FRE-GY-7773,
Machine Learning in Financial Engineering

Instructor Information

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Course Information

- FRE-GY-7773
- Machine Learning in Financial Engineering
- Course Description: Intro to Classical Machine Learning and Deep Learning.
- Prerequisite: Graduate standing; Basic probability, statistics, including linear regression, calculus; linear algebra, solid Python programming skills
- Face-to-face class meeting days and times: varies by semester

Course Overview and Goals

The goal of Machine Learning is to make predictions based on data. "Classical" machine learning has much in common with inference from traditional statistics (e.g., Linear Regression); newer ("Deep Learning") machine learning ventures into territory associated with Artificial Intelligence.

Machine Learning is widely used in many domains outside of Finance. The use within Finance is largely identified (to date) with numerical data and Classical methods. Other domains are blessed with vast quantities of non-numerical data (images, text) that necessitate the use of New methods. But history is not destiny: these alternative types of data will no doubt become integral to Finance. Thus, with an eye on the future, the course will focus on Machine Learning broadly (not just for Finance), frequently drawing on inspiration and examples from other domains.

The first half of the course will focus on "Classical" Machine Learning methods (e.g., Regression, Bayesian methods) while the second half will focus on Deep Learning (e.g., Neural Networks).

The course philosophy is that Machine Learning is an experimental art in which the real learning comes from doing, i.e., conducting experiments. While we will discuss the theory and mathematics underlying Machine Learning, this course will have a heavy computational focus.

Homework assignments and projects will all involve programming in Python, using Jupyter notebooks.

Course Structure

One lecture per week; each lecture will have both assigned readings and a Jupyter notebook (a combination of descriptive text and executable code) illustrating the concepts. Students will be expected to understand both the readings and the code, and have the ability to experiment/change the notebook's code to deepen their understanding.

Consistent with the philosophy of being an experimental art, the early weeks will be a sprint to get students up to speed with the programming tools involved. Only a small amount of class time will be spent introducing the programming tools (Python, numpy, Pandas, scikit-learn, TensorFlow, Keras) ; students will be expected to acquire these skills via self-directed learning. Students will rapidly gain the ability to experiment.

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

- take a data set and make predictions, using a variety of methods.
- succeed in completing a practical machine learning assignment that a potential employer may use as part of the job interview process
- use the standard tools of Machine Learning: Python, scikit-learn, Jupyter notebooks, TensorFlow/Keras.

Course Requirements

Class Participation

Students are strongly encouraged to participate by raising questions, offering insights and participating in class discussion. The best way to be prepared to participate is by reviewing the weekly notebook and reading material in advance of class.

Assignments

There will be 4-6 assignments, usually due 1 or 2 weeks subsequent to being assigned. The primary objective of the assignments is ensuring that students keep up with the material, particularly becoming adept with the technical aspects (e.g., programming).

In addition, there will be two more substantial projects: a Midterm Project and a Final Project. These will usually be due 2-3 weeks subsequent to being assigned.

Tests & Quizzes

None

Assigned Readings

Readings for each week will be posted online as part of the course schedule. It is suggested that students read the material prior to class so as to enable them to participate in discussion.

Grading of Assignments

The assignments and projects will be assigned numeric grades. For each: there will be a number Bmax assigned as the maximum number of "base points" that may be earned by successfully completing a required task and a number Emax assigned as the maximum number of "extra points" awarded as extra credit for succeeding at optional tasks or for exceptional approaches to the required tasks.

The grade for the assignment/project will be a sum of the "base points" earned (B) and the "extra points" earned (E) with no distinction between the two.

The Course Letter Grade will be determined by taking a weighted sum W (over assignments/projects) of the normalized points earned for each. The points for each assignment/project will be normalized by dividing the points earned (B+E) by the maximum number of base points (Bmax)

$$(B + E)/Bmax$$

The weights used to compute the Letter Grade will be determined according to the following formula:

Assignments/Activities	% of Final Grade
Assignments	20%
Midterm Project	30%
Final Project	50%

Letter Grades

Letter grades for the entire course will be assigned as follows:
The Letter Grade will be based on the weighted sum W (across assignments and projects) of the normalized points.

The threshold for earning each letter grade will depend on the distribution of W across the students. The threshold for earning the highest letter grade is usually in excess of 100% (so earning extra credit is highly encouraged) but the threshold is not predetermined.

View Grades

Grades will be posted on Brightspace

Course Schedule

The course schedule will be available online (Brightspace). The posted schedule is approximate and will be adjusted based on actual progress.

My goal is to keep slightly ahead of schedule so we will typically complete the current lecture's plan and make a head-start on the following lecture. This will give us a buffer to spend more time on subjects that the students find challenging or particularly interesting.

The exact content and material for each week's lecture (and the following week's lecture, so that we can get a head-start) will be posted at least one day in advance of the course meeting.

Course Materials

Required Textbooks & Materials

Textbooks

- **Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition (**https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/)
- **Python Data Science Handbook, by Jake VanderPlas**
  - Also available as a free, online book **https://jakevdp.github.io/PythonDataScienceHandbook**
- **Deep Learning, by Ian Goodfellow, Yoshua Bengio, and Aaron Courville**
  - Also available as a free online book **https://www.deeplearningbook.org/**

Lecture Materials

Lecture materials will be distributed in advance of each class as a Jupyter notebook.

On the class Brightspace page, there is a section entitled "Week 0" with preparation to be performed prior to the first class.

1. Setting up your Machine Learning environment, e.g. Jupyter
2. Obtaining lesson materials

Resources

- **Access your course materials**: NYU Brightspace
- **Databases, journal articles, and more**: Bern Dibner Library (library.nyu.edu)
  NYU Virtual Business Library (guides.nyu.edu/vbl)
- **Obtain 24/7 technology assistance:** Tandon IT Help Desk (soehelpdesk@nyu.edu, 646.997.3123)
  NYU IT Service Desk (AskIT@nyu.edu, 212-998-3333)

Policies

Academic Misconduct

A. Introduction: The School of Engineering encourages academic excellence in an environment that promotes honesty, integrity, and fairness, and students at the School of Engineering are expected to exhibit those qualities in their academic work. It is through the process of submitting their own work and receiving honest feedback on that work that students may progress academically. Any act of academic dishonesty is seen as an attack upon the School and will not be tolerated. Furthermore, those who breach the School's rules on academic integrity will be sanctioned under this Policy. Students are responsible for familiarizing themselves with the School's Policy on Academic Misconduct.

B. Definition: Academic dishonesty may include misrepresentation, deception, dishonesty, or any act of falsification committed by a student to influence a grade or other academic evaluation. Academic dishonesty also includes intentionally damaging the academic work of others or assisting other students in acts of dishonesty. Common examples of academically dishonest behavior include, but are not limited to, the following:
   1. Cheating: intentionally using or attempting to use unauthorized notes, books, electronic media, or electronic communications in an exam; talking with fellow students or looking at another person's work during an exam; submitting work prepared in advance for an in-class examination; having someone take an exam for you or taking an exam for someone else; violating other rules governing the administration of examinations.
   2. Fabrication: including but not limited to, falsifying experimental data and/or citations.
   3. Plagiarism: Intentionally or knowingly representing the words or ideas of another as one's own in any academic exercise; failure to attribute direct quotations, paraphrases, or borrowed facts or information.
   4. Unauthorized collaboration: working together on work that was meant to be done individually.
   5. Duplicating work: presenting for grading the same work for more than one project or in more than one class, unless express and prior permission have been received from the course instructor(s) or research adviser involved.
   6. Forgery: altering any academic document, including, but not limited to, academic records, admissions materials, or medical excuses.

Disability Disclosure Statement

Academic accommodations are available for students with disabilities. Please contact the **Moses Center for Students with Disabilities** (212-998-4980 or mosescsd@nyu.edu) for further information. Students who are requesting academic accommodations are advised to reach out to the Moses Center as early as possible in the semester for assistance.

Inclusion Statement

The NYU Tandon School values an inclusive and equitable environment for all our students. I hope to foster a sense of community in this class and consider it a place where individuals of all backgrounds, beliefs, ethnicities, national origins, gender identities, sexual orientations, religious and political affiliations, and abilities will be treated with respect. It is my intent that all students' learning needs be addressed both in and out of class, and that the diversity that students bring to this class be viewed as a resource, strength and benefit. If this standard is not being upheld, please feel free to speak with me.