EECS 545: Machine Learning

University of Michigan, Winter 2025

Course Information

Section 001
Instructor: Honglak Lee (honglak@umich.edu)
Classroom: Stamps Auditorium (1226 Murfin Ave, Ann Arbor, MI 48109)
Time: Mondays and Wednesdays 9:00 - 10:30 AM

GSI:
- Violet Fu (violetfy@umich.edu)
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For office hours, please check the course calendar as the time slots/format are subject to change occasionally.

Contact: For all course-related questions, please use Piazza (registration required). For private questions, please post to Piazza anonymously or you can reach out to us via the following mailing list: <eecs545.staff@gmail.com>. For most course related inquiries, please avoid sending emails to individual teaching staff as it may delay the response time.
NOTE: Please note that this is a tentative syllabus and subject to change.

Course Description

The goal of machine learning is to develop computer algorithms that can learn from data or past experience to predict well on the new unseen data. In the past few decades, machine learning has become a powerful tool in artificial intelligence and data mining, and it has made major impacts in many real-world applications. This course will give a graduate-level introduction of machine learning and provide foundations of machine learning, mathematical derivation and implementation of the algorithms, and their applications. Topics include supervised learning, unsupervised learning, learning theory, probabilistic models, and reinforcement learning. This course will also cover recent research topics such as deep learning. In addition to mathematical foundations, this course will also put an emphasis on practical applications of machine learning to artificial intelligence, such as computer vision, speech recognition, natural language processing, and robot perception and control. The course will require completing a research project.

- Chris Bishop, "Pattern Recognition and Machine Learning," October 1, 2007. (available online)
- Kevin Murphy, "Machine Learning: A Probabilistic Perspective", 2012. (available online)
- David Barber, "Bayesian Reasoning and Machine Learning", 2017. (available online)
- Ian Goodfellow and Yoshua Bengio and Aaron Courville, "Deep Learning", (available online)
- Hastie, Tibshrani, Friedman, "Elements of Statistical Learning," Springer, Second Edition, February 2009. (available online)
- Sutton and Barto, "Reinforcement Learning: An Introduction," 2nd edition. MIT Press, 2018 (available online)
- Boyd and Vandenberghe, "Convex Optimization," Cambridge University Press, 2004. (available online)
- Mackay, "Information Theory, Inference, and Learning Algorithms," Cambridge University Press, 2003. (available online)

Prerequisites

- Undergraduate level linear algebra (e.g., MATH 217, MATH 417) OR graduate matrix methods courses (EECS 505 / EECS 551) which cover several important/relevant linear algebra concepts
- Multivariate calculus
- Probability (equivalent to EECS 301)
- Programming skills (equivalent to EECS 280, EECS 281, and experience in python)

*** NOTE: If you have not taken all of the above (or don't have equivalent background knowledge/skills), please do not take EECS 545 this semester (otherwise, your workload will be extremely high).** Instead, we strongly recommend that you finish them first before taking this course.

Homework

There will be five (approximately bi-weekly) problem sets to strengthen the understanding of the fundamental concepts, mathematical formulations, algorithms, and the applications. The problem sets will also include programming assignments to implement algorithms covered in the class. While you are encouraged to discuss problems in a small group (up to 5 people), you should submit your own solutions and source codes independently. In case you worked in a group for the homework, please include the names of your collaborators in the homework submission. Please also note that out of the 5 problem sets, we will use the best **FOUR** scores for final grading (e.g., dropping worst **ONE** scores out of five).

Late day policy: Total **9** late days will be allowed. We will allow 3 maximum late days per assignment, and no homework will be accepted 3 days after the due date. **After using up all late days, your assignment will be penalized by 20% from your scores, and this will cause a significant drop in your homework grade.**

Note: HW #1 will be out no later than 01/14 and will be due 01/28. Note that the Add / Drop deadline is on 01/28.

Up to 3 maximum late days will be allowed for the project proposal and project progress report (we won't accept them if they are late by more than 3 days). **However, no late days will be allowed for the final project report submission.** In general, we recommend

Project

This course offers an opportunity for getting involved in a research project in machine learning. Students are encouraged to develop new theories and algorithms in machine learning, or apply existing algorithms to new problems, or apply to their own research problems. Please talk to the instructor before deciding about the project topic. Students will be required to complete their project proposals, progress reports, poster presentations and the final report.
This course offers an opportunity to get involved in a research project in machine learning. This year's machine learning course adopts a closed-end format, providing students with a predefined list of project topics, ranging from selected ML competitions to ideas suggested by our teaching staff. While maintaining essential elements like project proposals, progress reports, poster presentations, and final reports, this structured approach aims to offer focused learning experiences in line with current trends in machine learning. Detailed information on topic selection and processes will be made available, and students are encouraged to discuss their preferences with the instructor to find a suitable project.
We will provide more details soon.

Grading

Homework: 45%
Exam: 25%
Project: 25% (progress report 5%; poster presentation 5%; final project report 15%)
Quiz: 5%
Participation: up to 3% (extra credit)

* Participation score will be awarded for active participation in class and piazza contributions.

* References: EECS 545 in Winter 2022, 2023, 2024
Note: This is aggregate statistics just for your reference and we **don't** guarantee that the grading distribution and criteria will be exactly the same.

[Aggregate letter grade distribution of WN 2022 - WN 2024]

Grade	Percentage
A+	2%
A	30%
A-	29%
B+	23%
B	8%
B-	2%
C+	1%
D	1%
F / Withdrawn	5%

[Average performance statistics of WN 2022 - WN 2024]

Grade (letter)	Total points (%)	HW (%)	Exam (%)	Project (%)
A+	96	100	90	89
A	90	99	77	84
A-	85	97	67	81
B+	80	93	61	~79
B	75	82	60	~79
B-	68	69	50	~79

Important dates (TBD)

Link: Shared Google Calendar (public)
(Tip: you can add EECS 545 calendar to your personal google calendar by clicking "+ Google Calendar" in the bottom right corner.)
Note: These dates are tentative and subject to change.

- Project proposal due: February 4, 2024
- Project progress report due: March 14, 2024
- Exam: (approximately) April 9, 2024
- Final project poster presentation: April 25, 2024 **(Friday)**
- Final project report due: May 1, 2024 **(No Late Days)**

Topics to be covered (tentative)

- IntroductionSzL
- Regression
    - Linear regression
    - Gradient descent and stochastic gradient
    - Newton method
    - Probabilistic interpretation of linear regression: Maximum likelihood
- Classification
    - k-nearest neighbors (kNN)
    - Naive Bayes
    - Linear discriminant analysis/ Gaussian discriminant analysis
    - Logistic regression
    - Generalized linear models, softmax regression
- Kernel methods
    - Kernel density estimation, kernel regression
    - Support vector machines
    - Convex optimization
    - Gaussian processes
- Regularization
    - L2 regularization
    - L1 regularization, sparsity and feature selection
    - Bias-Variance tradeoff
    - Overfitting
    - Cross validation, model selection
    - Advice for developing machine learning algorithms
- Neural networks and Deep Learning
    - Perceptron
    - MLP and back-propagation
    - Deep neural networks
    - Convolutional neural networks
    - Recurrent neural networks
    - Transformers
- Learning theory
    - Sample complexity
    - VC dimension
    - PAC learning
    - Error bounds
- Unsupervised learning
    - Clustering: K-means
    - Gaussian mixtures
    - Expectation Maximization (revisited)
    - Principal Component Analysis
    - Dimensionality reduction
    - Independent Component Analysis
    - Sparse coding
    - Autoencoders (Variational Autoencoders)
    - Generative Adversarial Networks
    - Other SOTA deep generative models
- Reinforcement learning

- Direct preference optimization

Lecture schedule, reading lists, and handouts

Tentative schedule (Winter 2025) can be found here (draft).
[Google Calendar]
(Tip: you can add EECS 545 calendar to your personal google calendar by clicking "+ Google Calendar" in the bottom right corner.)

Optional Review sessions

* **NOTE**: Attendance is optional and not mandatory.

No	Date	Place	Review session	Topics	Readings and useful Links
1	1/13 Starts 4pm	https://umich.zoom.us/j/92675548643 Passcode: 252420	Linear Algebra review	Overview of linear algebra, matrix operations and calculus;	Stanford CS229 linear algebra rev http://cs229.stanford.edu/section/c linalg.pdf
2	1/17 Starts 11am	https://umich.zoom.us/j/4616794101?omn=91879783476 Passcode : 652198	Probability Review	Overview of probability	Stanford CS229 probability review http://cs229.stanford.edu/section/c prob.pdf
3	1/14 Starts 4pm	https://umich.zoom.us/j/96636335586 Passcode: 501702	Python / numpy tutorial	Tutorial on python / numpy	Stanford Python Numpy Tutorial (v Jupyter and Colab) https://cs231n.github.io/python-nu tutorial/
4	TBD	TBD	PyTorch Review	Review of PyTorch Basics	Colab Notebook

Frequently Asked Questions

Q. What is the expected workload of EECS 545?

Please note that while EECS 545 is a 3 unit course, the expected workload will be comparable to **very heavy 4 unit courses**. Machine learning is a rapidly progressing field, and we try our best to design the course material to reflect the latest advances in ML (e.g., deep learning, reinforcement learning, generative models, etc.). As such, you can expect to learn a lot of things but the workload could feel **extremely heavy** if you don't have sufficient background in math (e.g., linear algebra, calculus, probabilities, statistics) and/or programming (e.g., nontrivial programming background). Typically, students who take EECS 545 report the workload as "high" or "very high". If you are concerned, please talk to the instructor and/or GSIs.

Q. I am on the waitlist. Can you please provide me with an override so I can get registered to the class?

Currently, the class is full and we cannot provide overrides due to the limitation of teaching staff capacity. However, we expect that

Add" deadline. All students who are waitlisted will be added to the Canvas. If you cannot access Canvas yet, please write us an email.

Q. What are the differences between EECS 445 and EECS 545?

The topics will still largely overlap between EECS 445 and EECS 545, but the specific topics will vary depending on the instructor. In general 545 has more theoretical and advanced topics (e.g., deep learning, reinforcement learning, etc.).

Q, Can I take both EECS 445 and EECS 545?

A. If you are a UM CSE undergrad or grad student, **you cannot take both EECS 445 or EECS 545** and get both counted towards your degree requirements. Please consult your program coordinator or advising office to see more specifics of how EECS 545 (or EECS 445) can contribute to satisfying your degree requirement.

Q. Will the lectures be recorded?

The lectures will be recorded. However, we might look into some active learning sessions that will benefit students who attend the class real-time. A small portion of grade advantages (up to 3% out of 100% total grade) may be awarded for active participation in lectures, piazza, etc.

Q. What are specific topics to review for multivariate calculus, linear algebra and probability, programming, etc?

You might find the following materials useful:
Stanford CS229 linear algebra review:
http://cs229.stanford.edu/section/cs229-linalg.pdf
Stanford CS229 probability review:
http://cs229.stanford.edu/section/cs229-prob.pdf
Python Numpy Tutorial (with Jupyter and Colab)
https://cs231n.github.io/python-numpy-tutorial/