

DS-GA 3001.007

Reinforcement Learning

Professor Jeremy Curuksu

Center for Data Science

New York University

jeremy.cur@nyu.edu

Syllabus

Overview:

Reinforcement Learning (RL) is the *science of learning to make decisions from interactions with an environment*. The goal of this course is to understand the entire range of reinforcement learning methods and applications, and teach the tools necessary both to formulate RL problems and develop RL solutions. The lectures cover fundamental and more advanced concepts. The labs focus on case studies implementing RL agents in simulation environments. The homework cover both. In contrast to supervised and unsupervised learning, by interacting with an environment reinforcement learning methods can learn optimal decisions from limited data and/or feedback (labels), including "sequential" decisions in order to reach a preset, potentially delayed goal. Advances in RL applications such as video games, board games, robotics and autonomous driving, have recently been made by combining RL with function approximation methods. These include deep learning and tree search which enable generalizing to very large state-action spaces e.g., an RL agent developed in 2016 defeated the world human champion at the boardgame Go which has over 10^{170} possible positions, by learning patterns across the space of all possible positions. The course progressively builds on mathematical concepts leading up to these recent RL developments, practices implementation of key RL algorithms in Python, and closes with a review of industrial applications and RL development frameworks.

Prerequisites:

Intro to Data Science (DS-GA 1001), Machine Learning (DS-GA 1003), or similar

Topics covered:

The class covers the following material.

There may be some changes to best fit the class.

- **Introduction to Reinforcement Learning Problems and Solutions:** The first lecture introduces key RL concepts: agent, environment, states, actions, goals, rewards, policy *vs.* value optimization, Bandit *vs.* sequential decision making, exploration *vs.* exploitation, and the OpenAI Gym library
- **Multi-armed Bandit:** Action values methods, ϵ -greedy, Upper Confidence Bound, policy-gradient, Bayesian methods, contextual Bandit
- **Markov Decision Process and Dynamic Programming:** MDP model for sequential decision problems, state-value function, action-value function, Bellman equations, iterative algorithms using asynchronous dynamic programming
- **Model free RL Prediction and Control:** Sampling sequences of state-action-reward, Monte Carlo, Temporal Difference, bias-variance tradeoff, n -step TD/TD(λ), off-policy learning, importance sampling, tracking *vs.* convergence
- **RL with Function Approximation:** Generalization of RL to large state-action spaces, semi-gradient descent, feature engineering and linear approximation, non-linear approximation with deep neural network, DQN, DDQN
- **Reinforcement Learning using Policy Optimization:** Parametric policy function, Policy Gradient Theorem, Reinforce, Actor-Critic, A3C, PPO, DDPG
- **Planning from a RL Model:** Stochastic (generative) models, trajectory sampling, integrated planning, acting and learning, experience replay, prioritized sweeping, Dyna, Monte Carlo Tree Search, DeepMind AlphaGo and AlphaZero
- **Examples of Industrial Applications:** RL in video gaming, autonomous driving, robotics, finance, retail, energy, natural language processing, chatbots
- **Advanced RL Topics:** Continuous state-action space, inverse RL, adversarial RL, multi-agent RL, RL in neuroscience and psychology
- **Distributed RL Frameworks:** DeepMind Acme, AWS SageMaker RL, Meta AI ReAgent, Ray RLlib, Intel AI Coach

Labs and Project:

The labs focus on concrete case studies though examples implementing RL solutions in Python, with optional exercises. Each session covers a key RL topic covered during the lecture. Case studies will range from classical control use cases (Black Jack, Cart Pole, Moon Lander, Frozen lake, Multi-Armed Bandits, Grid Lock) and simple video games (Breakout, Space Invader, Flappy Bird, Super Mario Bros) to more custom applications such as financial trading, robotics and natural language processing.

The project consists in proposing a reinforcement learning problem and developing a solution to this problem. A complete project description and list of recommended RL problems will be posted on Brightspace within the first week of the semester.

Day, Time and Place

DS-GA 3001.007 Lecture

Thursdays from 4:55pm-6:35pm EST

Location: GCASL, 238 Thompson St, Room 361

DS-GA 3001.008 Lab

Wednesdays from 8:10pm-9:00pm EST

Location: Bobst Library, Room LL138

Teaching Assistants

- Anudeep Tubati, at5373@nyu.edu
- Shreya Sinha, ss14468@nyu.edu

Lecture Notes, Textbook & Documentation

- The material provided during the Lectures and Labs is sufficient for this course, but is best when complemented by reading the following material
- Recommended textbook: "Reinforcement Learning: An introduction" (2018) by R. Sutton and A. Barto (free online version also available: Sutton & Barto)

- The main open source RL library used in this course (in addition to standard Python and Tensorflow libraries) is OpenAI Gym (maintained as Gymnasium since 2022), which has a freely accessible, online documentation, and which we recommend you consult regularly during your practices

Grading Policy

- Homework during the whole semester: 50% of the final grade
- Final Project at the end of the semester: 50% of the final grade