

Syllabus for Introduction to Machine Learning (MLearn 210) Machine Learning Certificate Program

Bellevue / Online

Thursdays, Jan 12 – Mar 16, 2017: 6-9pm

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Course Description:

This course is designed to discuss fundamental concepts of statistical analyses, mathematical modeling, optimization techniques, and how they relate to a set of fundamental algorithms and concepts that are the foundation for machine learning. The topics for the course will include:

- Basics of probability and statistics
- Attribute types, distance measures and tools
- Introduction to optimization
- Discriminative models: supervised learning
- Generative models
- Model evaluation and parameter tuning
- Ensemble methods

Course Learning Objectives:

The student should be able to ...

- Translate a real-world task into a machine learning problem
- Recognize common properties of machine learning models
- Describe common algorithms for constructing machine learning models
- Construct machine learning models using popular machine learning algorithms
- Select the best machine learning model for a task
- Assess the generalization performance of a machine learning model

Course Format:

The course will consist of both lecture and demonstration. Students will need access to a computer to complete weekly assignments. Please bring your computer to class.

Course Materials:

We will be using "An Introduction to Statistical Learning with Applications in R" as the text book for this course. It can be downloaded for free from the book's web site: <u>www.StatLearning.com</u>, or it can be purchased from Amazon: <u>https://www.amazon.com/Introduction-Statistical-Learning-Applications-Statistics/dp/1461471370/</u>

Technical Requirements:

The tools we will use in this class include R and related software packages.

Program Links:

Canvas Web Page (for Homework and Discussions): <u>https://canvas.uw.edu/courses/1122352</u> Connect Link (for Online Attendance): <u>http://uweoconnect.extn.washington.edu/mlearn210/</u>

Course Topics by Date:

- Jan 12, 2017
 - Chapter 1: Introduction
 - Chapter 2: Statistical Learning
 - What is statistical learning?
 - Assessing Model Accuracy
 - Lab: Introduction to R
- Jan 19, 2017
 - Chapter 3: Linear Regression
 - Simple Linear Regression
 - Multiple Linear Regression
 - Lab: Linear Regression
- Jan 26, 2017
 - Chapter 4: Classification
 - Logistic Regression
 - Linear Discriminant Analysis
 - Lab: Linear Discriminant Analysis, Quadratic Discriminant Analysis, and K Nearest Neighbor
- Feb 2, 2017
 - Chapter 5: Resampling Methods
 - Cross-Validation
 - The Bootstrap
 - Lab: Cross-Validation and the Bootstrap
- Feb 9, 2017
 - Chapter 6: Linear Model Selection and Regularization
 - Subset Selection
 - Shrinkage Methods
 - Dimension Reduction Methods
 - Lab 1: Subset Selection Methods
 - Lab 2: Ridge Regression and the Least Absolute Shrinkage and Selection Operator
 - Lab 3: Principal Components Regression and Partial Least Squares Regression
- Feb 16, 2017
 - Chapter 7: Moving Beyond Linearity
 - Polynomial Regression, Step Functions, and Basis Functions
 - Regression Splines and Smoothing Splines
 - Local Regression
 - Generalized Additive Models
 - Lab: Non-Linear Modeling



- Feb 23, 2017
 - Chapter 8: Tree-Based Methods
 - The Basics of the Decision Tree
 - Bagging, Random Forests, and Boosting
 - Lab: Decision Trees
- Mar 2, 2017
 - Chapter 9: Support Vector Machines
 - Maximal Margin Classifier
 - Support Vector Machines
 - Support Vector Machines with More than Two Classes
 - Lab: Support Vector Machines
- Mar 9, 2017
 - Chapter 10: Unsupervised Learning
 - Principal Component Analysis
 - Clustering Methods
 - Lab 1: Principal Component Analysis
 - Lab 2: Clustering
 - Lab 3: National Cancer Institute 60 Data Example
- Mar 16, 2017
 - Neural Networks
 - Genetic Algorithms

Student Assessment:

There will be a brief take-home quiz each week covering the week's material (50% of the grade). There will be hands-on assignments each week as well (50% of the grade).

Policies and Values:

You must attend at least 6 of the 10 sessions to be given credit for the course. You must satisfactorily complete at least 80% of the assigned work to receive credit for the course. We value both academic and personal integrity, as well as respect for others and the free exchange of ideas.