

Reinforcement Learning

Introduction

Stefano V. Albrecht, Michael Herrmann

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THE UNIVERSITY *of* EDINBURGH
informatics

Lecture Outline

- Course details and admin
- What is reinforcement learning?
- Examples

Course organiser:

- Dr. Stefano V. Albrecht
- Dr. Michael Herrmann

TAs:

- Mhairi Dunion
- Trevor McInroe
- Adam Jelley (tutorials)
- Eric Liu (tutorials)

Course page:

- <https://opencourse.inf.ed.ac.uk/rl>

Announcements:

- via course page (“Announcements”) and email to rl-students@inf.ed.ac.uk

Lectures:

- Time: Tuesdays & Fridays, 14.10–15.00
- Place: Appleton Tower Lecture Theatre 1
- Lectures will be recorded (see “Lecture Recordings”)

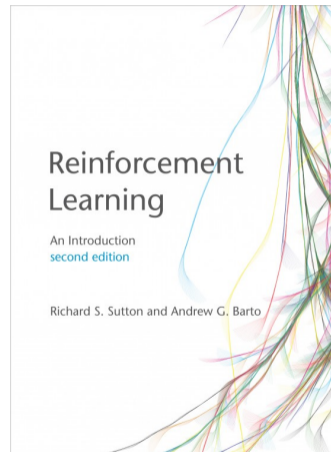
Course book:

Reinforcement Learning: An Introduction (2nd edition)

by Richard Sutton & Andrew Barto

Download free PDF:

<http://incompleteideas.net/book/the-book-2nd.html>



New: The MARL Book

New book published by MIT Press (2024):

Multi-Agent Reinforcement Learning: Foundations and Modern Approaches

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer

Download free PDF:

<https://www.mar1-book.com>

Multi-Agent Reinforcement Learning: Foundations and Modern Approaches

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer

To be published by MIT Press
(print version scheduled for fall 2024)

Course Topics

- Multi-armed bandits*
 - Markov decision processes*
 - Dynamic programming*
 - Monte Carlo methods*
 - Temporal-difference learning*
 - Planning*
 - Tutorial lecture: building a RL system
 - Value function approximation*
 - Policy gradient methods*
 - Deep reinforcement learning
 - Multi-agent reinforcement learning
- *Examined - based on chapter in RL book*

*Highly recommended to read chapter/slides **before** lecture!*

A note on notation:

- RL book uses notation S_t, A_t, R_{t+1} (reward received at $t + 1$), $p(s', r|s, a)$

We will use this notation for lectures that are based on the RL book

- Other notation also widely used (e.g. in MARL book)
e.g. $s^t, a^t, r^t, T(s, a, s'), R(s, a)$

Tutorials:

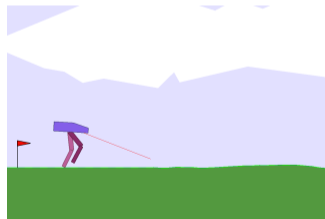
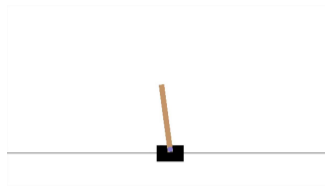
- Weekly, in weeks 2–10
 - Optional attendance – not graded
 - Tutorial sheets released Tuesday noon of previous week (on course page)
 - Solutions released in following week
- ⇒ See “Tutorials” page on course page for more details

Assignment to tutorial slots is done automatically by ITO

⇒ **Contact ITO if you need to change your slot**

Coursework — 50% of final grade

- Implement and test RL algorithms in Python
- Out: 13 Feb / Due: 31 March
- Lab sessions in weeks 5–8
- Coursework will be introduced in lecture on 13 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>

We use **Piazza**:

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

Course Pre-requisites

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 not an introduction to programming!**
- Use our **Coding Proficiency Self-Check** PDF on course page

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?

What is Reinforcement Learning?

Reinforcement learning (RL):

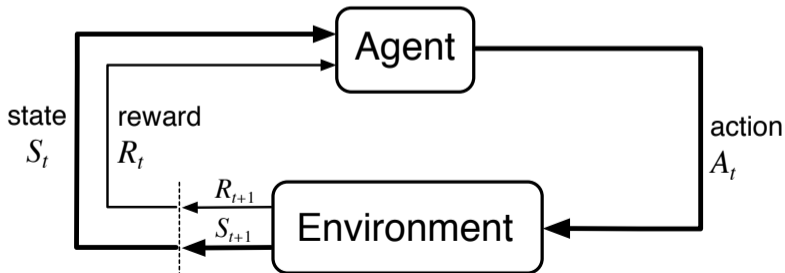
Learning to solve sequential decision problems via **repeated interaction with environment**

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

What is Reinforcement Learning?

Agent takes actions in environment

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



What is Reinforcement Learning?

Example: human infant learning

- Agent: baby
- Environment: physical workspace with coloured rings and stacking pole
- Actions: motor control of arms, legs, ...
- Reward: curiosity, satisfaction upon completion (rings stacked)

Agent does not know what actions to take

⇒ *Must discover!*



Video: ring stacker

Reward Hypothesis

Reward hypothesis:

All goals can be described by the maximisation of the expected value of cumulative scalar rewards.

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- Manage investment portfolio: reward?
- Make humanoid robot walk: reward?

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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*)?
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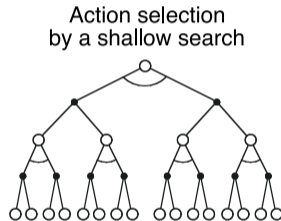
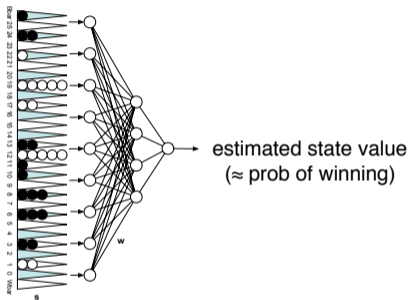
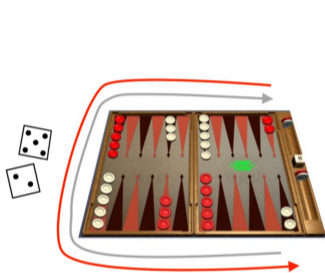
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How do actions affect environment state and rewards?
- **Exploration-exploitation dilemma:**
When to try new actions (*explore*)?
When to stick with what we think is best (*exploit*)?
- **Delayed rewards:**
Actions may have long-term consequences and affect future rewards
When we get reward, which prior actions led to it? (*credit assignment*)

Example: Backgammon

Learning to play Backgammon (Tesauro, 1992-1995)



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

Example: Atari

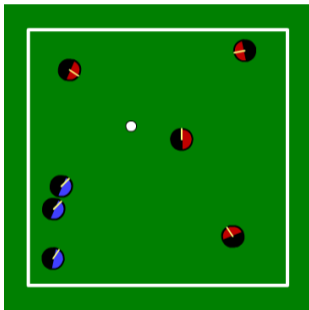
Learning to play Atari games (Mnih et al., 2013, 2015)



Video: DQN in Atari games

Example: Soccer

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: Starcraft II

Starcraft Multi-Agent Challenge (Samvelyan et al., 2019)

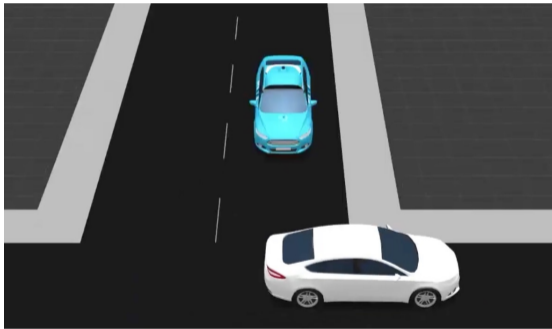


Video: SMAC

EPyMARL codebase: <https://github.com/uoε-agents/epymar1>

Example: Autonomous Driving

IGP2 autonomous driving system (Five AI, 2021)

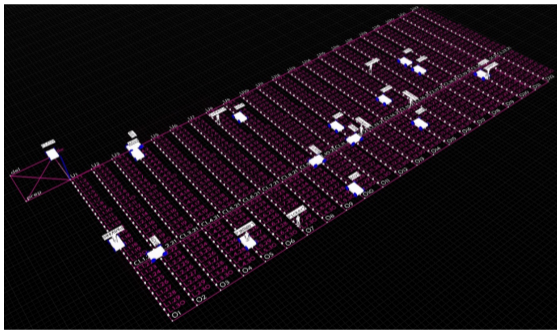


Video: IGP2 autonomous driving system

Source: <https://www.five.ai/igp2>

Example: Warehouse Control

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



Video: Multi-robot warehouse

Source: <https://sites.google.com/view/scalablemarlwarehouse>

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/>