New York University Tandon School of Engineering
Department of Electrical and Computer Engineering

Advanced Machine Learning

Spring 2020

Instructor: Anna Choromanska

Course Prerequisites

1) Linear algebra and calculus.
2) A grade of A- or better in (ECE-GY 6143 or CS-GY 6923) and a grade of B+ or better in ECE-GY 6303
3) Mathematical maturity: https://en.wikipedia.org/wiki/Mathematical_maturity

Course Description

Machine Learning is nowadays one of the most rapidly developing technical fields both in the academia and industry. It is also a fundamental tool used in a wide range of different data science fields. This course presents the main concepts, techniques, algorithms, and state-of-the-art approaches in modern machine learning from both theoretical and practical perspective. Students will also be exposed to new mathematical proof techniques and up-to-date machine learning coding environments and benchmark datasets. The course also emphasizes interesting and important open problems in the field. The program of the course includes empirical risk minimization, support vector machines, kernels, optimization techniques for machine learning, clustering, principal component analysis, Expectation-Maximization, online learning algorithms, boosting, decision trees, graphical models, and deep learning.

Textbook

There is no textbook required. The list of recommended texts:

- *Pettern recognition and machine learning*, C.M. Bishop
- *Understanding machine learning: from theory to algorithms*, S.Shalev-Shwartz and S. Ben-David
- *Pattern classification, R. O. Duda, P. E. Hart, and D.G. Stork*
- *Prediction, Learning, and games*, N.Cesa-Bianchi and G. Lugosi
- *Introductory Lectures on Convex Optimization*, Y. Nesterov
- *A Probabilistic Theory of Pattern Recognition*, L. Devroye, L. Gyorfi, G. Lugosi
- *The Elements of Statistical Learning*, T. Hastie, R. Tibshirani, and J. Friedman
- *Spectral Algorithms*, R. Kannan and S. Vempala
- *Boosting*, R. E. Schapire and Y. Freund
- *Deep learning*, I. Goodfellow, Y. Bengio and A. Courville
- *T. Jebara. Course notes, Machine Learning*
- *R. Castro, 2DI70 - Statistical Learning Theory Lecture Note*
- *S. Dasgupta. Course notes, CSE 291: Topics in unsupervised learning*

- *Selected research papers and additional material that will be recommended during the course*

Projects and homeworks

Course project will either be theoretically-oriented, practical or both. For coding, preferred environments are Matlab, Torch, and/or Vowpal Wabbit (tutorials will be provided).

Course Work and Grading
Your final grade will be determined roughly as follows:

Homework	20%
Project	30%
Midterm	30%
Final	20%

Tentative Schedule

- Week 1 and 2: Introduction to machine learning: learning frameworks, loss functions, model selection, overfitting, cross-validation, regularization, linear regression, least squares, logistic regression, probabilistic approaches, maximum likelihood, naïve Bayes classifier, bag of words, Bayes rule, Bayesian Inference

  Week 2: Homework 1 is released.
  Project topics are released.

- Week 3: Perceptron, Exponentiated Gradient, Experts advice, online multi-class classification

  Due date for forming groups. Groups are announced.

- Week 4 and 5: Deep learning, feed-forward naural networks, back-propagation algorithm, convolutional neural networks (CNNs), regularization, adversarial networks, auto-encoders, LISTA, non-convexity and optimization landscape in deep learning

  Week 4: Due date for Homework 1.
  Homework 2 is released.
  Due date for selecting project topics by groups. Topics

of each group are announced.

- Week 6: Tutorials on Torch and/or Vowpal Wabbit (VW) – two most efficient environments for implementing machine learning algorithms

  Due date for Homework 2.
  Homework 3 is released.

- Week 7: Empirical Risk Minimization, PAC bounds

- **Week 8: Midterm**

- Week 9: Occam's Razor, VC dimension, VC inequality, Structural Risk Minimization, Support Vector Machines (SVM), kernels

  Due date for Homework 3.
  Homework 4 is released.

- Week 10 and 11: Introduction to optimization (convexity, convergence rate, convexity, Lipschitzness and smoothness, Jensen's inequality, convergence rates, optimization methods (GD, SGD, Netwon, BFGS, LBFGS, ISTA, FISTA, bound majorization), convergence guarantees

  Week 11: Due date for Homework 4.
  Homework 5 is released and due 05.09.2017.

- Week 12: Expectation Maximization (EM): basics and modern statistical view

- Week 13: Curse of dimensionality, Johnson–Lindenstrauss lemma, principal component analysis (PCA), clustering (k-center clustering, k-means clustering, spectral clustering, hierarchical clustering, doubling algorithm, cover tree algorithm, spectral clustering)

  Due date for Projects.
  Poster session for projects with be held soon.

- Week 14 and 15: Graphical models, Hidden Markov Models (HMMs)

  Week 15: Due date for Homework 5.