Reinforcement Learning WS 2024/25
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Final Project
Competition: 24.02.2025, In-person get-together 25.02.2025 14:15-16:00 in N10 (Morgenstelle). Report, Video and Code is due: 26.02.2025 23:55
February 18, 2025, Version 1.2

Update version 1.1: details on competition
Update version 1.2: corrected typo in the competition date on page 2

1 Reinforcement Learning Project

The final project of the lecture will be on developing a Reinforcement learning agent for a small game. You can form teams of 2 or 3 people. You will implement different reinforcement learning algorithms and evaluate their performance on simpler tasks first and then apply them to a simulated `hockey` game. We are using the gymnasium API (former Open AI gym), see `https://gymnasium.farama.org/` with a custom environment. It uses the same packages as we had for the exercises. The code for the hockey game is at the git repository `https://github.com/martius-lab/hockey-env` (*HockeyEnv* / `Hockey-v0` / `Hockey-One-v0`). Try out the notebook `Hockeyenv.ipynb`.
All teams will compete against each other in the game at the end. Details on the tournament mode will follow. There are intermediate checkpoints, see below, that we will discuss in the remaining tutorial sessions.
Please register your team as soon as possible, but not later than 20th of January at this google form[1]. You will then get account information for the teaching compute cluster.
For the final evaluation, you have to prepare:

(a) A report using the latex template uploaded to ILIAS next to the project description, with:

   (i) an introduction, including a description of the game/problem **(1/2 page)**

   (ii) a methods section, including relevant implementation details, modifications and math, e.g. the objective functions of the implemented algorithms **(min 1 page per algorithm/person)**

   (iii) an experimental evaluation for all the methods and environments (it needs to including the performance against the basic opponent (weak)). **(min 1 page per algorithm/person)**

   (iv) a final discussion, including a comparison of the different algorithms **(≈ 1 page)**

[1] `https://forms.gle/tRzxWyCZF9GzQRkT7`

For a single person, the report should not be longer than **5** pages excluding references.

For a team of two people, the report should not be longer than **8** pages excluding references.

For a team of three people, the report should not be longer than **11** pages excluding references.

Each **team member** should have **one algorithm** implemented and his/her independent contribution should be clearly marked in the **report and the source code**. **Significant modifications** of the same base algorithm are possible, for instance, based on DQN, two modifications mentioned in the *Rainbow* paper [8] would be significant per person. For instance, just adding some Gaussian noise to the actions would not be significant. For a top grade self-play or other techniques to account the "game" aspect are expected.

Regarding the usage of existing code you have the following options:

- you implement an algorithm yourself (except the ones we had in the exercises), or
- you base your implementation on some existing code (needs to be specified where it comes from) and you make a non-trivial modification. A non-trivial modification is something that is or might be a main contribution in a paper.

If in doubt, contact the tutors during the exercise sessions in advance.

(b) A video-presentation:

- 3 min for a single person
- 4 min for two-person team
- 6 min for three-person team

(c) The source code

The submission deadline for the report, video, and code is on **26.02.2025 23:55** via ILIAS.
The code needs to be running in the tournament starting on the 24.02. from 10am onward for 12h. Test runs will happen earlier and will be announced.

Requirements:

(a) Teams of two should implement 2 algorithms

(b) Teams of three should implement 3 algorithms

(c) In order to pass the exam report, presentation and code have to be handed in on time.

(d) The code has to run and if the hockey does not work at least a simple environment must be solved.

Usage of GPT Large language models are great tools for various tasks and can help you be more efficient, however, you need to know how to do things yourself properly first, before relying on the LLMs. Since this is part of YOUR education, the usage of chatGPT, or similar, for writing the report is not allowed.

Grading

(a) The mark will be determined based on all parts. You are expected to deliver a nicely written report, a clear presentation, and a good performance.

(b) The final mark will be computed from the individual scores with the following weighting: 60% report, 20% presentation, 20% performance.

(c) The minimum performance is measures against the basic opponent (in weak mode). If an agent cannot win against it consistently (more than 55% of times) performance grade is 5.0. If you are not taking part in the tournament, your performance score can only be 3.0. If in the tournament, you consistently win against the strong basic opponent, you get a 2.0. Better marks are given according to the rank in the tournament. The top 3 teams in the competition get an overall bonus of 0.35 marks. For teams until rank 9 the bonus is 0.2 marks.

1.1 Checkpoint 1: Get your algorithms up and running

Start with the Pendulum-v0 from exercise 8 and 9 or with other simple environments. Be aware that some environments (such as the pendulum) contains an exploration problem that is not necessarily quickly solved by all algorithms. You can also try LunarLander-v2 (exercise 9) or HalfCheetah. Important is to see that the reward is optimized and the behavior is reasonable. This should allow you to debug your code.
Implement your algorithms of choice. I recommend to consider off-policy algorithms: Dueling Deep Q-learning (DDQN) [10], Deep deterministic policy gradient (DDPG) [9] or Twin Delayed DDPG (TD3) [4], Soft/Natural Actor Critic (SAC [5]) or model-based algorithms such as Dreamer [6] or TD-MPC [7]. The versions from our exercises can be a good starting point, but need to be modified (as we provided a solution). You can also use existing implementations. Inspiration for modifications are:

- *Rainbow* paper [8] (for DQN)
- *Pink-noise* paper for exploration [3]
- *CrossQ*: batch normalization for DeepRL [1]
- *RND*: enhance exploration by using adding an exploration reward [2]
- *Two-hot Q*: Using the categorical Q-value representation using symexp twohot loss, see page 7 in [6].

Make appropriate analysis and track your performance etc. Don't forget this procedure during the rest of the project. Remember that you want to create a report with plots giving detail about the training, comparisons etc.

1.2 Checkpoint 2: Hockey – learning to handle the puck

Start working on the Hockey game[2]. The repository provides the environment and a little notebook to see how the environment works. It is actually installable via pip, see the `README.md` file.
The game has some training camp modes that you can test. These are:

TRAIN SHOOTING hitting a static ball into the goal (other agent is static)

TRAIN DEFENSE defending your goal against incoming shots (other agent is static)

However, it usually does not help much to train the agent in stages, so you finally need to train using

NORMAL normal gameplay against another agent.

You can enable the game-modes with
`HockerEnv(mode=NORMAL|TRAIN_SHOOTING|TRAIN_DEFENSE)`.

1.3 Checkpoint 3: Play in normal mode against the basic opponent

The basic opponent has a weak and a strong mode. Train your agent against it in normal game mode. Think how to exploit the fact that you are using an off-policy algorithm.

1.4 Checkpoint 4: Self-play

Let your agents play against each other in normal game mode. Make appropriate analysis and track your performance etc. Experiment with different tournament modes.

1.5 Final

Updated in version 1.1
The tournament server, as described below, will be restarted on Monday 24th of February at 10am. From that time point on your client should be running and play against others. You can update the client during the tournament. The tournament will finish at 10pm on the same day (so 12h in total).
The server is already running as of Jan. 27th in a test mode.

[2] `https://github.com/martius-lab/hockey-env`

For the final tournament, teams have to connect to the tournament server with a special client[3]. The host address of the server is `comprl.cs.uni-tuebingen.de` and the port is `65335`. It also has an http interface that you need to register etc.
Please check the provided `run_client.py` file and implement an `Agent` following the `HockeyAgent` example. The actions are supposed to be a list of actions.
Number of algorithms:

- Each member should run their algorithm in the tournament (`teamname_algoname`)
- Each team as a whole can have an additional team agent (`teamname`)

The best of the agents per team is used for the potential team bonus.
The tournament server will constantly pair up teams which will play against each other by receiving observations from and sending actions to the server. For this to work, the client needs to run in the background permanently. We recommend to use a terminal multiplexer such as tmux[4] or screen[5] which allow you to keep a process running (by detaching the tmux/screen session) after closing a terminal/ssh session. Also checkout a the `autorestart.sh` script to make your client resilient to server restarts or other crashes.

Already before the final tournament, you can play on our server. On the day of the competition, we will reset the scores and restart the server.
The leaderboard can be accessed via `http://comprl.cs.uni-tuebingen.de`.
We are using a ranking system for two-player games using Trueskill (similar to an ELO score) that is listed as the "score". As many games need to be played to be sure about the score (and thus the rank) there is an uncertainty attached to the current score and the LCB column corresponds to the "lower confidence bound". We consider the latter to be more trustworthy for ranking the agents.
To participate in the final tournament, your agent should primarily be trained by maximizing the reward provided by the environment (including the additional reward info and via reinforcement learning). You can use other techniques such as behavioral cloning as long as they do not contribute the most to your implementation efforts/training of the agent.
So you can use your own computer or use create an interactive job at the cluster, for instance. We suggest you have two instances per agent running at the same time. To run multiple instances of a client, here an example using a tmux session via ssh:

- Connect via ssh from your local machine to the remote machine:

  ```
  local> ssh $remote_machine
  ```

- Change to the directory with the client:

  ```
  remote_machine> cd $dir_with_client
  ```

[3] `https://github.com/martius-lab/comprl-hockey-agent`, check for updates.
[4] `https://github.com/tmux/tmux/wiki`
[5] `https://www.gnu.org/software/screen/`

- Start a tmux session:

  ```
  remote_machine> tmux
  ```

- Start the first instance by running your script
- Press <ctrl>-b c (first control+b together and afterwards c) to open a new window. Start the next instance either with the same name (they will play in parallel) or with a different name
- If all your instances are up and running you can detach the tmux session with <ctrl>+b d and logout.
- If you login again later, you can re-attach your session with:

  ```
  remote_machine> tmux a
  ```

References

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[6] Danijar Hafner, Jurgis Pasukonis, Jimmy Ba, and Timothy Lillicrap. Mastering diverse domains through world models, 2024.

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