due date as posted on GitHub. No late submission accepted except under extraordinary circumstances and must be approved in advance by the instructor. HW and Labs are to be hand-in on NYUClasses. Solutions will be posted on NYUClasses.

Pre-requisites:

- Undergraduate probability and linear algebra. No ML experience is expected for this class.
- Students may NOT enroll in this class if they have taken any one of: CSE-GY 6923 (Grad Intro ML), EE-UY 4563 (UG Intro ML), EL-GY 9133 (Grad Advanced ML).
- Students with prior ML experience are encouraged to take graduate-level Probability (EL-GY 6303) in the Fall and advanced ML in the Spring.
- Programming experience is essential, including some exposure or willingness to learn object-oriented programming. No experience in python is required as python will be taught as part of the class.

Tentative Course Schedule

Lecture notes, demos and labs and HWs organized in course units are available at https://github.com/yaowangatpoly/introml/blob/master/sequence.md

These materials are developed by Prof. Sundeep Rangan, and I will be updating during the semester.

Week 1 (2/1): Introduction to machine learning: Examples, types of ML problems. Course logistics. Intro to python and jupyter and GitHub. Single variable linear regression (Unit 1) (Brief introduction).

HW: Students should download python, jupyter, github, and do the lab and HW in Unit 1.

Week 2 (2/8): Linear regression (Unit2): Linear models, least squares formula; Extensions for non-linear models.

No class on 2/15.

Week 4 (2/22) & 5 (3/1): Model selection and regularization (Unit 3): Understanding underfitting and overfitting with polynomial fitting; Irreducible error due to measurement noise;   Bias and variance tradeoff; Cross validation; Lasso and regularization

Week 6 (3/8): Logistic regression and classification (Unit 4);

Week 6 (3/15): Numerical optimization (Unit 5): Unconstrained optimization, gradient descent, global vs. local minima, convexity. Example with logistic regression. Implementation with Python (Possibly move some of the notation of tensor and gradient with respect to tensor in Unit 7 here)

Week 7 (3/22): Support vector machines (Unit 6): Image classification; SVM formulation, support vectors; Duality, kernel methods

Week 8 (3/29): Midterm

Week 9 (4/5): Neural networks (Unit 7): Formulation, motivation; Computation graphs, backpropagation; Introduction to tensorflow and keras; Stochastic gradient descent.

Week 10-11 (4/12, 4/19): Convolutional and deep networks (Unit 8): Convolutional layers, Pooling, batch normalization; Advanced Tensorflow features; Using GPUs

Week 12 (4/26): Dimensionality reduction (Unit 9): Principle component analysis (unsupervised), linear discriminant analysis (supervised), LDA SVDs

Week 13 (5/3): Unsupervised Clustering (Unit 10):   K-means, Mixture models, EM methods

Week 14 (5/10): Tree based methods: Decision tree, Random Forest, Boosting. (Material to be uploaded)

Week 15 (5/17): Final exam