Learning to Walk Efficiently

Reinforcement Learning Summative Assignment

Epiphany Term 2025

Cover sheet

Module code and title	COMP3667 Reinforcement Learning	
Academic year	2024-25	
Coursework title	Setup	Final Submission
Coursework credits	1 credit	9 credits
% of module's final mark	10%	90%
Lecturer	Robert Lieck	
Submission date*	Thursday, 13 March 2025 at 14:00	Tuesday, 6 May 2025 at 14:00
Estimated hours of work	2 hours	18 hours
Submission method	Ultra	

* This is the deadline for all submissions except where an approved extension is in place. For benchtests taking place in practical sessions, the given date is the Monday of the week in which the benchtests will take place.

Late submissions received within 5 working days of the deadline will be capped at 40%. Late submissions received later than 5 days after the deadline will receive a mark of 0. It is your responsibility to check that your submission has uploaded successfully and obtain a submission receipt.

Your work must be done by yourself (or your group, if there is an assigned groupwork component) and comply with the university rules about plagiarism and collusion. Students suspected of plagiarism, either of published or unpublished sources, including the work of other students, or of collusion will be dealt with according to University guidelines.

Introduction

This assignment consists of two parts, the *Setup* (10%) and the *Final Submission* (90%). Both are identical in terms of what has to be submitted (number and structure of files, see below) and differ only in how it is being evaluated. For the *Setup*, completeness and formal correctness of the submission is the main criterion, the actual performance not evaluated. The *Final Submission* also has to be complete and formally correct, but the evaluation focuses on the quality of the results and the report.

The assignment is to train a bipedal robot to learn to walk efficiently in a 2D physics simulation. It should be *sample efficient*, learning with the least amount of interaction with the environment as possible, and also it should learn to walk *quickly*—eventually running as quickly and smoothly as possible. In the *Setup* assignment, it is only evaluated if you are able to train an agent at all (i.e. provide correct log files etc. as described below), while in the *Final Submission*, it is evaluated how well the agent has actually learned to walk and how quickly it has learned.

You are to write a short scientific report for the method, experimental results, and limitations in a provided LaTeX template that closely follows parts of the ICLR conference style guidelines. For the *Setup* assignment, you can simply submit the report template unchanged. You are to also provide a video of the agent and a log file as later explained. These files must all be zipped together, replacing the dummy username (`xxxx00`) with your CIS username (this is the same for both *Setup* and *Final Submission*):

```
xxxx00.zip
   xxxx00-agent-paper.pdf
```

```
xxxx00-agent-code.ipynb (or .py)
xxxx00-agent-log.txt
xxxx00-agent-video,episode=210,score=85.mp4
xxxx00-agent-hardcore-log.txt
xxxx00-agent-hardcore-video,episode=350,score=-92.mp4
```

You may not submit any additional files. To assist in this, the following template reports and starter code are provided to build on:

- [Reinforcement Learning Paper Template]
- [Google Colab Coursework Template Starter Code]

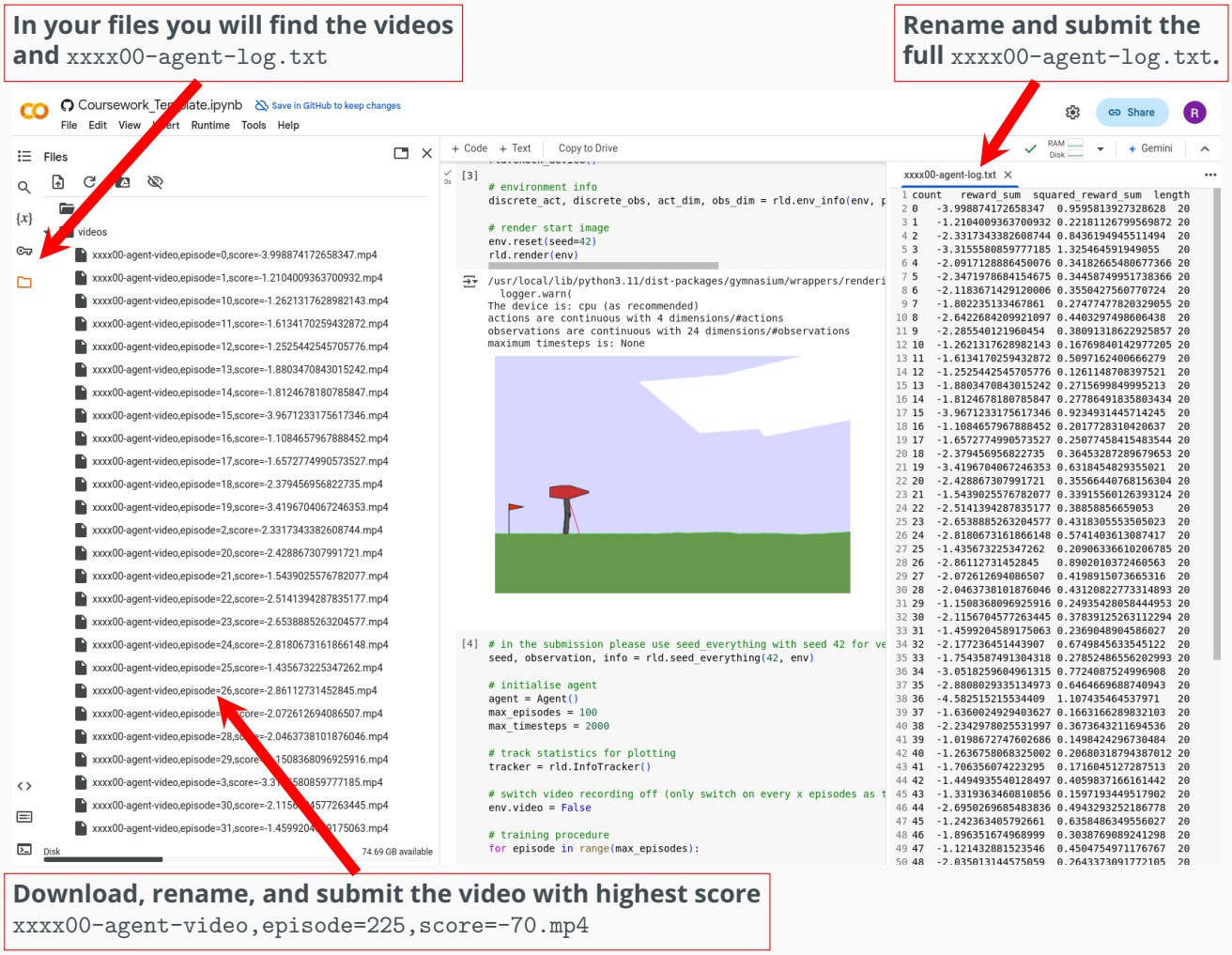
Note: The only difference between *Setup* and *Final Submission* is how these files are evaluated. For *Setup* you only need to have code for a basic training loop set up and running and provide correctly formatted log files and videos; your report can just be the template. For the *Final Submission*, we will evaluate the quality of your final report and how good your agent performs in the environments (see below).

Learning to walk efficiently

The task is to use deep reinforcement learning to train a small bipedal robot to learn to walk efficiently. This means you will be marked on how quickly you can train the agent to learn to walk by taking the smallest amount of environment steps possible. You will first develop and train your agent in an easy version of the `rldurham/Walker` environment (`hardcore=False`) and, in a second step, run it in a much more challenging version (`hardcore=True`). Both environments are based on the BipedalWaker environments provided by Gymnasium, which uses Box2D for its physics simulation. Use the previously linked code to get started. After your agent consistently gets scores over 300 and you are happy with how quickly it converges when trained from scratch in the easy version, you should transition to the more challenging one.

Submission

You must submit the full `xxxx00-agent-log.txt` and you must not change how its contents are formatted. The submitted video should show the highest score that you are able to successfully record. Repeat this also for any experiments you have conducted in the hardcore environment. Recording a video is quite slow, so you may wish to do it every 25 or more episodes. Increasing this interval may slightly improve training performance, but you may miss recording a good episode. The following image explains how and what to submit:



The code submission must be written with clarity and minimalism. You can submit an .ipynb or .py file. You do not need to strictly follow PEP-8 or any departmental guidelines for code quality with this assignment and may keep comments to a minimum.

Restrictions

The log files must be collected in exactly the same way as the template code as we will run an automated marking script on them for assessing the algorithm convergence and score. You must submit at least 1000 episodes of log data (unless your agent consistently reaches optimal scores in fewer than 1000 episodes). Please keep the max environment step count as 2000. The paper.pdf is restricted to a maximum of 4 pages (excluding references). Every page over this will incur a -10 mark penalty.

You can implement any RL algorithm that you like in your final solution. You do not necessarily have to use backpropagation, however you should use *deep* reinforcement learning (so the agent must be deep in the sense that it needs to have multiple layers).

Hardcore mode

After your agent consistently scores over 300 in the `Walker(hardcore=False)` environment and you're happy with its learning efficiency, train the agent on the `Walker(hardcore=True)` environment and submit a separate hardcore video.mp4 and log.txt showcasing how well your agent performs in this much more difficult setting. We will examine how well the agent navigates the terrain in this setting. This is a tough environment, so don't be disheartened if the agent is unable to perform well in it. You can write about such experiments in your report, but make sure to also present the convergence results of the basic environment.

Reinforcement learning marking scheme

The paper, code, videos, and log submissions will be marked as follows:

Setup (10%)

- **[1 mark]** Report
  - Was a report submitted (content may be unchanged from template)?
- **[1 mark]** Code
  - Does the submitted code contain any non-trivial implementation of an RL agent (i.e. not just the dummy implementation from the template)?
- **[3 marks]** Log files
  - Are the log files correctly formatted?
  - Do they contain at least 100 episodes?
- **[3 marks]** Videos
  - Do the videos show the correct environments (easy and hardcore)?
  - Do the scores match those from the log files?
- **[2 marks]** Convergence
  - Does the agent show any sign of improvement in the easy environment?

Final Submission (90%)

- **[50 marks]** Convergence and score
  - Does the agent consistently get high scores and learn the optimal policy?
  - How many training episodes are needed to get high scores?
  - Is the algorithm stable? Will it always converge or does it sometimes get stuck?
- **[25 marks]** Sophistication and mastery of the domain
  - What quality is the presentation of the underpinning theory?
  - Do the experimental results demonstrate scientific rigour?
  - How hackish is your implementation, or is it robust and well-designed?
  - Have you just cited and pasted code, or is there evidence of comprehension with further study and novel design extending beyond the lecture materials?
- **[15 marks]** Intuition of the videos
  - Is the agent walking fluently or with undesirable behaviour?
  - How fast is the agent running?
  - How effectively is it able to navigate the terrain?

Closing Comment

I hope that you enjoy this coursework and find watching your robot learn to walk rewarding! If you are struggling, please ask questions where we can discuss any issues, such as with programming or relevant theory.

Guidance

Before starting, here is some guidance for this environment:

1. I encourage starting with a modern method like TD3 (covered in lecture 8). The environment has a continuous action space (not suitable for DQN) and most of the classic continuous action space algorithms that work out-of-the-box on Pendulum-v0 (like SAC, PPO and DDPG) will need additional tricks and a lot of patience/tuning before showing any signs of convergence in the `Walker` environment.
2. Even a good agent for this environment will take 1-2 hours training before it starts to show signs of learning anything sensible, and perhaps a few more hours before it starts to get non-negative scores and walk forwards. So leave Colab/NCC running and take a long break when it's training. Note that the iterative process and long training times imply that you will benefit from starting early with this coursework to be able to complete it with good results.
3. It's common to implement a non-robust algorithm that sometimes works and other times doesn't due to poor initialisation and exploration (where the agent can get stuck in a minima, such as the robot always doing the splits and being unable to recover). If you've been training for several hours and your last few videos all have the same undesirable agent behaviour, this is an indicator that more exploration is needed. Try resetting Colab and retraining the same agent for another hour and compare the logs/videos and see if it gets stuck doing the same undesirable behaviour again.
4. Unless you are prepared to spend time fiddling with vectorised environments, only train on the CPU (in Colab, go Runtime $>$ Change Runtime Type $>$ None)—unlike the DL model where you will want to use a GPU. This will give you more Colab time and you will likely be I/O bound by the `Walker` environment simulation where further transfer to GPU is often slower. In marking, we strongly favour environment sample efficiency (few steps) above parallelism and GPU occupancy.
5. I would not suggest trying to design and build a new agent for this completely from scratch (without reference code) unless you are reimplementing a paper that provides extensive technical details. You are allowed to re-implement and cite existing implementations that you have found on GitHub, and even re-use existing hyperparameters that people have found for this specific environment. But, by doing so, you must cite all author code you use and detail your own individual experiments in attempting to further improve their work in your report. Also, as stated in the marking scheme above, we do grade comprehension and novelty of the design, so implementations that mainly reproduce existing work will be held to higher standards for demonstrating understanding.