Intro to Machine Learning

An EJP course offered for credit through UIUC

CS 398

Spring 2019

Instructor Info —

Matt Zhang

Overview

This course will focus on taking students with no machine learning experience through the basics of how machine learning (ML) works and what it can be used for. We will cover basic theory regarding how ML algorithms are trained, and how to produce a full ML analysis starting from a simple dataset. Students will gain familiarity with a variety of ML techniques, including dense and convolutional neural nets, genetic algorithms, reinforcement learners, recurrent neural nets, and generative nets. They will also understand how to choose architectures for problems, tune nets, and troubleshoot common problems.

This course is very code-focused, and each class will involve solving sets of problems or building and training various ML nets. Students will learn to use PyTorch and gain experience with Python programming in the process.

CS 398 will differ from a typical machine learning course taken by students at UIUC in the following ways: First, there will be less emphasis on calculations and proofs. For example, though students will understand the principle behind gradient descent via backpropagation, and be exposed to concepts such as the vanishing gradient problem and the curse of dimensionality, little time will be spent on performing calculations or deriving proofs. Second, we will cover a broader range of topics than is typically seen in an introductory machine learning course. The focus is on giving students tools to begin working on real machine learning applications, and to expose them to topics that they can further explore on their own.

Prerequisites

Knowledge of Python is a requirement for this class. We begin with a bit of review on basic programming skills in the first lecture, but due to the heavy amount of hands-on work in this course, realistically it would be extremely hard to follow along without some form of prior experience with programming. Familiarity with a code editor such as vim or emacs would also be extremely beneficial, but is not required.

Linear algebra is useful but definitely not required. Though we discuss the mathematics behind concepts such as loss function minimization during the course, there is no pen and paper calculation. We use software packages that perform all calculations behind the scenes. The goal of the course is to understand the architectures of various machine learning algorithms and to build working applications, without going too deep into theory.

Reading Materials

Course Reserve Texts

Goodfellow, Bengio, and Courville. *Deep Learning*.
Halterman. *Learning to Program with Python*.

Grading

This course will be offered pass-fail, and students will be accessed on their ability to complete the hands-on programming exercises offered during each lecture, and their ability to perform full machine learning analyses at the end of the course.

About the Instructor

Matt Zhang is a sixth-year graduate student at UIUC in the Physics department. His area of expertise is in high-energy physics, specifically in using machine learning techniques to improve searches for new physics at the Large Hadron Collider.

Class Schedule

Introduction to Machine Learning

Week 1	What Is Machine Learning?	History and uses of machine learning. Review of basic programming concepts.
Week 2	Math Review	Functions. Differentiation. Finding minima and maxima. Linear algebra.
Week 3	Building a Model and Guaging Performance	How machine learning works. The basics of building a model. How to determine if model performance is improving. Reading and writing data. Loss functions.
Week 4	Training Your Models	Back propagation. Gradient descent. Data visualization.
Week 5	A Complete Analysis	Comparison of gradient descent methods. Splitting testing and training data. Overfitting and underfitting.

Neural Nets

Week 6	Neural Nets	The biological basis for neural nets. Neural nets. Spiking neural nets. Tensorflow and PyTorch.
Week 7	Classification	Binary and multiclass classification. Softmax. MNIST.
Week 8	Neural Net Tips and Tricks	Activation functions. Vanishing gradient problem. Pooling methods. Dropout. Batch normalization. Regularization.
Week 9	Convolutional Neural Nets	Image processing. Kernel operators. Convolutional layers. Biological visual systems. CIFAR.
Week 10	Deeper Networks	ImageNet. AlexNet, GoogLeNet, ResNet.

Advanced ML Architectures

Week 11	Genetic Algorithms	The biological basis for genetic algorithms. Mutations and selection.
Week 12	Reinforcement Learning	Game playing. States, actions, and rewards. Value, policy, and quality functions. Bellman equation. Q-learning. TD algorithm.
Week 13	Generative Adversarial Nets	Unsupervised learning. Autoencoders. GANs.
Week 14	Recurrent Neural Nets	Applications of RNNs. Recurrent architectures. LSTM. GRU.
Week 15	Additional Topics	Small dataset training. Deep reinforcement learning methods. Natural language processing. Brain computer interfacing.