Course Syllabus

CSE 40625 — Machine Learning (Spring 2017)

T/R — 3:30pm–4:45pm ET
DeBartolo Hall 116

Instructor: Dr. Reid Johnson
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Office Hours: M/W 1–2pm and by appointment

Course Description

This course on machine learning will give an overview of many concepts, learning theory, techniques, and algorithms in machine learning, such as in reinforcement learning, supervised learning, unsupervised and semi-supervised learning, genetic algorithms, including advanced methods such as sequential learning, active learning, support vector machines, graphical and relational models. The course will give the student the basic ideas and intuition behind modern machine learning methods as well as a bit more formal understanding of how, why, and when they work. The course will also include discussions on some of the recent applications, and the interface with computer vision, systems, bioinformatics, and architecture. The course will have a strong focus on project and assignments, with emphasis on writing implementations of learning algorithms. The goal is to make this course a **fun and exciting elective**, such that you maximize learning in the areas that are of particular interest to YOU.

Prerequisite(s)

Students enrolling in this course should have taken Data Science (CSE 40647 or CSE 44648) or an equivalent course.

Credit Hours: 3

Recommended Textbooks for Reference (Not Mandatory)

Machine Learning
Authors: Mitchell
Publication Date: 1997
ISBN: 978-0-070-42807-2

The Elements of Statistical Learning
Author: Hastie, Tibshirani, Friedman
Publication Date: 2009
ISBN: 978-0-387-21606-5

Course Goals

Upon completion of this course, students will be able to:

1. Understand the key principles and concepts of machine learning.
2. Implement a variety of core machine learning methods.
3. Apply appropriate machine learning techniques in a given set of circumstances.
4. Compare supervised and unsupervised learning techniques.
5. Recognize the emergent methods and applications of machine learning.
6. Describe social and ethical implications of machine learning.

Grading Procedure

Participation	10%
Midterm Exam	20%
Assignments	30%
Course Project	40%

Letter Grade Distribution

≥ 90.00	A	73.00–76.99	C+
87.00–89.99	A-	70.00–72.99	C
83.00–86.99	B+	67.00–69.99	C-
80.00–82.99	B	63.00–66.99	D
77.00–79.99	B-	≤ 59.99	F

Grading Discrepancies

Any questions regarding how any assignment, project, exam, or other coursework is graded should be communicated to the instructor via email within seven days of receiving the grade. No regrade requests will be accepted orally, and no regrade requests will be considered after this deadline.

Course Policies

- **Collaboration Policy**
  Unless instructed otherwise, students must turn in work that is their own. Students must write their own code, run their own methods, and write up their own results and answers to assignment questions.
- **Assignments**
  There will be several assignments. Unless announced otherwise, assignments will

be due at 11:59pm ET on the provided submission date. For programming assignments, you may use Python libraries for handling data preprocessing and visualization, including but not limited to NumPy, SciPy, pandas, and Matplotlib. You may NOT use any Python libraries that employ machine learning models, including but not limited to scikit-learn, StatsModels, TensorFlow, or Orange, unless otherwise receiving explicit approval from the instructor.

- **Exams**
  Make-up exams will be allowed as per the du Lac Class Absence Policy. Whenever possible, students are expected to provide advance notice if they will be unable to take an exam. Make-up exams for travel to academic events will be provided at the discretion of the instructor.
- **Course Project**
  For the course project, students will be expected to collect a dataset (online or otherwise), formulate a question of interest, and perform machine learning to address that question by using whatever tools they find appropriate. The project will involve a proposal, milestones, final term paper, and presentation of the project.
- **Late Policy**
  Assignments submitted after the submission deadline but within the next day are counted as one day late. The next 24 hours will be counted as two days late, and so on. Each day late contributes a 10% penalty to the original assignment value. Assignments more than three days late will ordinarily receive a 0.
- **Office Hours**
  Office hours are provided in the syllabus and may be scheduled by appointment. Students are encouraged to take advantage of the instructor's availability both inside and outside of the classroom to answer questions.
- **Academic Honesty**
  A commitment to honesty is expected of all students. The du Lac Academic Codes, which relate to academic integrity, will be strictly followed. All references and sources, both to text and code, should be properly cited in all submitted work. *The full Code and a Student Guide to the Academic Code of Honor are available at: http://honorcode.nd.edu.*

Course Contents

- **General Topics**
  - **Learning Theory**
  - **Supervised Learning**
  - **Real-World Applications**
- **Learning Theory Topics**
  - **The Learning Process:** target function; input distribution; training instances; hypothesis set; learning algorithm; error measure; final hypothesis
  - **Types of Learning:** classification; regression; structured learning; supervised learning; discriminative learning; generative learning; unsupervised learning; clustering; semi-supervised learning; reinforcement learning; batch learning; online learning; active learning
  - **Generalization:** probabilistic learning; no free lunch; growth function; hypothesis sets; break point; VC dimension; VC generalization bound
  - **Overfitting:** learning curves; deterministic noise; bias-variance tradeoff
  - **Regularization:** hard and soft constraint; augmented error; weight decay
  - **Validation:** validation set; model selection; cross-validation; bootstrap
- **Supervised Learning Topics**
  - **Perceptron:** threshold; vector notation; iterative learning; linear separability
  - **Linear Regression:** squared-error; pseudo-inverse; nonlinear transformations
  - **Logistic Regression:** sigmoid function; cross-entropy error; gradient descent
  - **Bayesian Learning:** Bayes' theorem; optimal Bayes classifier; conditional independence; multinomial and Gaussian naïve Bayes; Bayesian networks
  - **Decision Tree:** splitting criteria; entropy; information gain; gain ratio; Gini index
  - **Support Vector Machine:** maximum margin; support vectors; dual problem; Lagrangian formulation; soft-margin SVM; kernel trick; radial basis function
  - **Artificial Neural Network:** multi-layer perceptron; stochastic gradient descent; backpropagation; softmax function; multi-layer neural network; deep learning
- **Real-World Applications**
  - **Computer Vision:** convolutional neural network (CNN); padding; pooling
  - **Generative Modeling:** denoising autoencoder (DAE); variational autoencoder (VAE); generative adversarial networks (GAN)
  - **Sequential Learning:** recurrent neural network (RNN); long short-term memory (LSTM); word embeddings; Word2Vec
  - **Reinforcement Learning:** Bellman equation; Q-learning; deep Q-learning