CS 7140: Advanced Machine Learning

Spring 2026

Logistics

Lecture schedule: 11:45am - 1:25pm
Location: Hayden Hall 321
Instructor: Ryan Zhang
Office hours: Wednesday 5:30pm - 7pm (or after class), WVH 3rd floor
TA: TBA
TA office hours: TBA

Course description

This course introduces statistical or theoretical machine learning, which is the theoretical underpinning and the foundation of machine learning and artificial intelligence. This is a second course in machine learning, and we assume that you have already taken an introductory machine learning class (such as CS 6140 or DS 5220, DS 4400). The course will involve a mix of materials from different subjects, such as machine learning theory, probability and statistics, neural networks and deep learning, information theory, reinforcement learning, and natural language processing.

We will primarily draw on mathematical analysis, involving extensive use of applied probability, calculus, and linear algebra, to rigorously analyze the behavior of machine learning models and algorithms (though we will emphasize their practical implications as much as possible).

The coursework will involve three homework assignments (including both math questions and examples), a course project presentation, and a final course project report. There will be no exams in this class.

Prerequisites

- Students are expected to be familiar with basic calculus and linear algebra and comfortable reading and writing proofs.
- Prior knowledge in probability and linear algebra.
- Having taken an introductory machine learning class.

Syllabus

The lectures are divided into three modules. The course schedule will be updated periodically to keep pace with the lectures.

The lecture number is tentative and is subject to change.

Part I: Fundamental concepts of statistical learning (7 lectures)

Lecture 1: Basic setup of supervised learning, neural networks, and generative models

Lecture 2: Empirical risk minimization and examples

Lecture 3: Generalization theory, uniform convergence

Lecture 4: Concentration, Hoeffding, Bernstein inequalities, bounded difference inequalities.

Lecture 5: Rademacher complexity and examples

Lecture 6: Wrapping up the proof of Rademacher complexity-based generalization bounds

Lecture 7: Examples, matrix completion, two-layer neural networks

Part II: Generalization and optimization of neural networks and deep learning (7 lectures)

Lecture 8: Over-parameterized neural networks

Lecture 9: Neural tangent kernel

Lecture 10: Implicit regularization

Lecture 11: Implicit regularization and benign overfitting

Lecture 12: PAC-Bayes bounds

Lecture 13: Noise-sensitivity bounds and applications (e.g., to graph neural networks and language models)

Lecture 14: Reinforcement learning and policy gradient

Part III: Statistical modeling of emerging learning paradigms (2 lectures)

Lecture 15: Statistical transfer learning and minimax lower bounds

Lecture 16: Policy iteration, value iteration, and Q-learning

Part IV: Course presentations (10 lectures)

Lectures 17 - 26: Course project presentations

Lecture 26: Wrapping up the class

Coursework and grading

There will be three homework, for a total of 40% of the overall grade. The homework should be completed individually and submitted separately as well. Each homework is assigned and due as follows:

- Homework 1 is handed out on **Jan 19**, due after three weeks on **Feb 12.**
- Homework 2 is handed out on **Feb 12**, due after three weeks on **Mar 5.**
- Homework 3 is handed out on **Mar 9** (after spring break), due after three weeks on **March 30.**

The course project includes delivering an in-class presentation (40%) and a final course project report (20%). The presentations are scheduled from **Mar 23** until **Apr 23**. The report will be due by **Apr 20** (Monday). Note that the final grade is due on **Apr 28, 2pm, 2026**.

Textbooks and references

There isn't a single textbook that covers all of the lectures, though the following are good references for the course materials.

Statistical learning theory: https://github.com/percyliang/cs229t/blob/master/lectures/notes.pdf

Mathematical analysis of machine learning algorithms:
https://tongzhang-ml.org/lt-book/lt-book.pdf

Learning theory from first principles: https://www.di.ens.fr/~fbach/ltfp_book.pdf

Similar courses at other universities
Stanford: https://web.stanford.edu/class/stats214/, Machine Learning Theory

UC Berkeley: https://www.stat.berkeley.edu/~bartlett/courses/2014spring-cs281bstat241b/, Statistical Learning Theory

UW: https://homes.cs.washington.edu/~sham/courses/stat928/index.html, Statistical Learning Theory

Columbia: https://djhsu.notion.site/COMS-4773-Spring-2024-ed665b71e9d4414b8de13db9c8d4d556, Machine Learning Theory

Additionally, the instructor will release typed PDF lecture notes before and after every lecture for you to catch up on the lecture materials.

Honor Code

All students enrolled at NEU are expected to abide by the University's Honor Code. Any type of academic misconduct is not allowed, which includes 1) receiving or giving information about the content or conduct of an examination, knowing that the release of such information is not allowed, and 2) plagiarizing, whether intentionally or unintentionally, in any assignment. For the activities that are considered to be academically dishonest, refer to the Honor Code: https://catalog.northeastern.edu/handbook/policies-regulations/academic-integrity/.

Accessibility and Accommodations

As the instructor of this course, I endeavor to provide an inclusive learning environment. I want every student to succeed. The Disability Access Services (DAS) works with students who have disabilities to provide reasonable accommodations. It is your responsibility to request accommodations. In order to receive consideration for reasonable accommodations, you must register with the DAS at https://disabilityaccessservices.sites.northeastern.edu/incomingandsunregisteredstudents/. Accommodations cannot be retroactively applied, so you need to contact DAS as early as possible and contact me as early as possible in the semester to discuss the plan for implementation of your accommodations.

For additional information about accessibility and accommodations, please contact the Disability Access Services https://disabilityaccessservices.sites.northeastern.edu/about/.