Course #: Computer Science 189
Course Title: Introduction to Machine Learning
Instructors: Jitendra Malik
Alexei Efros
Offering: Spring 2014
Location: 100 GPB
Time: TuTh 2-330P
Prerequisites: Mathematics 53, 54; Computer Science 70; Computer Science 188 or consent of instructor.

Requirements:
• Homework will include both traditional written problems as well as programming exercises.
• One midterm exam and one final exam.

Grading (approximate)**:**
Homework 40%, Midterm 20%, Final Exam 40%

Late policy
Everyone can have 5 slip days for the entire course.

Textbook:
• *Kevin Murphy, "Machine Learning: A Probabilistic Perspective," MIT Press (2012).*
Additional References:
• *Trevor Hastie, Rob Tibshirani, and Jerry Friedman, "Elements of Statistical Learning" (2nd edition), Springer, 2009* (pdf online)
• *A. Rajaraman, J. Leskovec and J. Ullman, Mining of Massive Datasets, v2* (pdf online)

Syllabus (approximate)**:**

• Introduction: applications, approaches. Two canonical problems: digit recognition and spam detection. Performance assessment.
• Linear classification
  • Perceptron algorithm
  • Support vector machines (SVMs)
  • The importance of good features
• Statistical background
  • Decision theory; Bayes risk
  • Maximum likelihood estimation
  • Frequentist vs. Bayesian approaches
  • The multivariate normal distribution
• Linear regression
  • Least squares
  • Shrinkage methods-ridge regression, lasso

- Linear Classification, revisited
    - Logistic regression
    - Linear Discriminant Analysis
- Brief primer on optimization
- Support vector machines revisited
    - Algorithms
    - The kernel trick
- Neural networks
    - Multilayer perceptrons
    - Variations such as convolutional nets; examples
    - Deep Learning
- Decision trees
    - Classification and regression trees
    - Random Forests
- Boosting
- Nearest neighbor methods
    - k-nearest-neighbor
    - Properties of high-dimensional spaces
    - distance learning
    - Efficient indexing and retrieval methods
- Theoretical analysis of machine learning problems and algorithms
    - Generalization error bounds; VC dimension
- Unsupervised methods
    - Dimensionality reduction
    - Clustering
    - Density estimation
- Applications in Data Mining
    - collaborative filtering
    - the power and the peril of Big Data