UAB

Universitat Autònoma de Barcelona

Universitat Autònoma de Barcelona (UAB)

Bachelor's Degree in Artificial Intelligence

PROJECT

Reinforcement Learning

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Contents

1 Introduction

Some relevant remarks about the project:

- The project will be developed throughout the semester, during which students will address a **problem of considerable complexity**.
- Projects will be completed in **groups of 2 or 3 students**. These groups must remain consistent throughout the project and will be responsible for self-managing tasks such as role distribution, work planning, task assignment, resource management, and conflict resolution.
- Each group will **work independently** to develop their project.
- The project requires students to collaboratively design a **comprehensive solution** to the assigned challenge.
- In addition, students must demonstrate teamwork skills and **present their results to the class**.
- Each project will be evaluated based on a **deliverable** and an **oral presentation** to the class. Active participation in both the preparation of the deliverable and the presentation is essential to receive a project grade.

Punctuation:

- **Part 1**: 4 points
- **Part 2**: 5 points
- **Part 3**: 1 point (+1 extra point)

2 Part 1: Solving a "simple" ALE environment

The Arcade Learning Environment[1] (ALE), commonly referred to as Atari, is a framework that allows researchers and hobbyists to develop AI agents for Atari 2600 roms. It is built on top of the Atari 2600 emulator Stella and separates the details of emulation from agent design. Users can interact with the games through the Gymnasium API[2].

In this section, you are required to apply the knowledge gained from the course to:

1. Choose a scenario from the ALE Gymnasium library. You are free to select any available scenario, but for this initial part of the project, it is recommended to opt for a **relatively simple environment**, such as Pong or a similar game.

   - Gymnasium (https://gymnasium.farama.org/)
   - ALE (https://ale.farama.org/)

2. Select two or more models from the course material —either from the tabular methods or deep reinforcement learning approaches— and compare their performance in the chosen environment.

   You are **not allowed** to use library implementations or third-party code for this task. However, you may write your own code and reuse code from course examples, activities, or other publicly available source code repositories or examples found online.

Remarks:

- You are required to use **Gymnasium version 1.0.0** for this task.

Questions:

1. Describe the environment selected for the experiment.

[1] https://ale.farama.org/
[2] https://gymnasium.farama.org/

2. Provide a detailed description of the chosen agents or models.

3. Train the models, applying fine-tuning or hyperparameter optimization as necessary.

4. Save the best-performing models and generate visualizations of their behaviour and learning curves.

5. Evaluate the trained models within the environment, reporting the average success rate.

6. Present the results, discuss the findings, and justify the selection of the best model for this environment.

3 Part 2: Trying to solve a "complex" ALE environment

In this section, you are required to apply the knowledge gained from the previous exercise to:

1. Select a scenario from the ALE Gymnasium library. You are free to choose any available scenario, but for this part of the project, a **more complex environment** than the one chosen in the first part is required. Keep in mind that the complexity of the selected environment will be considered when grading this activity.

   - Gymnasium (https://gymnasium.farama.org/)
   - ALE (https://ale.farama.org/)

2. Select two or more models and compare their performance in the chosen environment. You may use available implementations from **libraries** or **third-party code** for this task.

   For instance, you can have a look at:

   - Stable Baselines 3[3] (SB3) [Raffin et al., 2021] is a popular library providing a collection of state-of-the-art RL algorithms implemented in PyTorch. It builds upon the functionality of OpenAI Baselines (Dhariwal et al., 2017), aiming to deliver reliable and scalable implementations of algorithms like PPO, DQN, and SAC.
   - CleanRL[4] [Huang et al., 2022] is designed to provide clean, minimalistic implementations of RL algorithms. It focuses on simplicity and transparency, making it easier for researchers to understand and experiment with different RL techniques.

[3] https://github.com/DLR-RM/stable-baselines3
[4] https://github.com/vwxyzjn/cleanrl

- Tianshou[5] [Weng et al., 2022] is a versatile library for RL research that supports various training paradigms, including off-policy, on-policy, and multi-agent settings. It offers a modular design that allows users to easily customize and extend the library's components.
- Ray Rllib[6] [Liang et al., 2018] is part of the Ray ecosystem and is known for its scalability and support for distributed RL training. Rllib provides a diverse range of algorithms and tools for both single-agent and multi-agent scenarios.
- Dopamine[7] [Castro et al., 2018] is a research framework developed by Google for experimenting with reinforcement learning algorithms. It is designed to provide a clean, minimalistic codebase that focuses on implementing and evaluating RL algorithms such as DQN and its variants. Dopamine emphasizes reproducibility and simplicity, offering well-structured, modular components that make it easy for researchers to implement and test new algorithms.

Further information could be found at [Kwiatkowski et al., 2024].

Questions:

1. Describe the environment selected for the experiment.
2. Provide a detailed description of the chosen agents or models.
3. Train the models, applying fine-tuning or hyperparameter optimization as necessary.
4. Save the best-performing models and generate visualizations of their behaviour and learning curves.

[5] https://github.com/thu-ml/tianshou/
[6] https://docs.ray.io/en/latest/rllib/index.html
[7] https://github.com/google/dopamine

5. Evaluate the trained models within the environment, reporting the average success rate.

6. Present the results, discuss the findings, and justify the selection of the best model for this environment.

4 Part 3: Pong World Tournament

The PettingZoo[8] is a simple, pythonic interface capable of representing **general multi-agent reinforcement learning** (MARL) problems. PettingZoo includes a wide variety of reference environments, helpful utilities, and tools to create your own custom environments. This activity uses the **AEC API**, which supports sequential turn-based environments. PettingZoo could be combined with Stable Baselines 3[9] or any other library to train the models.

The following libraries are required to properly run this activity:

```
> pip install swig
> pip install box2d-py
> pip install gymnasium
> pip install "gymnasium[atari,accept-rom-license]"
> pip install "stable-baselines3[extra]"
> pip install "pettingzoo[all]"
> pip install supersuit
```

Notes:

- **AutoROM** must be installed on the Python environment and then execute "AutoROM" from the command line to install it.

  ```
  > pip install "autorom[accept-rom-license]"
  > AutoROM
  ```

The primary goal of this section is to train an agent to play the Pong game in a multi-agent environment, adhering to the rules outlined earlier (see details https://pettingzoo.farama.org/environments/atari/pong/).

For your reference, three accompanying notebooks are provided to assist with this task:

1. 20241_Project PML_Part 3: Contains foundational and preliminary information on the environment.

[8] https://pettingzoo.farama.org/index.html
[9] https://stable-baselines3.readthedocs.io/en/master/

2. 20241_Project PML_Part 3 (Sup material 1): Provides specific guidance on training an agent using the SB3 library.

3. 20241_Project PML_Part 3 (Sup material 2): Details the steps for loading a trained agent to play in a Gymnasium single-agent environment.

Questions:

1. **Select** one RL model to play this game.

2. Tune the **parameters** to optimize the agent:

   (a) Indicate the range of parameters and the results obtained for each one.

   (b) Compare them and select and justify your decision.

3. **Train** the agent with these parameters:

   (a) Report the results of your agent in a single-player environment (for instance, Pong[10] from Gymnasium or Gym).

4. **Export** your trained agent to a file:

   (a) Save and load[11] from SB3 could be used.

   (b) Or include the code needed to load and run your trained agent.

5. **Playing Pong**: Using the model (or models) trained in the previous exercise, answer the following questions:

   (a) Test your model (or models) in 100 episodes of Pong (using the *PettingZoo* environment). Report the results (win rates, rewards, etc).

   (b) Export one video (*mp4* format) of a whole episode.

[10] https://gymnasium.farama.org/environments/atari/pong/

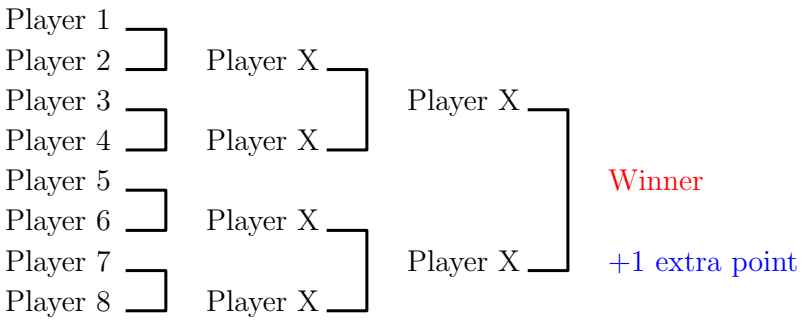
[11] https://stable-baselines3.readthedocs.io/en/master/guide/save_format.html

Pong World Tournament

We are excited to announce the Pong World Tournament, where all groups that have trained an agent to play Pong in a multi-agent environment using PettingZoo will compete!

Tournament rules:

- Players will be randomly assigned to a slot (Player 1 to Player 8).



- Each match will consist of 5 independent games, with players alternating sides of the board.
- The first player to win 3 or more games will be declared the winner.
- Winners will advance to the next phase and face new opponents.
- The winner of the tournament will earn **1 extra point**.

5 Delivery format

Students MUST deliver the following documentation (compressed in a ZIP file):

1. A **PDF document** (with the names and NIU of both group members) containing responses to all the questions mentioned above.

   The document should include images, graphs, plots, code snippets, and any other materials necessary to explain and justify your answers.

2. The **slides** (in PowerPoint or PDF format) to present your work to the class, including images, videos, and related materials to effectively showcase your project and results.

3. A folder containing the **source code** or a link to a code repository tool, such as GitHub[12] or any similar tool.

   You may use Jupyter Notebooks (.ipynb) or Python scripts (.py), but you **MUST** meet the following requirements:

   - The code should be well-commented, with explanations provided to ensure clarity and ease of understanding.
   - You must include a "requirements.txt" file that lists all the libraries necessary and their respective versions for the code to run correctly.
   - A "README.md" file should be provided with detailed instructions on how to execute each part of the project (e.g., training, testing). Any part that cannot be run will receive a grade of 0.

[12] https://github.com/

6 Presentation

Each group is required to deliver a **presentation** of their project to the rest of the class.

Criteria:

1. The presentations will last **15 minutes**, followed by **10 minutes** of questions from the class.

2. Support materials (e.g., slides, code, videos, demonstrations) must be used to showcase the work and the results obtained.

3. Presentations will take place on December 17 and 20 during regular class hours.

References

[Castro et al., 2018] Castro, P. S., Moitra, S., Gelada, C., Kumar, S., and Bellemare, M. G. (2018). Dopamine: A research framework for deep reinforcement learning.

[Huang et al., 2022] Huang, S., Dossa, R. F. J., Ye, C., Braga, J., Chakraborty, D., Mehta, K., and Araújo, J. G. (2022). Cleanrl: High-quality single-file implementations of deep reinforcement learning algorithms. *Journal of Machine Learning Research*, 23(274):1–18.

[Kwiatkowski et al., 2024] Kwiatkowski, A., Towers, M., Terry, J., Balis, J. U., Cola, G. D., Deleu, T., Goulão, M., Kallinteris, A., Krimmel, M., KG, A., Perez-Vicente, R., Pierré, A., Schulhoff, S., Tai, J. J., Tan, H., and Younis, O. G. (2024). Gymnasium: A standard interface for reinforcement learning environments.

[Liang et al., 2018] Liang, E., Liaw, R., Nishihara, R., Moritz, P., Fox, R., Goldberg, K., Gonzalez, J., Jordan, M., and Stoica, I. (2018). RLlib: Abstractions for distributed reinforcement learning. In Dy, J. and Krause, A., editors, *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pages 3053–3062. PMLR.

[Raffin et al., 2021] Raffin, A., Hill, A., Gleave, A., Kanervisto, A., Ernestus, M., and Dormann, N. (2021). Stable-baselines3: Reliable reinforcement learning implementations. *Journal of Machine Learning Research*, 22(268):1–8.

[Weng et al., 2022] Weng, J., Chen, H., Yan, D., You, K., Duburcq, A., Zhang, M., Su, Y., Su, H., and Zhu, J. (2022). Tianshou: A highly modularized deep reinforcement learning library. *Journal of Machine Learning Research*, 23(267):1–6.