Reinforcement Learning

Introduction

Michael Herrmann, David Abel Slides by Stefano V. Albrecht 14 January, 2025

- Course details and admin
- What is reinforcement learning?

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• Examples

Course Team

Course organiser:

• Dr. Michael Herrmann

Co-lecturer:

• Dr. David Abel

TAs:

- Qiyue Xia
- Adam Jelley (tutorials)
- Eric Liu (tutorials)
 - ... and others

Course page:

• https://opencourse.inf.ed.ac.uk/rl

Announcements:

• via course page ("Announcements"), via Learn and by email to rl-students@inf.ed.ac.uk

Lectures:

- Time: Tuesdays & Fridays, 14.10–15.00
- Place: 40 George Square, Lecture Theatre B
- Lectures will be recorded (see "Lecture Recordings")

First half of course based on:

Reinforcement Learning: An Introduction (2nd edition)

Richard Sutton & Andrew Barto

MIT Press (2018)

Download free PDF: http://incompleteideas.net/book/ the-book-2nd.html (2022 version)



For the second half of course this book will be useful:

Multi-Agent Reinforcement Learning: Foundations and Modern Approaches

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer MIT Press (2024)

> Download free PDF: https://www.marl-book.com

MULTI-AGENT REINFORCEMENT LEARNING

FOUNDATIONS AND MODERN APPROACHES



Stefano V. Albrecht Filippos Christianos Lukas Schäfer

- Multi-armed bandits
- Markov decision processes
- Dynamic programming
- Monte Carlo methods
- Temporal-difference learning

- Tutorial lecture: Building a RL system
- Value function approximation
- Policy gradient methods
- Deep reinforcement learning
- Current research in RL

Highly recommended to read the corresponding book chapters

Tutorials:

- Weekly, in weeks 2–10 (mostly on Wednesday)
- Not graded, but attendance will be monitored
- Tutorial sheets released Tuesday noon of previous week (on course page)
- Solutions released in following week
 - \Rightarrow See "Tutorials" page on course page for more details

Assignment to tutorial slots is done automatically by ITO

 \Rightarrow Use the form at Timetabling (Registry Services), if you need to change your slot

Coursework — 50% of final grade

- Implement and test RL algorithms in Python
- Out: 11 Feb / Due: 28 March (noon)
- Lab sessions in weeks 6–9
- Coursework will be introduced in lecture on 11 Feb



Exam — 50% of final grade

- Testing theoretical and applied knowledge
- Any material covered in *required readings* and *associated lectures* is examinable (excluding exercises and examples in RL book)
- Exams from previous years: https://exampapers.ed.ac.uk

Discussion Forum and Office hour

We use **Piazza**:

- Forum to post and discuss questions with peers
- Link to Piazza forum on course page
- Your fellow students as well as TAs and lecturers will answer questions
 - \Rightarrow First check whether your question has been answered, then post
 - \Rightarrow Use the folders to organise posts (makes it easier for people to find questions)
 - \Rightarrow Explain your thinking and where you are "stuck"

Office hour: Wednesdays, 4:10pm - 5pm, IF 1.42 (Michael H)

• Any issues where Piazza or tutorials are not suitable.

Maths:

- Basic statistics and probability theory
- Linear algebra and calculus (vectors, derivatives, limit analysis)
- See also last year's exam for maths requirements

Programming:

- Advanced programming for coursework (we use Python)
 ⇒ Course is <u>not</u> an introduction to programming!
- Use our Coding Proficiency Self-Check PDF on OpenCourse page

- "The lecture content was great."
- "Lecture was quite difficult to keep up with and felt rushed."
- "Slow down the lectures slightly to allow more time for questions."
- "I found the drawings in the tutorials (frog, monkey etc) confusingly weird and unclear (maybe its an artist view)."
- "In the labs, probably a 10 min introduction on what we're going to learn today."
- Coursework-related feedback will be discussed with CW release

More feedback from last year: Advice for this year's students

- "Read RL book to be in the loop with the lectures."
- "Go to tutorial. I found lecture extremely hard to keep up with, and the tutorial is the only way I managed to hold on."
- "Must attend tutorials."
- "You must know Python Fundamentals and have a decent mathematics background."
- "Also, be sure to practice pytorch before starting the coursework, as a lot of the CW relies on it"
- "Start coursework as soon as it is released."
- "For the coursework: Try to work on it weekly and visit each drop-in lab to ask questions."

Reading group meetings to discuss recent research papers

- Open to all students, but basic RL knowledge assumed
- Read paper before meeting to participate actively in discussion
- Sign up here:

https://agents.inf.ed.ac.uk/reading-group/

Questions about the course?

Learning to solve sequential decision problems via **repeated interaction with environment**

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Learning to solve sequential decision problems via **repeated interaction with environment**

- What is a sequential decision problem?
- What does it mean to "solve" the problem?
- What is learning by interaction?

What is Reinforcement Learning?



What is Reinforcement Learning?

Agent takes actions in environment

- Take action, observe new state and reward from environment
- Goal is to maximise total rewards received
 - \Rightarrow Learning: find best actions by *trying* them





• Agent: chicken



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- Environment: flat table with coloured circles



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- Actions: motor control of legs, beak.



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- Environment: flat table with coloured circles
- Actions: motor control of legs, beak.
- Reward: curiosity, food.



The Many Disciplines of RL



Thanks to Dave Silver for the inspiration for the diagram

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- Manage investment portfolio: reward?

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- Reach target state s*: reward is 1 if $S_t = s^*$, else 0 (or -1? what's the difference?)
- Win Chess game: reward is +1 if won, -1 if lost, 0 otherwise
- Manage investment portfolio: reward?
- Make humanoid robot walk: reward?

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Discussion Question (2 minutes): Is this true? False? What are some other goals or tasks that can be described through maximization of scalar values?

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Reinforcement learning is third category of ML: learning to act to maximise rewards

Reinforcement Learning Challenges

Key challenges in RL

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When to try new actions (*explore*)? When to stick with what we think is best (*exploit*)?

Reinforcement Learning Challenges

Key challenges in RL

• Unknown environment:

How do actions affect environment state and rewards?

• Exloration-exploitation dilemma:

When to try new actions (*explore*)? When to stick with what we think is best (*exploit*)?

• Delayed rewards:

Actions may have long-term consequences and affect future rewards When we get reward, which prior actions led to it? (*credit assignment*) Learning to play Backgammon (Tesauro, 1992-1995)





estimated state value (≈ prob of winning)



Start with a random Network

Play millions of games against itself

Learn a value function from this simulated experience

Six weeks later it's the best player of backgammon in the world Originally used expert handcrafted features, later repeated with raw board positions

Slide source: Richard Sutton 25

Learning to play Atari games (Mnih et al., 2013, 2015)



Video: DQN in Atari games

Learning to keep the ball in team (Stone et al., 2005)



Video: keepaway soccer Source: http://www.cs.utexas.edu/~AustinVilla/sim/keepaway

Example: Walking

Learning to walk and jump (DeepMind, 2017)



Video: learning to walk Source: https://www.youtube.com/watch?v=gn4nRCC9TwQ

Example: Autonomous Driving

IGP2 autonomous driving system (Five AI, 2021)



Video: IGP2 autonomous driving system
 Source: https://www.five.ai/igp2

Mobile robots and humans managing a warehouse (Dematic/KION, 2022)



Video: Multi-robot warehouse Source: https://sites.google.com/view/scalablemarlwarehouse

Reinforcement Learning: The Big Picture



Learning how to act

Reading

Required:

• RL book, Chapter 1 (1.1–1.4)

Optional (for keen students):

- Silver et al.: "Reward is enough". Artificial Intelligence (2021) https://doi.org/10.1016/j.artint.2021.103535
- List of survey papers for RL: https: //agents.inf.ed.ac.uk/blog/reinforcement-learning-surveys/
- Past MSc dissertations in RL: https://agents.inf.ed.ac.uk/blog/master-dissertations/