Harvard University
School of Engineering and Applied Sciences

ENG-SCI 201/APMTH 231: Decision Theory

Spring 2024
Course Information

Course information

Instructor:
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Office Hours: T 9:00-10:00 AM, 4:00-5:00 PM.

Teaching Fellows:
Nathan Sun. (nsun@college.harvard.edu)
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Section: F 10:30–11:30 AM, Maxwell-Dworkin 123
Office Hours: F 11:30 AM–12:30 PM, Maxwell-Dworkin 123.

Lecture:
T/Th 11:15 AM–12:30 PM, SEC 1.413

Course Administrator:
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Course Website:
`https://canvas.harvard.edu/courses/129105/`

Course overview

ES 201/AM 231 is a course in statistical inference and estimation from a signal processing perspective. The course will emphasize the entire pipeline from writing a model, estimating its parameters and performing inference utilizing real data. The first part of the course will focus on linear and nonlinear probabilistic generative/regression models (e.g. linear, logistic, Poisson regression), and algorithms for optimization (ML/MAP estimation) and Bayesian inference in these models. We will play particular attention to sparsity-induced regression models, because of their relation to artificial neural networks, the topic of the second part of the course. The second part of the course will introduce students to the nascent and exciting research area of model-based deep learning. At present, we lack a principled way to design artificial neural networks, the workhorses of modern AI systems. Moreover, modern AI systems lack the ability to explain how they reach their decisions. In other words, we cannot yet call AI explainable or interpretable which, as a society, poses important questions as to the responsible use of such technology. Model-based deep learning provides a framework to develop and constrain neural-network architectures in a principled fashion. We will see, for instance, how neural-networks with ReLU nonlinearites arise from sparse probabilistic generative models introduced in the first part of the course. This will form the basis for a rigorous recipe we will teach you to build interpretable deep neural networks, from the ground up. We will invite an exciting line up of speakers. Time permitting, we will provide a model-based pespective of the building blocks of modern language and image generative models. (

Prerequisites

The official prerequisites for this course are APPLIED MATH 21a or MATH 21a, and STATS 110 or equivalents. This is a highly interdisciplinary graduate-level course that will involve a combination of theory *and* computational modeling that are both motivated by data analysis problems. The key requirements are intellectual curiosity and a desire to learn to think about data in new ways. A certain level of mathematical maturity is assumed. In particular, prior exposure to abstract linear algebra and real analysis will deepen your understanding of the materials.

Textbook

Machine Learning: A Bayesian and Optimization Perspective, by Sergios Theodoridis, Academmic Press, 2015.

Policy on collaboration

To get the most out of this course, you are encouraged to struggle with the course assignments on your own and reach out to the course staff during Office Hours. **You are allowed to *discuss* the *content* of assignments with fellow students but *not* their *solutions*.** Your write-up of assignments must entirely be your own. Moreover, at the top of every assignment, you are kindly asked to acknowledge the students you have discussed said assignment with. We also ask you to acknowledge the use of books, articles, websites, lectures, discussions, etc., that you have consulted to complete your assignments.

Policy on Generative AI

I encourage you to use generative AI tools to, for instance, clarify your understanding of topics from class. In addition, if you find them useful, I encourage you to experiment with them to work on your problem sets. The course assignments have as a goal to teach you certain thinking processes/ways of tackling problems. In that sense, the actual solution to the problem itself matters very little to us. That's why, if you do use generative AI tools for your problem sets, we ask that you, for every problem, to submit the sequence of prompts and answers from the AI tool that led you to a solution.

Grading information

The final grade for this course will be based on your performance on problem sets, a midterm examinations and a final project/paper. There will not be a final exam in this class.

1. **Problem sets**: There will be **4** (roughly) bi-weekly **problem sets** that will count towards **45% of your final grade**. Problem sets will be due at the beginning of class on the date stated in the course calendar. Problem sets will consist of "pen-and-paper assignments" and/or computational assignments, which you will submit electronically.

2. **Midterms**: There will be **1 midterm examination** that will count towards **30% of your final grade**.

3. **Final project/paper**: You can choose to work on a **final project** or **final paper**, which will count towards **15% of your final grade**.

    - The final project can either be performed alone or in a group of up to three people. All members of a group will get the same grade on the final project. The bigger the group, the higher the expected output of the project. The goal of the final project is three-fold: we ask that you (a) formulate an interesting question that involves real data, (b) gather the data required to answer this question and (c) used concepts from the course to tell an interesting story, and (d) record a short (10 to 15-minute) presentation. The grade will be based on your ability to apply the concepts and tools taught in class, and your ability to integrate (a), (b), (c) and (d). We strongly encourage that you consult with the course staff as early as possible.
    - We will treat the final paper as a single-person assignment. We ask that you formulate a question based on a data-driven problem of your choice, that can utilize the tools for statistical inference we will learn in the class. This can either come from a problem related to your undergrad/grad thesis,

or simply a problem that interests you. We ask that you explain the problem/question, survey the current literature on approaches towards solving the problem, suggest new ways to solve the problem based on (a) tools you will learn in the first part of the class, and (b) using model-based deep learning approaches from the second part of the class. We ask that you submit the paper in 4-page, two-column, IEEE conference format. You can use an additional page for references, for a total of 5 pages.

4. **Project/paper proposal**: We ask that you put together a short one-page project/paper proposal to be discussed with the course staff following Spring Recess (see course calendar). The project/paper proposal will count towards **10% of your final grade**.

Policy on Late Assignments

Except for the exams and the final-project report, you get to turn in one assignment up to three days late, no questions asked.

Disclaimer

While the above weights are used for computing the final grade, I reserve my right to scale the grades based on the performance of the entire class.

Table 1: **Course Calendar**

	Date	Topic		Assignments
		Regression, Classification and Optimization		
T	01/23	Course overview		Lec. 1 slides
Th	01/25	Maximum likelihood estimation		**Pset 1 out**, Lec. 2 notes
T	01/30	Linear regression		Lec. 3 notes
Th	02/01	Intro to Convex Optimization I		Lec. 4 notes
T	02/06	Intro to Convex Optimization II		Lec. 5 notes
Th	02/08	Exp. family and weighted least-squares		**Pset 1 due, Pset 2 out** Lec. 6 notes
T	02/13			
Th	02/15	SVMs: classification meets optimization		Lec. 7 notes
T	02/20			
Th	02/22	Features space, kernels, RKHS		Lec. 8/9 notes
T	02/27			**Pset 2 due, Pset 3 out**
		Regularization, hierarchical models and Bayesian thinking		
Th	02/29	MAP estimation/regularized regression		Lec. 10 notes **Pset 2 due, Pset 3 out**
T	03/05	Cross-validation/parameter selection		Lec. 11 notes
Th	03/07	**Midterm 1**		
T	03/12	**Spring break**		**Reading assignment**
Th	03/14	**Spring break**		**Reading assignment**
		Deep Neural networks		
T	03/19	Perceptron, ANNs and learned feature extraction		**Pset 3 due, Pset 4 out** Lec. 12 notes
Th	03/21	Optimizing ANNs: back-propagation algorithm		
T	03/26	Model-based networks: deep unrolling, optimization layers, meta-learning	(**D. Ba**)	**Project proposal due** Reading assignment
Th	03/28	Applications of model-based deep learning	(**B. Tolooshams**)	**Reading assignment**
T	04/02	Physics-informed neural networks	(**G. Barbastathis**)	**Reading assignment**
Th	04/04	State-space models and Kalman filtering		**Pset 4 due** Lec. 15/16 notes
T	04/09	Kalman filtering, RNNs		
Th	04/11	LLMs, transformers and RNNs	(**TBD**)	
T	04/16	Generative modeling: VAEs, diffusion models, norm. flows	(**Alex Lin**)	
Th	04/18			**Reading assignment**
T	04/23	**Project presentations**		
Th	04/27	**Project presentations**		
Mon	05/06	**Final project due**		