Spring 2024 Syllabus

RO3002: Reinforcement Learning Fundamentals

Instructors: Prof. Sandeep Manjanna

Units:	3 (3 hr. lectures)
Expected Workload:	This course is worth 3 units of credit (3 credit for lectures). You should expect to work an average of 9 hours per week on this course to achieve the learning outcomes and earn a passing grade in this course. You will spend 5 of these hours attending and studying the weekly lectures, with the remaining 4 hours allotted to weekly practicing and check for understanding and working upon practice problems, homework assignments, and project. Some weeks may require more work and others less, but on average please plan to devote a total of 9 hours per week to your success in this course.
Catalog Description:	This course introduces the fundamental concepts and techniques of reinforcement learning (RL). Students will learn the basics of RL, explore key algorithms, gain practical experience through coding assignments, and discover real-world applications. Topics include Multi-armed Bandits, Markov Decision Processes, Q-Learning, Policy Gradient methods, Deep Reinforcement Learning, Multiagent RL, and Inverse RL. By the end of this course, students will have a strong foundation in RL and the ability to apply these concepts to practical problems.
Lectures:	M, W, and F 12:00 pm to 12:50 pm Classroom: 1001
Teaching Assistants and Office Hours:	Poonam Adhikari (Office Hour: Mon 2:00 to 3:00 pm) Keshav Sivakumar (Office Hour: Wed 11:00 to 12:00 pm) Instructor Office Hour: Mondays 3:00 to 4:00 pm

Course Objectives:

After successful completion of this class, the students will be able to:

Objective	Bloom's Taxonomy
1. Understand Reinforcement Learning Concepts: Define key concepts such as agents, environments, rewards, policies, and value functions.	Understand
2. Learn, apply, and implement basic Reinforcement Learning Algorithms: Introduce foundational reinforcement learning algorithms such as Q-learning, SARSA, and Monte Carlo methods.	Understand, Apply, Analyze,
3. Understand Markov Decision Processes (MDPs) and Explore Exploration and Exploitation Trade-offs.	Apply, Analyze, Synthesize
4. Apply reinforcement learning concepts through hands-on programming exercises using popular libraries like TensorFlow or PyTorch.	Apply, Analyze
5. Learn Model-Free and Model-Based Approaches. Evaluate and Analyze RL Models. Examine real-world applications of reinforcement learning in fields such as robotics, gaming, finance, and healthcare.	Understand, Apply, Create, Synthesize
6. Apply knowledge gained throughout the course in a comprehensive capstone project, demonstrating proficiency in reinforcement learning. Foster collaboration and communication skills through group projects, discussions, and presentations.	Apply, Create, Evaluate, Synthesize

Course website:

All course-related materials will be posted on the learning management system site. Activities/readings for each week will also be posted in weekly Modules.

Helpful Resources:

Reviews:

- Review of Linear Algebra : https://www.cs.mcgill.ca/~dprecup/courses/ML/Materials/linalg-review.pdf
- Review of Probability Theory: https://www.cs.mcgill.ca/~dprecup/courses/ML/Materials/prob-review.pdf

Other online courses:

- Reinforcement Learning by Prof. Balaraman Ravindran at IIT Madras.
- Foundations of Intelligent and Learning Agents by Prof. Shivaram Kalyanakrishnan at IIT Bombay.
- Reinforcement Learning by David Silver at Google DeepMind

GitHub Implementations:

- https://github.com/ShangtongZhang/reinforcement-learning-an-introduction

Required Textbook:	• **Textbook**: **An Introduction to Reinforcement Learning, by Sutton and Barto** MIT Press, Second edition Available free online! https://www.andrew.cmu.edu/course/10-703/textbook/BartoSutton.pdf • **Reference Book**: **Algorithms for Reinforcement Learning, by Szepesvari** Morgan and Claypool Publishers, 2010 Available free online! https://sites.ualberta.ca/~szepesva/papers/RLAlgsInMDPs.pdf
Academic Integrity:	It is expected that all students maintain their utmost integrity, as described in the Plaksha Academic Policy.
Assessment:	The assessments will comprise of the following (Subject to change): 50% for coursework • In-class surprise quizzes: 15% • In-class participation: 5% • In-class exams: 30% 50% for the project • Project proposal: 5% • Mid-term progress report: 10% • Final project presentation: 10% • Final project report and code: 25% # All homework and assignments need to be uploaded to BrightSpace in the format specified. Please note the following: Up to 10% may be deducted per working day late for a submission. Any re-grade request s for homework or assignments or exams must be made within one week of the return in class / lab.

RO3002: Reinforcement Learning Fundamentals (subject to change**):**
The syllabus is approximate. Lectures may occur in a slightly different order and some topics may end up taking less or more time than the predicted time.

Module	Week	Month	Topic	Reference Material
Introduction	1	Jan	Course Overview, RL Framework	Chapter 1
Multi-armed Bandit Problem	2	Jan	Bandit Algorithms, Value function	Chapter 2
	3	Jan	Upper Confidence Bound, Thompson Sampling	Chapter 2
Markov Decision Process	4	Feb	MDP modelling, Bellman equation, Optimal Policies, and Optimal Value functions	Chapter 3
	5	Feb	Dynamic Programming,	Chapter 4
	6	Feb	Value Iteration, Policy Iteration	Chapter 4
Monte Carlo Methods	7	Feb	Monte Carlo Prediction, Estimation, and Control	Chapter 5
	8	Mar	Off-policy prediction and Off-policy Monte Carlo Control	Chapter 5
Midterm	9	Mar	Midterm project review	
	10	Mar	Midterm exam week + Break	
Temporal Difference Learning	11	Mar	TD(0), Sarsa, Q-learning	Chapter 6
Policy Gradient Approaches	12	Apr	REINFORCE, Policy Gradient Theorem	Chapter 13
	13	Apr	Exploration and Exploitation	
Deep RL	14	Apr	DQN, Actor-critic	
Imitation Learning	15	Apr	Imitation learning vs. Inverse RL	
Final Project Review	16	May	Final Project Demo / Presentation	