

Frequently Asked Questions

Fraida Fund

Will we have live meetings? Is this course synchronous or asynchronous?

This course has both synchronous and asynchronous components:

- We will have a live, in-person “chalk talk” meeting every week.
- You will also have to watch pre-recorded video of a “Python notebook” session every week.

Am I required to attend the live meetings, or can I watch a recording later?

The live, in-person meeting will not be recorded.

How can I get help or ask questions about the course material?

There are two ways to get help:

- Post a question on the Q&A forum for this course.
- Attend an office hours session with the instructor or course assistants.

Note that you can ask questions **anonymously** on the Q&A forum, if you feel more comfortable that way.

How will my work in this course be evaluated?

Your mastery of the course material will be evaluated by your performance on:

- **Homework problem sets:** These are computer-graded, and you’ll have instant feedback as you work, so you’ll know whether your answers are correct or not. If you manage your time well, you’ll be able to get help or ask clarifying questions so that you can improve your understanding on questions you did not answer correctly, and re-submit a corrected answer for credit.
- **“Lab” assignments:** Some modules include a “lab” assignment that expands on the technique you learned that week. You’ll be given a Python notebook with some cells missing; you’ll have to fill in code or answer questions in the missing cells.
- **Exams:** The course will include a midterm exam and a final exam.
- **Project:** For your course project, I’m going to ask you to replicate and then build on a recently published result from a top machine learning conference. I’ll give you a list of published papers (with code!) to choose from.

The relative weight of each of these components will be shared via the course syllabus in the first week of the semester.

How much time should I expect to spend on this course?

This is a 3-credit course. During a fall or spring semester, the average student should spend at least 3 hours/week/credit → 9 hours/week for a 3 credit course.

A typical week will include the following:

- pre-lecture reading (some weeks) or study time (30-60 minutes)

- a live “chalkboard lecture” about 120-150 minutes long
- a “Python notebook” video about 90-120 minutes long
- a homework problem set (estimated time: 1-2 hours)
- a lab assignment (estimated time: 2-3 hours)

A student who is not very comfortable with the prerequisites may have to spend more time than the estimated 9 hours/week in order to do well.

What are the prerequisites for this course?

This course is mathematically oriented, and undergraduate-level knowledge of probability and linear algebra is required.

If you want to brush up, you can review:

- [Review of probability theory](http://cs229.stanford.edu/section/cs229-prob.pdf) (<http://cs229.stanford.edu/section/cs229-prob.pdf>)
- In [Boyd & Vandenberghe “Introduction to Applied Linear Algebra”](http://vmls-book.stanford.edu/vmls.pdf) (<http://vmls-book.stanford.edu/vmls.pdf>), these sections:
 - Section I, Chapter 1 (Vectors): vectors, vector addition, scalar-vector multiplication, inner product (dot product)
 - Section I, Chapter 3 (Norm and distance): Norm of a vector, euclidean distance
 - Section II, Chapter 5 (Matrices): matrix notation, zero and identity matrices, sparse matrices, matrix transposition, matrix addition, scalar-matrix multiplication, matrix norm, matrix-vector multiplication
 - Section II, Chapter 8 (Linear equations): systems of linear equations
 - Section II, Chapter 10 (Matrix multiplication): matrix-matrix multiplication
 - Section II, Chapter 11 (Matrix inverses): Inverse, solving a system of linear equations
 - Also a quick optimization review: Appendix C (Derivatives and optimization)

There will be a significant programming component to this course, and class and homework exercises will be in Python. You do not need to know Python a priori, but you should know basic programming concepts and have experience programming in some programming language. We will review some important Python basics in the first week of the course.

Do I need previous experience with machine learning for this course?

This is an introductory graduate level course and no prior machine learning knowledge will be assumed. If you already have significant ML experience, there is no need to take this class.

Do I need a computer with a GPU? Will I have to install some software on my computer?

In this course, we will use the Google Colab environment for practical programming demos and exercises. Colab is a free browser-based environment for Python programming. You don’t need to install anything to use Colab - you’ll just need a browser.

Do I need a textbook for this course?

You won’t need to buy a textbook - all of the materials you’ll need will be posted on the course site.

What topics will be included?

Here is a rough outline of the course content (subject to change):

1. Intro to ML, Python + numpy, exploratory data analysis
2. Linear regression
3. Gradient descent, bias-variance tradeoff

4. Model selection and regularization
5. Logistic regression for classification
6. K nearest neighbor
7. Decision trees, ensembles
8. Support vector machines, kernel trick
9. Neural networks
10. Deep learning, convolutional networks, transfer learning
11. Unsupervised learning
12. Reinforcement learning

The course includes a project. Can I do the project on whatever topic I want?

Not exactly. For your project, I'm going to ask you to replicate and then build on a recently published result from a top machine learning conference. I'll give you a list of published papers (with code!) to choose from, in various areas of ML:

- Understanding images
- Generating images
- Understanding text
- Generating text
- Audio (speech)
- Audio (music and other sounds)
- Security and robustness
- Reinforcement learning
- ML and society: Fairness, privacy, explainability

You'll choose your project from that list of papers.

Other important policies

Inclusion

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.

Disability

If you are student with a disability who is requesting accommodations, please contact New York University's Moses Center for Students with Disabilities (CSD) at 212-998-4980 or mosescsd@nyu.edu. You must be registered with CSD to receive accommodations. Information about the Moses Center can be found at www.nyu.edu/csd. The Moses Center is located at 726 Broadway on the 3rd floor.

Note for those who require accommodations for timed assessments: the final exam will be a timed exam.

Illness or other exceptional situation

If you are experiencing an illness or any other situation that might affect your academic performance in a class, please contact the student advocate: eng.studentadvocate@nyu.edu. The student advocate can reach out to your instructors to make arrangements on your behalf, when warranted.