

AIPI 531: Deep Reinforcement Learning Applications
Fall 2023: Course Syllabus

Course Times

Thursdays 7:00 pm-9:45 pm EST Zoom

Class meetings are recorded and available for asynchronous viewing via Sakai.

Instructor

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Office Hours:

TBD by appointment (Zoom)

Teaching Assistant

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Office Hours:

TBD by appointment (Zoom)

Course Description

Deep Reinforcement Learning Applications will cover advanced sequential decision-making topics in AI and will consist of two parts focused on 1) deep reinforcement learning theory and 2) deep reinforcement learning applications. Deep reinforcement learning combines reinforcement learning and deep learning. The theory module will introduce students to major deep reinforcement learning algorithms, modeling process, and programming. The applications module will include case studies on the practical applications of deep reinforcement learning in industry. This is a project-based course with extensive Pytorch/Tensorflow hands-on exercises. Students will also have an opportunity to improve their GitHub profile by working on the projects.

The main case studies include:

Product recommendations and personalization for marketing/retail/E-commerce.

Pre-Requisites

Students are expected to understand the main concepts of calculus, linear algebra, and probability & statistics, as well as possess a foundational level of proficiency in Python programming, Git/GitHub, and command line operations. Students are also expected to have experience in training/testing machine learning (e.g., supervised learning and deep learning) models using Pytorch or Tensorflow. Knowledge of reinforcement learning is not required. We will review reinforcement learning in the course. Foundational level of proficiency in deep learning applications will be very helpful but is not required.

Learning Objectives

1. Identify types of problems (e.g., product recommendations, personalization) which deep reinforcement learning can help solve.
2. Explain and perform the steps of the deep reinforcement learning modeling process.
3. Explain the pros/cons, assumptions, mathematical intuition, and use cases for the major types of deep reinforcement learning algorithms.
4. Describe the distribution shift issue and online-offline tradeoff, and apply best practices in building good deep reinforcement learning models.
5. Evaluate and interpret deep reinforcement learning model performance.

Course Materials

Videos/slides/assignments:

- Any pre-recorded/live recorded video lectures can be found on the Sakai course site, and the lecture slides can be found in the **Resources** folder on the Sakai course site. For all class and home activities, the problem descriptions (pdf) can be found in the **Resources** folder on the Sakai course site. Starter code can be found on **Github**.

Optional textbooks:

- “Reinforcement Learning: An Introduction” by [Richard S. Sutton](http://incompleteideas.net/book/the-book-2nd.html) and Andrew G. Barto. The pdf can be downloaded for free at <http://incompleteideas.net/book/the-book-2nd.html>.

Online Courses:

- CS 285, Berkeley, <http://rail.eecs.berkeley.edu/deeprlcourse/>
- David Silver RL Lectures, <https://www.davidsilver.uk/teaching/>

Free software:

Part A:

- Google Colab (Pro):
- Pytorch: <https://pytorch.org/>
- Tensorflow: <https://www.tensorflow.org/>
- Stable Baseline 3: <https://github.com/DLR-RM/stable-baselines3>
- d3rlpy: <https://github.com/takuseno/d3rlpy>

Part B:

- ...

References:

- Personalized Machine Learning (Julian McAuley, UCSD): <https://cseweb.ucsd.edu/~jmcauley/pml/>
- DL recommenders: <https://arxiv.org/abs/2104.13030>

Class Communication

Important notices from the instructor will be sent out via **Sakai Announcements**. For questions and discussions, we will use **Ed Discussion** on the course Sakai site.

Course Schedule

Module	Week	Topic	HW
PART A: Theory	Week 1 (08/31)	Course Overview	
	Week 2 (09/07)	Introduction to Deep RL & Tools (Pytorch/RL Libraries)	
	Week 3 (09/14)	Policy Gradients Methods	HW 1 Assigned
	Week 4 (09/21)	Recharge Week	
	Week 5 (09/28)	Value Function Methods	HW 1 Due HW2 Assigned
	Week 6 (10/05)	Recharge Week	
	Week 7 (10/12)	Deep RL Algorithms	HW 2 Due
	Week 8 (10/19)	Recharge Week	
PART B: Applications	Week 9 (10/26)	Offline Reinforcement Learning	HW 3 Assigned
	Week 10 (11/02)	Recharge Week	
	Week 11 (11/09)	Product Recs: ML Recommenders	HW 3 Due
	Week 12 (11/16)	Product Recs: DL Recommenders	Take Home Assigned
	Week 14 (11/30)	Product Recs: Deep RL Recommenders - 1	
	Week 15 (12/07)	Product Recs: Deep RL Recommenders - 2	
Deliverable	(12/14)		Take Home Due

Course Grading

- 40% Take Home Final Challenge
- 30% Homeworks (3 HWs, 10% each)
- 30% Github Repository Maintenance & Improvement

Course Grade Scale

A curve may be applied to final grades at the end of the semester at the discretion of the instructor.

- 97-99: A+
- 94-96: A
- 90-93: A-
- 87-89: B+
- 84-86: B
- 80-83: B-

Class Policy

Students are expected to follow the Duke community standard:

- 1) I will not lie, cheat or steal in my academic endeavors, nor will I accept the actions of those who do
- 2) I will conduct myself responsibly and honorably in all my activities as a Duke student

While homework is open book and open internet, all answers, code etc is to be original. Any sources used must be cited – plagiarism is a violation. Homework, projects or exams that violate this class policy will receive zero credit.

All assignments including three homework assignments, quizzes and take home challenges should be done individually.