EECE 5644: Introduction to Machine Learning and Pattern Recognition
2019 Fall Term

Prof. David Brady
Classes: Mon & Thu at 11:45am-1:25pm in Snell Library 033
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Prof. Deniz Erdogmus
Classes: Mon & Wed at 14:50-16:30 in Snell Library 033
E-mail: erdogmus@ece.neu.edu Please always include [EECE5644] in the subject line.
Group: eece5644@googlegroups.com Only for members of Erdogmus section
Office: Mon & Wed at 16:30-17:00 outside/after class; Google Hangout (by appointment for those in the video section)

TAs: Ozan Ozdenizci Email: oozdenizci@ece.neu.edu Office: Tue 10:00-11:00 in ISEC 510A

Course Objectives: Machine learning is the study and design of algorithms that enables computers/machines to learn from experience/data. This course is an introductory course on machine learning covering a range of algorithms, focusing on the underlying models behind each approach, to enable students to learn where and how to apply machine learning algorithms and why they work. The course also emphasizes the foundations to prepare students for research in machine learning. The subjects covered include: Bayes decision theory, maximum likelihood parameter estimation, model selection, mixture density estimation, probabilistic graphical models, support vector machines, neural networks, decision trees, feature selection and dimensionality reduction, ensemble methods: boosting and bagging.

Prerequisites: Probability EECE 3468/MATH3081 or equivalent for undergraduates, EECE 7204/DS5020 or equivalent for graduate students, knowledge of linear algebra

Programming Requirement: Must be able to code (Matlab, Python, C/C++, R are commonly used by students.)

Textbook: R. O. Duda, P. E. Hart, D. Stork, *Pattern Classification, 2nd Ed*, Wiley and Sons, 2001.

Other Suggested Texts:
Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Springer 2006.
Kevin P. Murphy, *Machine Learning: A Probabilistic Perspective*, MIT Press 2012.
T. Hastie, R. Tibshirani, J. H. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer, 2001.

Grading: Homeworks 20% (4 x 5%), Take-home Exams 40% (2 x 20%), Project 40% (Teams of 3-4)

Tentative Class Outline

Topics	Dates	Reading
Review of linear algebra, probability, numerical optimization Intro to machine learning: PCA & Fisher LDA	9/4-13 (3 lectures)	Ch 1
Bayesian decision theory (classification) Expected risk minimization	09/16-23 (3 lectures)	Ch 2
Bayesian estimation theory (model fitting) Expected loss minimization	09/25-30 (2 lectures) Homework1 9/23-9/30	Ch 3
EM algorithm Application to Gaussian mixture models	10/2-7 (2 lectures) Homework2 9/30-10/7	Ch 3.9, 10.1-10.4.2, 10.5
Model selection, hyperparameter optimization Bayesian Information Criterion, cross-validation (bootstrap, k-fold)	10/9-17 (2 lectures) No class 10/14 Exam1 10/11-10/21	Ch 9
Support vector machines support vector regression kernel density estimation	10/21-24 (2 lectures) Homework3 10/21-10/28	Ch 5.11,10
Clustering: k-means, hierarchical, mean-shift, spectral	10/28-31 (2 lectures) Homework3 10/28-11/4	Ch 5, 10, (esp 10.4.3, 10.9)
Neural networks: multiplayer perceptrons, recurrent NNs, CNNs, LSTMs, stochastic gradient parameter updates	11/4-7 (2 lectures) No class 11/11 Exam2 11/8-11/18	Ch 6
Decision trees	11/13-14 (1 lecture)	Ch 8.2-8.4
Combining classifiers: bagging, boosting	11/18	Ch 9
Independent component analysis	11/20-21 (1 lecture)	Ch 3.8, 4
Feature dimension reduction, kernel PCA (optional: kernel LDA)	11/25 No class 11/27-28	
Project presentations (Deliverables due on Dec2@ClassStartTime)	12/2-5	