Machine & Deep Learning from Theory to Practice

Module for M.Tech Data Science (Business Analytics) program at NMIMS

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Objectives: This applied data science module aims to cover the theoretical, computational, and statistical underpinnings of machine & deep learning. Statistical techniques and learning algorithms that can lend themselves to patterns and relationships in data will be introduced in this module. The applications of different algorithms will be discussed, with an emphasis on economics and finance. Finding patterns and relationships in large volumes of data is very useful in market research, business forecasting, decision support, and customer recommendation engines, among other applications. Integration of big data and deep learning algorithms into business analytics frameworks will be demonstrated using real-world examples. Course demonstrations will be in Python, and for showcases and exercises, we make use of Python scientific libraries. We also expose students to Google Colab so they can develop their coding skills by completing practical exercises on Colab. The data sets we will use for this course are from the World Bank Group, Kaggle, Federal Reserve Economic Data, Google Finance, and several other resources. For the sake of learning, we will apply the algorithms and topics step by step to the problem, both in standard Python libraries and from scratch.

Course Outline: The goal of this module is to give an applied, hands-on introduction to machine and deep learning methods. At the end of the course, students will be able to read and understand theoretical papers on the subject, implement the techniques themselves in Python, and apply the techniques to data used in economics and business. The style will be to first describe the theory and math behind algorithms, and then demonstrate how to use Python to create and run the models. This course introduces the student to classic machine learning algorithms and deep neural network structures, Autoencoders, Convolution Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Neural Networks (GRU), General Adversarial Networks (GAN) and reinforcement learning. High Performance Computing (HPC) aspects will demonstrate how deep learning can be leveraged both on graphical processing units (GPUs), as well as grids. The focus is primarily on the application of deep learning to problems, with some introduction to mathematical foundations.

Tentative Course Outline:

- Python Preliminaries & Essential scientific Libraries; (NumPy, pandas, matplotlib and statsmodels)
- Python for Machine Learning (scikit-learn, PyTorch, TensorFlow and Keras)
- Fundamentals of Linear Algebra and Optimisation for Machine Learning in Python
- A Gentle Introduction to Computational Learning Theory
- Types of Learning (Supervised, Unsupervised, and Reinforcement)
- Supervised Modeling: Regression vs Classification
- Parametric versus Semi and Nonparametric Models

- Kernel Methods: VC-Dimension, Support Vector Machines (SVM)
- Tree-Based Models and Random Forest
- Neural Networks and Deep Neural Networks
- Model Selection and Feature Extraction
- Model Selection and Boosting: XGBoost
- Unsupervised Modeling and Clustering
- Big Data Problems
- Hyperparameter Optimization (HPO)
- Practical Advice for ML projects

This is only a tentative course outline. During the development, some topics will likely need to be expanded, or split into multiple sub-topics.

Main References:: This is a restricted list of interesting and useful books that will be touched during the course. You need to consult them occasionally.

- Gilbert Strang, *Linear Algebra and Learning from Data*, Wellesley Cambridge Press, 2019.
- Trevor Hastie, Robert Tibshirani, Jerome Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*,Springer, 2017. (Available Online)
- Shai Shalev-Shwartz, and Shai Ben-David, *Understanding Machine Learning From Theory to Algorithms*, Cambridge University Press, 2014. (Available Online)
- Ian Goodfellow, Yoshua Bengio and Aaron Courville, *Deep Learning*, MIT Press, 2016. (Available Online)

Prerequisites: An undergraduate-level understanding of probability, statistics, linear algebra, and programming is assumed.

Grading Policy:

Assignments	(50%)
Final Project	(50%)

Assignments

Class assignments are due at 5:00pm on the due date, and no late assignments will be accepted. Students are welcome to collaborate with one another, but are required to submit their own work as well as be able to reproduce it. All work must be shown and software must be used, when appropriate, with attached software output. If there is a truly extenuating circumstance requiring an extension, please email me in advance and let me know as soon as possible.

Final Project

The final project will be on a topic of your choice but relating to the lectures. You should manage to submit a one-page proposal to get my feedback on your projects. Deadline for the final version will be end of the class.