Final Review

Machine Learning
Spring 2019
Final Exam

Mon, Apr 29, 2019
6:00pm - 8:00pm
WEB 1250 (in classroom)
Final Exam Policy

- Open book
- No cellphones/laptop/Ipad...
- No electrical devices that can connect to Internet
- Can bring calculators
Coverage

- The whole semester
- Problem types: homework assignments

Suggestion: (1) review the lecture slides (2) carefully go through the paper problems in the homework assignments
Throughout this semester

• What is machine learning
• A variety of learning models and algorithms
• Different learning principles
• Ideas about learning theory
• Implementation and practice
Learning = generalization

“A computer program is said to learn from experience $E$ with respect to some class of tasks $T$ and performance measure $P$, if its performance at tasks in $T$, as measured by $P$, improves with experience $E$.”

Tom Mitchell (1999)
The formulation of machine learning

\[ y = f(x) \]

**Instance Space**
The set of examples that need to be classified

**Label Space**
The set of all possible labels

Eg: The set of all possible names, documents, sentences, images, emails, etc

Eg: \{Spam, Not-Spam\}, \{+, -\}, etc.

The goal of learning: Find this target function
Supervised learning

$X$: Instance Space
The set of examples

$Y$: Label Space
The set of all possible labels

Target function $y = f(x)$

Learning algorithm only sees examples of the function $f$ in action

Labeled training data

Learning algorithm

A learned function $g: X \rightarrow Y$

Can you think of other protocols?
A variety of learning models

- Decision trees
- Boosting and ensembles: Adaboost, random forest
- Least mean square method for linear regression
- Perceptron
- Support vector machines (SVMs)
- Kernel Perceptron
- Kernel SVM
- Artificial neural networks, back propagation
- Logistic regression
- Naive Bayes
How to categorize ML models: linear/nonlinear

• Linear models
  – Least mean square method
  – Perceptron
  – SVM
  – Logistic regression
  – Naïve Bayes

• Nonlinear models (how to construct?)
  – Kernel methods: Kernel Perceptron, Kernel SVM
  – Neural networks
  – Decision trees
  – Adaboost and random forest
How to categorize ML models: probabilistic / non-probabilistic

• Probabilistic learning
  – Logistic regression
  – Naïve Bayes

• Non-probabilistic models
  – Neural networks
  – Decision trees
  – SVM
  – Perceptron
  – ...

The all have probabilistic version!
Basic concepts/conclusions in computational learning theory

- PAC framework
- What is PAC learnability?
- What is sample complexity bound? What is the generalization error bound?
- VC dimension (why?)
- How is the large margin principle derived by the generalization error bound?

No need to memorize. But you need to really understand it!
Principles to Learn ML models

• Empirical risk minimization (ERM)
  – Least mean square method
  – Perceptron
  – Artificial neural networks

• Regularized empirical risk minimization (RERM)
  – SVM
  – MAP estimation for logistic regression

• Maximum a posterior (MAP)

• Maximum likelihood (MLE)

Connection to ERM and RERM
Learning algorithms

- Gradient descent
- Stochastic gradient descent
- What are their advantages and disadvantages?
Practice

• How to select hyper-parameters?
  – Hold out dataset
  – Cross validation.
Review suggestions

• Go through all the lecture slides. Understand the details
  • Decision trees
  • Boosting and ensembles: Adaboost, random forest
  • Least mean square method for linear regression
  • Perceptron
  • Support vector machines (SVMs)
  • Kernel Perceptron
  • Kernel SVM
  • Artificial neural networks, back propagation
  • Logistic regression
  • Native Bayes
Review suggestions

• Go through all the homework problems you have worked. Do not need to go through the programming problems.
Good Luck!