APMTH 233/ES 203: Interplay between control and learning
Spring 2022

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Location: SEC 1.402, 150 Western Ave
Meeting Time: M/W: 9:45-11:00am
Teaching fellows: TBD

Office hours: Lina: Mon, 11am-12pm, Zoom: https://harvard.zoom.us/j/9607868063
TF: TBD

And by appointment

Prerequisites: This is an advanced theory-intensive course. Optimization (AM/ES 121 or more advanced courses) and probability (ES 150 or Stat 110 or more advanced) are required. ES 202/AM 232: Learning, estimation, and control of dynamical systems or equivalent is strongly recommended. Undergraduates need permission.

ES 202/AM 232 related materials:
https://www.dropbox.com/sh/kyeavicukcqueiv/AAAHE1TqsmmQgsQ_UyHJAfTSa?dl=0
If you haven't taken similar courses, please get yourself familiar with the notions and concepts that are covered in these lecture notes.

For Optimization, the following course would provide you with enough background:
https://ocw.mit.edu/courses/sloan-school-of-management/15-093j-optimization-methods-fall-2009/lecture-notes/

To help everyone catch up with the essential backgrounds quickly for this course, I have put several notes together (named as "Lecture 1: Review #") and posted them on our course website. On the first lecture, Dr. Yujie Tang will only go over note " Lecture 1: Review 1: Mathematical Background" in class. But students should go over the rest of review notes by themselves. I have already deleted the proofs for these review notes. **The minimum requirement is that you should understand the definition of these control concepts in these review notes**, e.g., state-space models, transfer function, stability, Laypunov stability theorems, input-output-stability, controllability, observability, state feedback, state estimator, and output feedback control. **And whenever we mention these terminologies, you know where you can find them and learn them on the fly.** We will dive into the core of the course, the interplay between control and learning, directly from lecture 2, rather than spending lectures on reviewing control concepts. All of these materials were studied in ES 202. If you would like to learn the theory behind these concepts, you can either check ES 202 lecture notes (https://www.dropbox.com/sh/kyeavicukcqueiv/AAAHE1TqsmmQgsQ_UyHJAfTSa?dl=0) or the text book “Linear Systems Theory” by Prof. Joao Hespanha (https://web.ece.ucsb.edu/~hespanha/linearsystems/)

If you feel these reviews are difficult for you, the class might not good for you.

Course Description:
This advanced graduate course will provide students with an introduction to current areas of research at the intersection of control and machine learning. The course will firstly focus on tailoring control tools to study algorithms in large-scale optimization and machine learning. Then students will study how to combine reinforcement learning and model-based control methods for control design problems.

Examples of topics include: first-order and zeroth-order optimization; dissipation inequality; stability of dynamical systems and Lyapunov functions; LMI (Linear Matrix Inequality); robust control; model predictive control, adaptive control; MDP and reinforcement learning; control-oriented analysis tools for temporal difference learning and Q-learning; sample complexity; policy gradient and policy optimization; uncertainty quantification and safe learning; iterative learning control; regularization of model-free control via prior model-based design; and multiagent reinforcement learning.

After the course, the student would be able to perform research in related fields and write papers for conferences such as L4DC, CDC, ICML, NeurIPS, IROS, ICRA, etc.

Notes:

Students are only allowed to take either Eng-Sci 203 or APMTH 233 for credit. There are no differences in the grading policy for the two courses.

Lectures

Course lectures are on Monday and Wednesday 9:45am to 11:00am at SEC 1.402.

The **first class** is on Jan 24th. However, Lina has a personal urgency on Jan 24th so Dr. Yujie Tang will give a review of the mathematical foundations for this course.

Lecture notes and course materials will be available on the course website after the lecture.

References:

There is no textbook for this course**.** The course will be a blending of lectures taught by the instructor, guest lectures by experts in the related field, and student presentations. Reading materials will be added on our course website. Please check the schedule/calendar page on course canvas to see the up-to-date-materials

Grading

First of all, I would like to highlight that this is a graduate level course. I hope you focus on learning the content rather than the grades. No matter whether you are a PhD student, master student, or undergraduate student, I would treat you as a highly-motivated PhD student!

The course will be a blending of lectures taught by the instructor, guest lectures by experts in the related field, and student presentations.

The final grade will be based on course participation, homework sets, presentations, and a final project. There will be 3-5 homework assignments, The final grade will be based on course participation, homework sets, a midterm exam and a final project.

- *Homework (20%):* We will have a small number of Psets.

  Late homework within 2 days of the due date is acceptable but the grades of the late homework will be 25% discounted. *No late homework after 2 days will be accepted* without a note from the health center or the student's Resident Dean.

- *Course Participation* (15%): Students are encouraged to ask questions, participate in the discussions, and provide feedbacks. Each student will need to scribe at least one lecture material. This is also counted as course participation.

- *Paper presentation, leading class discussions, a report (20%)*: Guideline will be posted later.

- *Reflection notes* for the papers we will read in class (15%): Guideline will be posted later.

- *Final project (30%):* The final project should be done in teams (2 team members). If you want to do the project solely, discuss with the instructor and provide a strong reason. **Though the course materials will be highly mathematical (proof-based), the project can be applications.**

  Students are encouraged to build off the material that is presented in class and that is related to their own research. Another example is that each team/student picks one (advanced) topic to review. This will require students to review papers or advanced textbooks. For each project, the team should finish a report and a presentation.

  Before the Spring break (March 11), each team must submit a short proposal (no more than 2 pages) about the final project topics. Before the April 10th, students should submit a progress report (around 4-6 pages).

  Students are welcome to discuss the topics with the instructor or ask for suggestions.

  The project final report must use the L4DC (PMLR) LaTex format. Your report should be 10 pages maximum (not including references and supplementary material).

Collaboration Policy

Collaboration on homework assignments is encouraged. You may consult outside reference materials, other students, the TA, or the instructor, but you cannot consult homework solutions from online or prior years, and you must cite any use of material from outside references. All solutions that are handed in should be written up individually and should reflect your own understanding of the subject matter at the time of writing.

Course website:
We will use the course website of AM 232 (https://canvas.harvard.edu/courses/102319) for both APMTH 233 and Eng-Sci 203. Please let me know if you have problem of accessing the website. Updates will be made daily as appropriate. It is essential that you check the website periodically. Posted will be lecture notes, problem set assignments, course announcements, changes in course materials, and answers to pertinent questions.

Tentative schedule (Check the course website for the up-to-date schedule)

	Date	Topic	Note
	1.24	Math foundations and linear system review (stability; observability; controllability; transfer functions; system norm; H2 and H\infnity)	Dr. Yujie Tang will cover this review class
	1.26	Course introduction; syllabus; control for learning and learing for control	Lina
Part I: Control for learning	1.31	The use of SDP/LMI in Control and Optimization	Lina
	2.2	Robust analysis in optimization methods: uncertainty modeling; Optimization methods as feedback systems; disspipation inequality	Lina
	2.7	Small gain, passivity, integral quadratic constraints, and their use in optimization	Lina
	2.9	Connection between stochastic optimization and feedback systems	Lina
	2.14	Nesterov's methods: control analysis tool; robustness of Nesterov's methods	Lina
	2.16	One paper reading: IQC for deep learning	students/or guest speaker: Yang Zheng
	2.21	**Holiday**	
Part II: Learing for control of dynamical systems	2.23	Review: LQR, LQG, MDP, Dynamical programming	Lina
	2.28	Model free LQR (global convergence of Lqr learning; LQG optimization landscape;)	students
	3.2	Zeroth-order Optimization (nesterov's paper)	Lina or Yujie
	3.7	System ID 1 (single trajectory; multi-trajectory; fully observable; partiall observable)	Lina
	3.9	system ID 2	Lina
	3.14 3.16	**Spring break**	

	3.21	(robust) Certainty equivalence control: (Dean et. Al.; Zheng et. al)	students
	3.23	Online control and Model predictive control 1 (basic and robust mpc): unknown disturbances	Lina
	3.28	Model predictive control: regret analysis (yingying online learning; adam's online learning)	Lina or students or guest speaker (yingying and Guanya)
	3.30	Improper learning for nonstochastic control (Singh et. Al;) & discuss of control parameterization	students or guest speaker Karan Singh
	4.4	Safe learning (Yingying's safe learning)	students or guest speaker Yingying Li
Part III: Reinforcement Learning	4.6	MDP/RL; exploration, exploitation; value-based RL; policy-based RL	Lina
	4.11	stochastic approximation (Q learning analysis)	Guest speaker: Zaiwei
	4.13	Bandit learning; Is Q learning efficient/RL is similar to bandit paper/Minimax Regret Bounds for Reinforcement Learning	students
	4.18	RL-representation: Linear MDP etc	students or guest speaker Bo Dai
	4.2	Policy gradient (argawal paper)	Students or guest speaker Jingchen Mei
	4.25	Police-based RL (trust region method; actor-critic etc)	students
	4.27	Multiagent RL: cooperative (Kaiqing; Guannan); noncooperative	students or guest speaker