Spring 2020

Stanford
AA 203: Optimal and Learning-based Control

Instructor:
Prof. Marco Pavone
Email: pavone@stanford.edu

Course Assistants:
James Harrison
Email: jharrison@stanford.edu
Matt Tsao
Email: mwtsao@stanford.edu
Sander Tonkens
Email: stonkens@stanford.edu

Collaborators:
Riccardo Bonalli
Email: rbonalli@stanford.edu
Boris Ivanovic
Email: borisi@stanford.edu

Logistics: This is an online class; lecture videos are available on Canvas. Course websites:

- For course content and announcements: http://asl.stanford.edu/aa203/
- For course-related questions: http://piazza.com/stanford/spring2020/aa203
- For homework submissions: https://www.gradescope.com/courses/114953
- For urgent questions: aa203-spr1920-staff@lists.stanford.edu

Office Hours:
Prof. Marco Pavone: Tuesdays, 10:00-11:00am
James Harrison: Mondays, 3:00-5:00pm
Matt Tsao: Wednesdays, 3:30-5:30pm

Units: 3.

Course Notes: A set of course notes will be provided covering all the content presented in the class. In addition to these notes, the textbooks below may be valuable for context or further reference.

Prerequisites: Familiarity with linear algebra (e.g., EE 263 or CME 200).

Textbooks (Optional):

- D. P. Bertsekas. Dynamic Programming and Optimal Control, Vol. I and II, Athena Scientific, 2012, ISBN-10: 188652908. Price: $134.50.
- D. P. Bertsekas. Nonlinear Programming, Athena Scientific, 2016, ISBN-10: 1886529051. Price: $89.00.
- D. P. Bertsekas. Reinforcement Learning and Optimal Control, Athena Scientific, 2019, ISBN-10: 1886529396. Price: $89.00.
- F. Borrelli, A. Bemporad, M. Morari. Predictive Control for Linear and Hybrid Systems, 2017, ISBN-10: 1107652871. Price: $68.78.
- D. K. Kirk. Optimal Control Theory: An introduction. Dover Publications, 2004, ISBN-10: 0486434842. Price: $17.60.
- J. B. Rawlings, D. Q. Mayne, M. M. Diehl. Model Predictive Control: Theory, Computation, and Design, 2nd Edition, Nob Hill Publishing LLC, 2017, ISBN-10: 0975937731. Price: $110.00.
- R. S. Sutton and A. G. Barto. Reinforcement Learning: An Introduction. MIT Press, 2018, ISBN-10: 0262039249. Available online at: `http://www.incompleteideas.net/book/RLbook2018.pdf`

Course Content: Optimal control solution techniques for systems with known and unknown dynamics. Dynamic programming, Hamilton-Jacobi reachability, and direct and indirect methods for trajectory optimization. Introduction to model predictive control. Model-based and model-free reinforcement learning, and connections between modern reinforcement learning and fundamental optimal control ideas.

Course Goals: To learn the *theoretical* and *implementation* aspects of main techniques in optimal control and model-based reinforcement learning. In particular, dynamic programming, Hamilton-Jacobi reachability, direct and indirect methods for optimal control, model predictive control (MPC), regression models used in model-based RL, practical aspects of model-based RL, and the basics of model-free RL. To learn how to use such techniques in applications and research work with tools such as MATLAB, Python, CVX, and PyTorch. At the end of the class the student will be able to:

- Apply optimal control techniques to optimize the operations of physical, social, and economic processes (e.g., aerospace vehicles, autonomous cars, robotic systems, financial systems, etc.).
- Design learning-based control schemes and apply them to the aforementioned applications.

Target audience: *Undergraduate* and *graduate* students interested in achieving an advanced knowledge of optimal control, learning-based control, and reinforcement learning. Specifically, this course should benefit anyone who performs research or plans to become a professional in the following fields of engineering: Electrical Engineering (control of electro-mechanical systems); Aero & Astro (guidance, navigation, and control of aerospace systems), Mechanical & Civil Engineering (especially robotics, automotive), Computer Science (especially machine learning, robotics), Chemical Engineering (control of complex chemical plants). The course may be useful to students and researchers in several other fields including Neuroscience, Mathematics, Political Science, Finance, Economics.

Course Grade Calculation:

- (60%) homework; there will be 6 homework assignments, assigned roughly every one and a half weeks.
- (40%) final project. Projects can be done in teams of up to three students. Guidelines for final projects will be posted on course website.

Homework Policy

- There will be a total of six problem sets (some of them requiring the use of MATLAB, Python or other software packages).
- Because of the multiple topics that will be pursued in the course, it is important to keep up with the assignments. To account for unforeseen extraordinary circumstances, students are given a total of 6 free late days that may be used for the homeworks; a maximum of 3 late days will be allowed on a given assignment.
- Cooperation is allowed in doing the homework. You are encouraged to discuss approaches to solving homework problems with your classmates, however **you must always write up the solutions on your own**. You **must** write on your problem set the names of the classmates you worked with. Copying solutions, in whole or in part, from other students or any other source will be considered a case of **academic dishonesty**.

Students with Documented Disabilities: Students who may need an academic accommodation based on the impact of a disability must initiate the request with the Office of Accessible Education (OAE). Professional staff will evaluate the request with required documentation, recommend reasonable accommodations, and prepare an Accommodation Letter for faculty dated in the current quarter in which the request is made. Students should contact the OAE as soon as possible since timely notice is needed to coordinate accommodations. The OAE is located at 563 Salvatierra Walk (phone: 723-1066, URL: `http://studentaffairs.stanford.edu/oae`).

Schedule (subject to some slippage):

Date	Topic	Assignment
04/06	Introduction, nonlinear optimization	HW1 out
04/08	Constrained nonlinear optimization	
04/13	Dynamic programming (DP), discrete LQR	
04/15	Stochastic DP, value iteration, policy iteration	HW2 out, HW1 due
04/20	Iterative LQR/ LQG, DDP	
04/22	Intro to RL, Q-learning, DQN, and policy gradient methods	
04/27	HJB and HJI equations, reachability analysis	HW3 out
04/29	Direct methods for optimal control	
05/01		Project proposal due, HW2 due
05/04	Direct collocation and sequential quadratic programming	
05/06	Introduction to MPC	HW4 out
05/08		HW3 due
05/11	Feasibility and stability of MPC	
05/13	Adaptive optimal control	
05/18	Model-based RL: linear and non-linear methods	HW5 out, HW4 due
05/20	Model-free RL: actor-critic methods and deep RL for robotics	
05/25	Memorial day (holiday, no classes)	
05/27	Model-based policy learning	
06/01	Calculus of variations	HW6 out, HW5 due
06/03	Indirect methods for optimal control	
06/08	Pontryagin's maximum principle	
06/10	Numerical aspects of indirect optimal control	HW6 due

Recitations:

Date	Topic
04/10	Linear dynamical systems
04/17	Nonlinear regression fundamentals and neural network basics
04/24	Introduction to Python
05/01	Linear, quadratic, convex, and mixed-integer linear programming
05/08	PyTorch and advanced neural network topics