

# Syllabus

(approximate)

- Introduction: applications, methods, concepts
- Good Machine Learning hygiene: test/training/validation, overfitting
- Linear classification
  - Perceptron algorithm
  - Support vector machines (SVMs)
- Statistical learning background
  - Decision theory; Bayes risk
  - Probabilistic models vs no model
  - Generative and discriminative models
  - Controlling complexity: regularization, bias-variance trade-off, priors.
  - Resampling, cross-validation.
  - The multivariate normal distribution.
- Linear regression
  - Least squares
  - Regularization: ridge regression, lasso
- Brief primer on optimization
- Linear Classification, revisited
  - Logistic regression
  - Linear Discriminant Analysis
  - Support vector machines revisited
    - Algorithms
    - The kernel trick
- Theoretical analysis of machine learning problems and algorithms
  - Generalization error bounds; VC dimension
- Nearest neighbor methods
  - k-nearest-neighbor
  - Properties of high-dimensional spaces
  - Distance learning
  - Efficient indexing and retrieval methods
- Decision trees
  - Classification and regression trees
  - Random Forests
  - Boosting
- Neural networks
  - Multilayer perceptrons
  - Variations such as convolutional nets
  - Applications
- Unsupervised methods
  - Clustering
  - Density estimation
  - Dimensionality reduction
- Applications in Data Mining
  - Collaborative filtering
  - The power and the peril of Big Data