Syllabus for CS 4885 – CS 5080: Reinforcement Learning
TuTh 4:45-6:00 p.m., Eng 109
University of Colorado at Colorado Springs

Objective:	Develop an understanding of the basic concepts and techniques employed in reinforcement learning, where an agent learns by performing tasks in an environment. The initial part of the class will focus on the fundamentals of reinforcement learning to prepare the students to appreciate the latest advances in function approximation using neural networks or deep learning, to be covered in the second part of the class. Learn how reinforcement learning can be used in application areas. Learn by research and self-reading, and by hands-on project work. Be highly motivated and capable of learning on one's own.
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Office:	Osborne A-340
Office Hours:	MW 1:00-2:30 PM, or by appointment

Textbooks

There are two required textbooks, the top two below. We will cover selected material from these books as appropriate. When we discuss a topic, you are urged to find the relevant content in the books and read to get a fundamental as well as deep-learning based view of the topic.

- Our main text is *Reinforcement Learning: An Introduction, Second Edition* by Richard Sutton and Andrew Barto, MIT Press 2018 (SB). It is the bible of reinforcement learning. It covers the fundamentals of reinforcement learning, without getting much into the latest developments, i.e., the use of deep learning in reinforcement learning. It covers conceptual as well as mathematical details. The book is 525 pages long.
- The second textbook is *Grokking Deep Reinforcement Learning* by Miguel Morales, 2020, Manning. This is a much gentler introduction to reinforcement learning. The mathematical formulas are usually copied from Sutton and Barto. It has many worked out examples and Python code.
- A very helpful "book" is *Spinning Up in Deep RL!* by OpenAI (SUDR). It is an online tutorial site that enables one to start working quickly in deep reinforcement learning. It also has links to some of the best papers in deep reinforcement learning.
- If you want to get a background on deep learning, there are a lot of online resources. However, the most acclaimed one is *Deep Learning* by Ian Goodfellow, Yoshua Bengio and Aaron Courville, 2016. Goodfellow et al.'s book requires a bit of background to follow. You may also want to download (or, buy) a book or consult websites on how to use

deep learning with a framework like Keras, TensorFlow and PyTorch. Since we have a complete and separate class on Neural Networks, our coverage of this topic in this class will be brief; you will have to pick things up on your own.

Videos

You don't have to watch these, but if you want to get ahead, especially to get started with semester projects, it may be worthwhile to watch on YouTube one or more videos from the two series of videos, given below. Or, you can pick a topic within reinforcement learning and look for the video on that topic.

- David Silver, *Introduction to Reinforcement Learning*, 10 videos, 2015. Each about 100 minutes long.
- Emma Brunskill, Stanford University, *CS 234: Reinforcement Learning*, 16 videos, 2024. Each about 75 minutes long.

Libraries and Resources

- When it comes to machine learning programming, the easiest way to program is using Python. There are many libraries for RL programming. There is a good summary here: Awesome Deep Learning by kengz.
- Here is a list of key papers on Reinforcement Learning from OpenAI. Here is another list from Github. You can find many other lists, but you could get lost following them all. There are too many papers on any topic you look at; you have to discriminate—i.e., learn to be choosy in what you decide to read.

Topics

Appropriate material is available in the books listed above. You will have to find them and read them. You can use other sources as well. Handouts will be given as and when necessary.

Schedule of Topics

The schedule of lectures given in the accompanying table is tentative. I will give handouts when appropriate; these days, it is likely that handouts will be uploaded to Canvas in PDF form.

Number of Classes	**Topics**	Chapter
2	Class administration, Introduction to Reinforcement Learning	SB1
2	Finite Markov Decision Processes	SB3, M2
2	Monte Carlo methods	SB5
2	Proposal presentations, Proposal papers due	
3	Temporal Difference Learning, Q-learning, SARSA	SB6, M6, M7
2	RL with function approximation, Deep Learning: Value function approximation	SB9, M5, M8, M9
2	Midterm presentations, midterm papers due	
4	Function approximation with Deep Learning: CNN, DQN, Double DQN, Dueling DQN, etc.	papers, SUDR
4	Policy search methods	SB13, papers
4	Actor-Critic Methods	papers, handouts
2	Monte Carlo Tree Search	papers, handouts
2	Final presentations (last day of classes, possibly + final exam day)	

Grading Scheme

The grading scheme reflects that it is an advanced research and practice-oriented self-driven class. The grading scheme has been designed to allow for independent research and implementation, and development of presentation skills. The assumption is that each one of you is motivated and is willing to be self-reliant. A semester long project, with accompanying papers, is one of the main deliverables for the class.

Undergraduate vs. Graduate Students: Since the class is relatively small, undergraduates have the choice of working alone on the semester projects or in groups of two, whereas the graduate students will work on their own. However, since there is only one undergraduate registered in class as of 1/19/2026, he will have to work alone. Graduate students papers are expected to be of higher quality than undergraduates, showing deeper understanding of the topics, with more references and better results. Each student will work on the homework assignments individually.

Grading for the class will be based on a class project, homework assignments, class participation and one or more short question to be answered on Canvas quickly on a regular basis. Each student will complete a substantial class project during the semester, as mentioned. From time to time, you will be required to present your progress on the project to the class, as specified below. Class participation will be evaluated in terms of physical presence in the class, reading the assigned material and participating in discussions in a manner that reflects the knowledge acquired from reading..

Semester Project: 50% of the class grade is based on a semester project. This includes 3 write-ups and 3 presentations.

- *Proposal*: The class prorject proposal is 2-3 pages long, written using LaTeX. Undergraduates should have at least 5 references from conferences and journals (no webpages) and graduates at least 10. You will talk to the class for about 10 minutes (depending on the number of students in the class) regarding what you want to accomplish in the class project. The exact amount of time will be announced before the presentations; you need to speak for the time given, not shorter or longer. The proposal presentation document and the presentation are worth 2.5% of the class grade. The proposal paper is worth 5%. The projects are expected to use modern or deep reinforcement learning. Theoretical topics are okay too, but concept implementations will be appreciated. The idea is that you learn from the project yourself, and also we all learn from what you do in the project.
- *Mid-term Exam*: The mid-term exam will be worth 12.5% of the class grade. It will be comprised of a presentation, (2.5%) a paper (7.5%) and a demo (2.5%) of your class project accomplishments so far. You will do a presentation that is about 10 minutes long, again depending on the number of speakers. The write-up will be 4-5 pages. There should be at least 10 references. You will do the demo during office hours. You *must* make visible progress by the mid-term date to get full credit. I.e., you must have some implementation by this date, even if it is very simple, followed by analysis of your approach and results.
- *Final Exam*: The final exam is worth 30% of the class grade. The final exam will be comprised of a slightly longer presentation (5%), a paper (17.5%) and a demo (7.5%) of the class project. The write-up will be 6-8 pages long. You will demo the final accomplishments for the project before the day of the final exam.

Homework Assignments: There will be three to four homework assignments. Assignments are worth 45% of the grade. Graduate students may have additional work compared to undergraduates. You will have to hand in a 2-4 page paper, written as if it is a conference paper, with a section for each of the questions asked in the assignment. It will have a title, abstract, introduction and conclusions sections as well, along with any necessary references. If you can, it is always a great idea to go beyond what is asked. In case you do substantial additional work, extra credit may be given. Each homework assignment will have to be demoed.

Short Questions: 15% of the grade will be based on your answer to one or more short questions based on lecture content at the end of a number of classes, to be answered briefly on Canvas or with PDF upload.

Class Participation: 5% of the grade will be based on class participation. You should read ahead, read the material taught by finding suitable chapters/sections in the books listed above and/or anywhere else you like, and be able to participate in class discussions. Regular attendance is absolutely necessary.

Format

Papers: Use AAAI author style in LaTeX (no Microsoft Word!) for all your reports[1]. Your papers—proposals, mid-term and final reports—must read (in terms of content) and look (formatting) professional, as if ready for "submission" to a reputed conference (e.g., AAAI, ICML, IJCAI) or a journal (e.g., Machine Learning, Machine Learning Research, an IEEE journal), without any additional changes. It is a semester project and results are not expected to be publishable quality, but you should do the best possible work you can. Generally speaking, only 50-60% or so of research is actual work and the rest is how it's communicated, i.e., the paper you write and the way you present, if you are invited to present somewhere. If you need to get your papers proofed by someone, please do so before you submit it to me. You will lose points if a paper has lots of spelling or grammatical errors, or doesn't follow the format requested.

Presentations: As mentioned earlier, you have to do a brief proposal presentation for your semester project in the class. You will also have to do a mid-term presentation and a final presentation. All presentations will be in a conference-like format using PowerPoint or a LaTeX-based presentation library. The amount of time you have for the three presentations will depend on the number of students enrolled in the class at the time. Please practice your presentations and make them well-structured, with a smooth flow, with good technical and relevant vocabulary. The presentation slides must be uploaded by noon on the date when your presentation is scheduled to Canvas.

Semester Project Proposal Presentations:	2/17,19 (maybe partial)
Project Proposal Report:	2/19/2026
Midterm Presentations:	3/31,4/1 (maybe partial)
Midterm Project Report:	4/1/2026
Midterm Project Demo:	The week of 4/1/2026
Final Exam Presentations:	5/7 (possibly partial), 5/12/2026—12:40-2:40
Final Report:	On or before 5/12/2026
Final Demo:	Week of 5/12/2026

The proposal presentations will be in alphabetical order by last name; if there are two presenters, the earlier last name will be used to sort. The midterm presentations will be in reverse alphabetical order. The final presentation order will be obtained by a random draw of names, and announced the prior week.

Presentations Schedules are Firm: If you have special reasons for not being able to hand in an assignment on time or take an examination (i.e., make presentation or hand-in paper) on a scheduled date, please make prior arrangements. If you cannot make the presentation on

[1] On Google, search for "AAAI Author Kit" to find the style files.

the day of your presentation for unavoidable reasons, you will have to make a video recording of your presentation available for streaming/playing along with your slides during the scheduled time, unless you are (genuinely) sick or unable and there is proof of it. Already, a lot of class periods are scheduled for student presentations and no other days will be spent on them. In general, *without a presentation on the scheduled date or a streamed recording of it available on that date, you get zero for it.*

Honesty: All writing must be yours. You can use AI tools for grammar and spell-checking only, not for content. Anything copied from a source, including AI authors like ChatGPT must be quoted and attributed. The quoted content cannot be more than 5% of a paper. The first instance of plagiarism will lead to a grade of F on the relevant deliverable. Two or more instances will lead to an F in the class. Egregious cases will be reported to the department and the campus, and may lead to expulsion from the university.