Shanghai Jiao Tong University

RL C3316 Final Project

Ng Tze Kean
Student number: 721370290002

Introduction

In this experiment we implement value based RL for Atari and policy based RL for MuJuCo. In both environments we make use of OpenAI gym environment to simulate the environment for the agent. In each of the environment,we allow multiple choices for the user to test the agents on different choice of environment as stated in the requirements.

Requirements

The code can be run as specified. Examples will be provided in this section on how to use the the program. There will be a need to install all packages before the code can run. Note the following requirements after installing all prompted packages:

- Python 3.11.19
- gymnasium[atari,accept-rom-license]
- gymnasium[mujoco]

To install the following requirements you can run the script below

```
    pip install "gymnasium[atari,accept-rom-license]"
    pip install "gymnasium[mujoco]"
```

Usage

For Atari experiment specify the first argument as `atari` with the following optional arguments. The environments that will work in this setup are the following [VideoPinball-ramNoFrameskip-v4, BreakoutNoFrameskip-v4, PongNoFrameskip-v4, BoxingNoFrameskip-v4] and the dueling argument is a boolean specifier. Do note that you have to specify the argument as a capitalized option.

```
python3.11 run.py --exp atari --env_name ENV --is_dueling BOOL
```

For Mujoco, the following arguments can also be specified. That is, only the first option is required. Note that for the environments that can be specified, the following environments can be tested on: [Hopper-v4, Humanoid-v4, HalfCheetah-v4, Ant-v4] and the method option allows the user to choose between [PPO, SAC] as the agent of choice.

```
python3.11 run.py --exp mujoco --env_name ENV --method METHOD
```

Implementation

The implementation of the code is as follows. The code is split into two main files, namely `atari.py` and `mujoco.py`. The code is then imported into the main file `run.py` to run the experiment. In both experiments we make use of the OpenAI gym environment to simulate the environment for the agent.

Atari

The Atari environment consists of classic video games like Pong, Breakout, and Space Invaders. Unlike MuJoCo's focus on physics simulation, Atari environments provide a high-dimensional visual input space with discrete action sets (e.g., up, down, jump, fire). The agent interacts with the game through its actions and observes the screen as its primary source of information. Rewards are typically sparse, meaning they are only received for achieving specific goals (e.g., points in a game).

In the atari experiment, we implement a value based RL agent. The agent designed are the DQN and Dueling DQN.

Value based agent

DQN (Deep Q-Network): DQN is a deep learning-based off-policy algorithm that utilizes a neural network to approximate the Q-value function. This function estimates the expected future reward for taking a specific action in a given state. The agent interacts with the Atari environment, observes the screen, and takes an action. Based on the reward received and the next observed state, the Q-network is updated to improve its estimation of future rewards.

The key components of DQN include:

1. Q-Network: A neural network that approximates the Q-value function. It takes the state as input and outputs Q-values for all possible actions.

2. Target Network: A copy of the Q-network, used to compute target Q-values. It is updated periodically to stabilize training.

3. Experience Replay: A buffer that stores past experiences (state, action, reward, next state). Mini-batches are sampled from this buffer to break the correlation between consecutive experiences.

Training process:

1. Initialization: Initialize the Q-network with random weights. Create a copy of the Q-network as the target network.

2. Interaction: The agent interacts with the environment, observing states and taking actions based on an epsilon-greedy policy (choosing random actions with probability ϵ and greedy actions with probability $1 - \epsilon$)

3. Experience Storage: Store the experiences (state, action, reward, next state) in the replay buffer.

4. Mini-Batch Sampling: Randomly sample a mini-batch of experiences from the replay buffer.

5. Q-Value Update: Update the Q-values using the Bellman equation

6. Target Network Update: Periodically update the target network with the Q-network weights.

DDQN (Double DQN): DDQN is an improvement over DQN that addresses the overestimation issue sometimes encountered with DQN. It introduces separate networks for estimating the Q-value (evaluation network) and selecting the action (target network). This separation reduces the overestimation bias and can lead to more stable learning. The overall training process is similar in nature to DQN as explained above and we will examine the advantage of separating the network for estimating the Q-value. The class for DDQN can also be examined under the code base in the class `dueling_DQN`.

Set up

The agent is then trained on the environment specified by the `env_name` argument. The agent is then trained for a number of episodes which is currently fixed at 8000000 as we have found that the agent is likely to converge at when the number of episodes is around 8000000.

As the agent is being trained, we evaluate per some fixed number of episodes to see how well the agent is performing. The evaluation is done by running the agent on the environment without updating the weights of the agent. We log the performance of the agent in a csv file which can then be used to plot the performance of the agent.

Since there are are a variety of atari games, we allow the user to specify the atari game that they want to train the agent on. For this experiment, we have trained the agent over different environments listed in the requirements and we compare the performance of the agent on each of the environment. Some of the environments trained on include Breakout and Pong which we will use to analyse the performance of the agent.

MuJoCo

MuJoCo is a physics engine specifically designed for simulating physical systems commonly encountered in robotics. It provides a rich set of environments for reinforcement learning tasks, often involving legged locomotion or manipulation. These environments typically involve a simulated character interacting with the environment, receiving rewards based on its actions and achieving specific goals (e.g., walking forward for a certain distance).

In the mujoco experiment, we implement a policy based RL agent. The agent designed are the SAC and PPO.

Policy based agent

Soft Actor-Critic (SAC): SAC is an off-policy algorithm that combines elements of Deep Deterministic Policy Gradients (DDPG) and maximum entropy policies. It learns a policy that maximizes expected return while also encouraging exploration. The agent interacts with the environment, taking actions and receiving rewards. This information is used to update both the policy and a value function that estimates the expected future return. The entropy bonus term in the objective function promotes diverse exploration, potentially leading to better performance in the long run.

Training process:

1. Initialization: Initialize the policy network, Q-networks, and the target Q-networks with random weights.

2. Interaction: The agent interacts with the environment, collecting transitions of states, actions, rewards, and next states.

3. Experience Storage: Store the transitions in a replay buffer.

4. Q-Value Update: Sample mini-batches from the replay buffer and update the Q-networks by minimizing the mean squared error loss.

5. Policy Update: Update the policy network by minimizing the entropy-augmented objective.

6. Target Network Update: Periodically update the target Q-networks to slowly track the Q-networks.

7. Repeat: Continue the process until convergence.

Overall, SAC leverages entropy maximization to balance exploration and exploitation, ensuring robust learning. The use of twin Q-networks reduces overestimation bias, leading to more accurate value estimates and improved policy performance.

Proximal Policy Optimization (PPO): PPO is an on-policy algorithm that focuses on maintaining a policy close to the one used for collecting data during training. This is achieved by clipping the policy update during training to ensure it remains similar to the original policy. PPO interacts with the environment, collects data, and then updates the policy to improve its performance while maintaining stability by keeping the updates within a certain range.

1. Clipped Surrogate Objective PPO uses a clipped objective function to restrict the change in policy:
$$L^{CLIP}(\theta) = E_t \left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right]$$
where $r_t(\theta)$ is the probability ratio between the new and old policies, $\hat{A}_t$ is the estimated advantage, and ϵ is a hyperparameter controlling the clipping range.

2. Advantage Estimation PPO uses Generalized Advantage Estimation (GAE) to compute the advantage function, providing a trade-off between bias and variance:
$$\hat{A}_t = \sum_{l=0}^{\infty} (\gamma\lambda)^l \delta_{t+l}$$
where $\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t)$, and λ is the GAE parameter.

Training Process:

1. Initialization: Initialize the policy and value networks with random weights.
2. Interaction: The agent interacts with the environment, collecting trajectories of states, actions, rewards, and next states.
3. Advantage Calculation: Compute the advantage estimates using GAE.
4. Policy Update: Update the policy network by optimizing the clipped surrogate objective using gradient ascent.
5. Value Update: Update the value network by minimizing the mean squared error between the predicted and actual returns.
6. Repeat: Continue the process until convergence.

PPO optimizes a surrogate objective that balances exploration and exploitation, ensuring stable updates to the policy. The clipping mechanism prevents large deviations in policy updates, leading to more reliable and efficient learning.

We also train the agent on a variety of environments in the mujoco environment. Some of the environments trained on include HalfCheetah and Hopper which we will analyze the agent on in the next section.

Results

Atari

Both DQN and DDQN agents learn through trial and error by interacting with the Atari games. They process the screen images as input and predict the Q-values for each possible action. The agent then selects the action with the highest predicted Q-value (greedy action selection) or explores alternative options with a certain probability (exploration strategy). As the agent receives rewards and experiences new states, it updates its Q-network to improve its understanding of the environment and the value of different actions within each state.

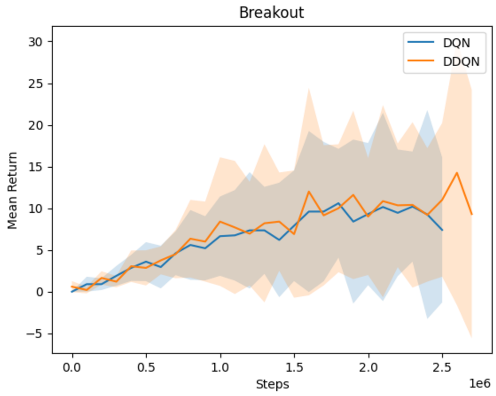


Figure 1: Performance DQN and DDQN on Atari Breakout

As you can see from the graph above that the agent is has not been able to learn from the environment given the number of episodes. As we are training the agent on a personal laptop with limited computational power, we are unable to train the agent sufficiently fast enough such that it converges. Hence, for the evaluation of the agent, we will refer to online sources that have achieved results for comparison. We look to github to search for graphs and we find that that the number of episodes needed ranges in the value of 20million to 50million episodes which we are not able to achieve. Currently to reach 5million episodes, my personal laptop has to run for over 2 days. We now proceed to perform the comparison of these 2 agents over Breakout and Pong environment.

Learning Speed and Convergence: DDQN generally exhibits faster and more stable convergence compared to DQN. This is because DDQN mitigates the overestimation bias in Q-value estimation, leading to more accurate learning.

Algorithm Stability: DDQN is considered more stable than DQN due to the decoupling of the evaluation and target networks. This reduces the compounding effect of overestimation errors in DQN, leading to smoother learning in DDQN.

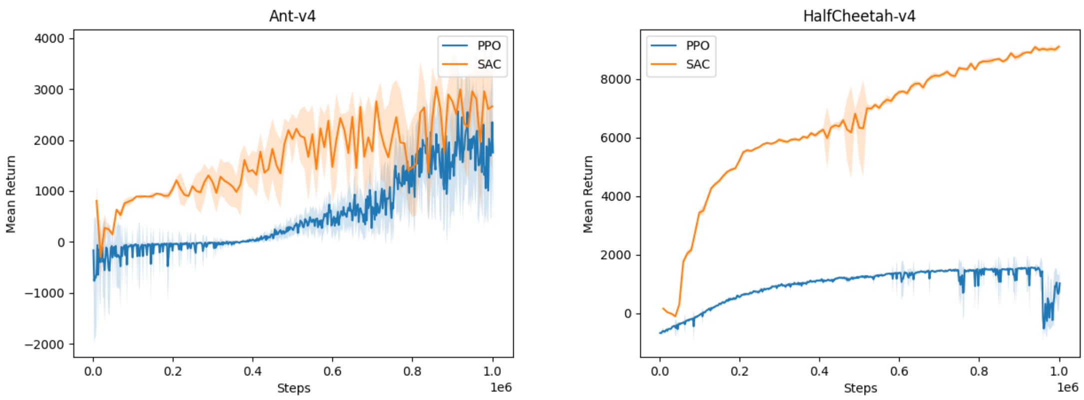
Training Time and Efficiency: Due to its improved stability and learning speed, DDQN can achieve good performance in less training time compared to DQN. While DQN might require extensive training to overcome overestimation issues, DDQN can reach convergence faster with potentially less computational resources needed.

Mujoco

Unlike the case of Atari which we are not able to achieve

Learning Speed and Convergence: SAC often exhibits faster initial learning compared to PPO. This is because SAC's entropy bonus encourages exploration, allowing it to discover effective strategies quicker. However, PPO's focus on policy stability ensures smoother convergence in the later stages of training.

Algorithm Stability: PPO is generally considered more stable than SAC. PPO's clipped objective function prevents drastic policy changes, reducing the risk of the agent diverging from good policies during training. SAC, while effective at exploration, can sometimes lead to unstable learning behavior if hyperparameters are not carefully tuned.



(a) Ant (b) Half Cheetah

Figure 2: Performance SAC and PPO on Mujoco environment

Training Time and Efficiency: Due to its faster initial learning, SAC might achieve good performance in less training time compared to PPO. However, PPO's stability can lead to more efficient training in the long run, as it avoids the need for extensive hyperparameter tuning to prevent divergence.

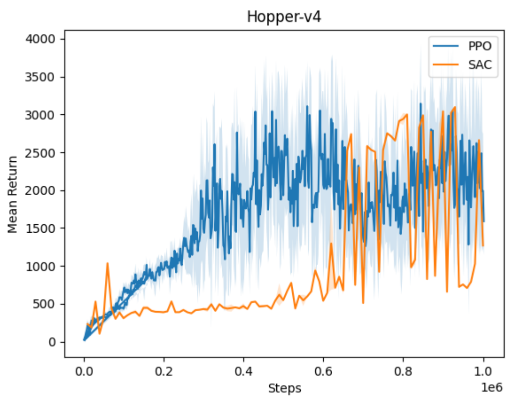


Figure 3: Performance SAC and PPO on Mujoco Hopper

Although, it is interesting to note that in the case of Hopper, the PPO agent is able to perform better than the SAC agent. This is likely due to the nature of the environment and the characteristics of the algorithms. The Hopper environment may benefit from PPO's stability and policy consistency, leading to better performance compared to SAC.