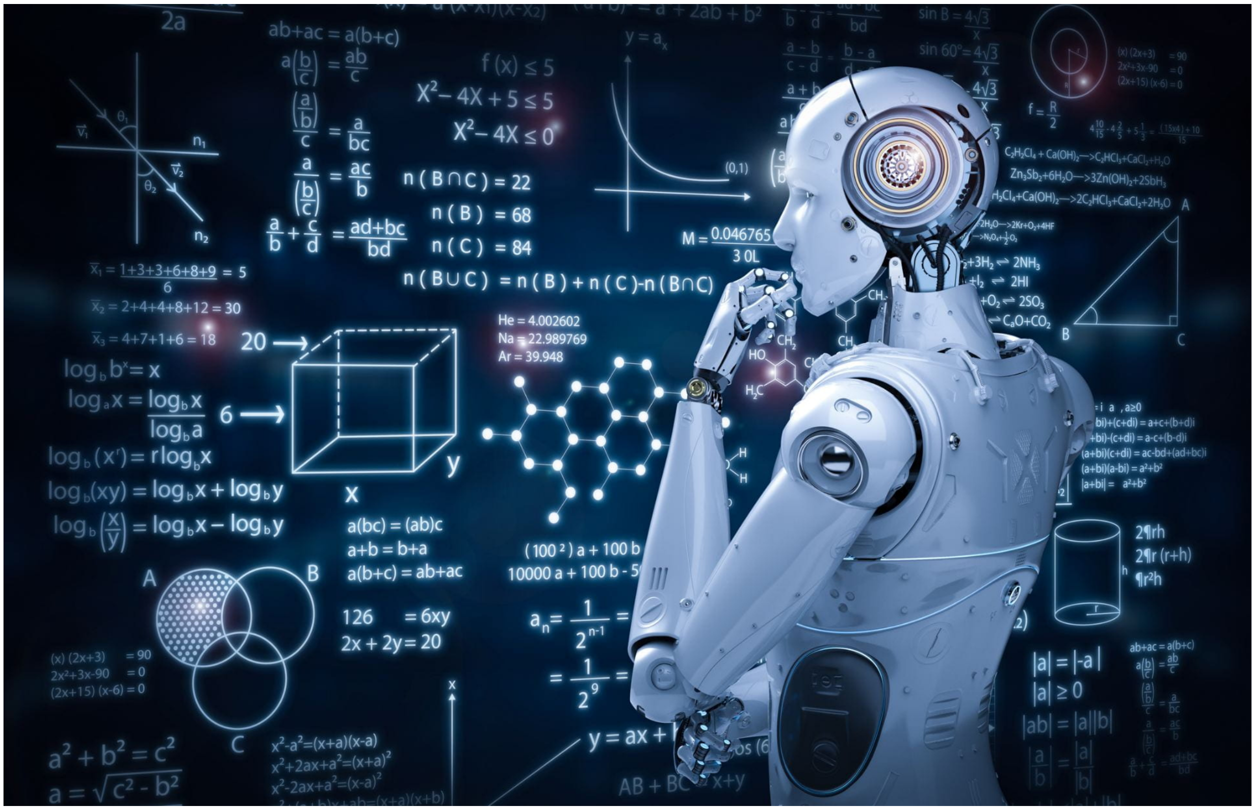
CS 6501/SYS 6581: Learning in Robotics (Fall 2022)



Instructor
Madhur Behl (madhur.behl@virginia.edu)

Teaching Assistants

Website:
https://linklab-uva.github.io/robotlearning/

Course Description
A robot is a machine that senses its environment using sensors, interacts with this environment using actuators to perform a given task and does so efficiently using previous experience of performing similar tasks. We will cover the fundamentals of these three aspects of robotics: perception, planning and learning. A tentative list of topics includes state estimation (EKF, UKF, Particle Filters, visual-inertial odometry), control and planning (LQR, MDPs, sampling-based planning, bayesian methods), reinforcement learning (policy gradients, Q-learning, Imitation Learning, Offline RL) and some miscellaneous topics (meta-learning and formal verification). The coursework will have both applied and theoretical aspects. This is a graduate level class;

undergraduates will need permission from the instructor to enroll. Some experience with, or appreciation of, robotics is recommended.

The content will undergo minor changes in Fall 2022 (see the syllabus below).

Prerequisites
Required

1. Proficiency in programming. All assignments will be based on Python but if you have used a similar language like MATLAB before, you should be able to pick up Python easily. Recitation sessions will provide preparatory material.
2. Probability
3. Linear Algebra

Recommended

1. Machine Learning or Data Analysis
2. (Soft recommendation) Optimization

Evaluation

- 4 homeworks (60% in total)
- Mid-term exam (20%)
- Final project (teams of 3) (15%)
- You will write a summary (it can be as elaborate as you like but at least 2 pages) that demonstrates your understanding of the material *in your own words* for each of the 3 modules in the course. These summaries will together make up for 5% of your final grade. There is no partial credit here, depending on the quality of your summary, you either get all the 5% or none.

Each student will have 5 "late days" to use during the semester which can be used to submit the deliverables later than they are due. Deliverables that are submitted late after exhausting this quota will result in 50% credit deduction per day.

Textbook
Detailed instructor notes in addition to supplementary reading material from the following books.

1. (Thrun) "Probabilistic Robotics" by Sebastian Thrun, Wolfram Burgard and Dieter Fox. PDF
2. (Barfoot) "State Estimation for Robotics" by Tim Barfoot. PDF
3. (Lavalle) "Planning Algorithms" by Steve Lavalle. PDF
4. (Sutton) "Reinforcement Learning: An Introduction" by Richard Sutton and Andrew Barto PDF
5. (d2l) Dive into Deep Learning by Aston Zhang, Zack Lipton, Mu Li and Alex Smola available at https://d2l.ai is a good reference to read about deep learning.

6. (Russell) “Artificial Intelligence: A Modern Approach” by Stuart Russell and Peter Norvig. PDF

The following books contain some advanced material. You can use it for your own reference and to brush up fundamentals of machine learning and optimization.

1. “Pattern Recognition and Machine Learning” by Christopher Bishop. PDF
2. “An Invitation to 3-D Vision: From Images to Models“ by Yi Ma, Stefano Soatto, Jana Kosecka, Shankar Sastry. PDF
3. “Reinforcement Learning and Optimal Control” by Dmitri Bertsekas. Material
4. “Feedback Systems: An Introduction for Scientists and Engineers” by Karl Johan Astrom and Richard M. Murray, PDF
5. (Advanced) “Linear Systems Theory” by João P. Hespanha. Website
6. (Fairly advanced) “Stochastic Models, Information Theory, and Lie Groups, Volume 1: Classical Results and Geometric Methods” by Gregory Chirikjian. PDF

Computational Resources

Almost all coursework can be done using your laptop. We will use PyTorch (https://pytorch.org) and MuJoCo (http://www.mujoco.org) in the later parts of the course for reinforcement learning. If you want additional computational resources, you can take a look at the following.

1. Free: Google Colab (https://colab.research.google.com) is a very good platform with a good GPU that you can use for most small-scale experiments. Gradient (https://gradient.paperspace.com) is another free tool with more generous compute resources (6-hour timeouts and persistent sessions). If you haven’t used it already Google Cloud Project gives $300 of starter credits (https://cloud.google.com/free).
2. Paid: You can also sign up for Google Colab Pro (https://colab.research.google.com/signup) for a very reasonable $10/month to get access to faster GPUs and less restrictive preemption of jobs.

Course Syllabus

Module 1: State Estimation (11 lectures)

Background on probability

Topics: Markov chains, Hidden Markov Models, Kalman Filter, Extended and Unscented Kalman Filter, particle filters, occupancy grids, transformations

Module 2: Control and Planning (5-6 lectures)

Background on linear control, dynamic programming

Topics: Markov Decision Processes, Value and Policy Iteration, Bellman equation, Linear Quadratic Regulator, Linear Quadratic Gaussian, sampling-based motion planning

Module 3: Reinforcement Learning (7 lectures)

Background on deep learning and optimization

Topics: Imitation Learning, Policy gradient, Q-Learning, Inverse RL, Model-based RL, Offline RL

Module 4: Miscellaneous topics (2 lecture)
Meta-Learning, Formal verification methods

Lecture	Date	Day	Topic	Notes
1			Introduction	HW 0 out (not graded)
2			Background on probability	HW 1 out
3			Markov chains	
4			Hidden Markov Models I	Course selection period ends
5			Hidden Markov Models II	
6			Kalman Filter	HW 1 due
7			Extended Kalman Filter	
8			Unscented Kalman Filter	HW 2 out
9			Particle Filter	
10			Rigid Transforms, Quaternions	
11			Occupancy Grids	Summary on Lec 4-10 due
12			The Robot Operating System	Drop period ends on
13			Dynamic Programming, Bellman equation	HW 2 due
14			Value Iteration	
15			Policy Iteration	HW 3 out
16			Background on linear control, LQR, Stochastic LQR	
17			LQG, Iterated LQR	

18			Midterm	
19				
20			Sampling-based motion planning	HW 3 due
21			Background on machine learning, optimization, Imitation Learning	
22			Policy Gradient	
23			Tabular Q-Learning	
24			Continuous Q-Learning	HW 4 out
25			Inverse RL, Model-based RL	
26			Offline RL	
27			Topics: Meta-Learning	
28			Topics: Formal verification methods	HW 4 due
				Project due

Academic Integrity

You are encouraged to collaborate with your peers for solving problems in the homework, reading books and curating other instructional materials to improve your understanding of the concepts taught in the class. While doing so, you might generate code/pseudo-code/solutions for the homeworks/project. When you begin to write your submission you should keep aside all these materials (including your friends) and do things "from scratch". In short, everything you write/code and submit should be your own work done independently.

You should disclose all collaborations in your submission at the top. If you came across some code as a part of your homework/project you must mention it.

Collaboration is different from cheating. The latter will have serious consequences. Cheating is defined as attempting, abetting or using unauthorized assistance (knowledgeable friend who is not taking the class) or material (e.g., online code). Some examples of cheating are: copying someone else's work for homework/exams, handing in someone else's work as your own or handing in stuff from the Internet as your own work. These will not be tolerated. Your score for that particular homework or exam will be zeroed out if found guilty, you will be penalized one letter grade *and* this incident will be reported to the university.

I trust every student in this course to fully comply with all of the provisions of the University's Honor Code. By enrolling in this course, you have agreed to abide by and uphold the Honor System of the University of Virginia, as well as the following policies specific to this course. All suspected violations will be forwarded to the Honor Committee, and you may, at my discretion, receive an immediate zero on that assignment regardless of any action taken by the Honor Committee. Please let me know if you have any questions regarding the course Honor policy. If you believe you may have committed an Honor Offense, you may wish to file a Conscientious Retraction by calling the Honor Offices at (434) 924-7602. For your retraction to be considered valid, it must, among other things, be filed with the Honor Committee before you are aware that the act in question has come under suspicion by anyone. More information can be found at http://honor.virginia.edu Your Honor representatives can be found at: http://honor.virginia.edu/representatives. Additionally, [Support Officer, if any enrolled], an Honor support officer enrolled in this class, is also available for questions.

Inclusive Environment

It is my goal to create a learning experience that is as accessible as possible. If you anticipate any issues related to the format, materials, or requirements of this course, please meet with me outside of class so we can explore potential options. Students with disabilities may also wish to work with the Student Disability Access Center to discuss a range of options to removing barriers in this course, including official accommodations. Please visit their website for information on this process and to apply for services online: sdac.studenthealth.virginia.edu. If you have already been approved for accommodations through SDAC, please send me your accommodation letter and meet with me so we can develop an implementation plan together.