Cart Pole-Q learning

COMP562: Final Project Report

Zhaokun Xu, Jiazhen Wu, Shuyi Chen
Instructor: Jorge Silva

8 May 2023

1 Problem and application

The cart pole game is a well-known problem in the field of control theory and has been widely used to test reinforcement learning algorithms. In this game, a pendulum with a center of gravity above its pivot point is attached to a cart that moves horizontally along a track. The goal is to keep the pendulum balanced by applying appropriate forces to the cart.

Despite its apparent simplicity, this game is challenging for humans to control. The pendulum is inherently unstable, and even small disturbances can cause it to fall over. It requires continuous adjustments and quick reactions to maintain its balance. Achieving a high score in this game is no easy task.

To address this challenge, machine learning techniques such as reinforcement learning have been used to train agents to control the cart pole game. Reinforcement learning involves training an agent to make decisions based on feedback in the form of rewards or punishments. By repeating the game thousands of times, the agent can learn from its failures and achieve a high score by avoiding the actions that lead to failure.

The implementation of machine learning in the cart pole game is not only critical for solving this specific game problem. It is also for showing machine learning's effectiveness in solving real world problems. By mastering this game using machine learning algorithms, we can gain insights into more complex problems that involve decision-making in dynamic environments. Additionally, machine learning can be used to control physical systems in robotics and other fields.

2 Motivation

The rapid advancements in machine learning and artificial intelligence have paved the way for innovative solutions across various domains. Among these, reinforcement learning has shown great promise in enabling machines to master complex tasks autonomously. The motivation behind our project, Cart Pole-

Q learning, is to harness the power of Q-learning, a model-free reinforcement learning algorithm, to excel in the car-pole game. This game serves as a valuable benchmark for evaluating the adaptability and learning capabilities of our model. By achieving high scores in the car-pole game, we aim to demonstrate the potential of Q-learning algorithms for real-world applications, such as self-driving cars and robotics. Additionally, our project seeks to contribute to the ongoing research in reinforcement learning, inspiring further exploration and innovation in this exciting field.

3 Approach

We approach the cart-pole problem using the Q-learning algorithm. The Python code provided demonstrates the complete process, from setting up the environment to training the model and evaluating its performance.

First, we import the required libraries and create the cart-pole environment using OpenAI Gym. To balance the trade-off between exploration and exploitation, we employ an epsilon-greedy strategy, where epsilon decays over time, allowing the agent to explore initially and exploit learned knowledge later.

The Q-table is initialized with a random uniform distribution and is updated iteratively during training. We discretize the continuous state space into bins to create a manageable Q-table size. To update the Q-table, we follow the standard Q-learning update rule, considering the learning rate and discount factor. A negative reward is assigned when the pole falls over or goes out of bounds.

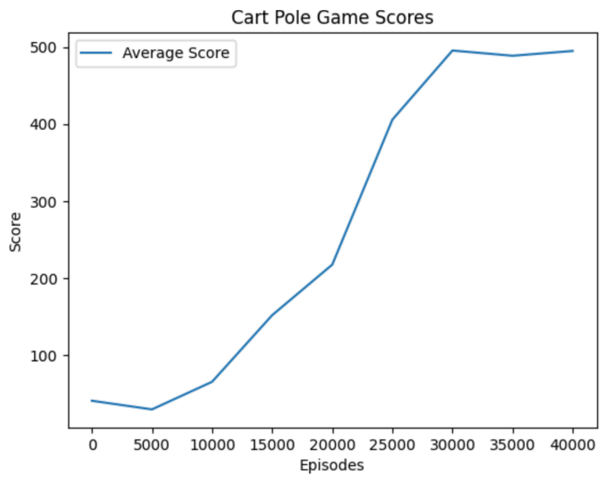
Our training process consists of a pre-defined number of episodes. During each episode, the agent interacts with the environment by selecting an action based on the epsilon-greedy strategy and updating the Q-table accordingly. The agent's performance is evaluated every 5,000 episodes by calculating the average, minimum, and maximum scores.

After the training is completed, we visualize the agent's performance in the cart-pole environment by rendering the game in "human" mode. This allows us to observe how well the agent has learned to balance the pole and achieve high scores.

4 Results and conclusion

The results of our project demonstrate the effectiveness of the Q-learning algorithm in learning to balance the cart-pole. As the training progressed, we observed significant improvements in the agent's performance, particularly in average scores. The figures below show the performance metrics at different episodes during the training:

```
episode: 0 average_score: 41.0 ,min_score: 41 max_score: 41
episode: 5000 average_score: 29.79 ,min_score: 8 max_score: 173
episode: 10000 average_score: 65.564 ,min_score: 8 max_score: 359
episode: 15000 average_score: 151.9796 ,min_score: 11 max_score: 589
episode: 20000 average_score: 217.5822 ,min_score: 10 max_score: 6888
episode: 25000 average_score: 405.5996 ,min_score: 147 max_score: 6455
episode: 30000 average_score: 495.315 ,min_score: 211 max_score: 5216
episode: 35000 average_score: 488.5066 ,min_score: 211 max_score: 4358
episode: 40000 average_score: 494.7502 ,min_score: 201 max_score: 4425
```



These results indicate that the Q-learning algorithm successfully learned an effective policy for the cart-pole problem. As training progressed, the agent's average score increased, suggesting that it was learning to balance the pole more effectively over time.

However, there were fluctuations in the minimum and maximum scores. The fluctuations in the scores during the training process can be partially explained by the exploration-exploitation trade-off, initial Q-table initialization, and learning rate. The epsilon-greedy strategy employed in our approach allows the agent to explore the action space by taking random actions with a probability of epsilon, which decays over time. During the exploration phase, the agent may take suboptimal actions, leading to lower scores. Furthermore, the initial Q-table is populated with random values, which may cause the agent to make poor decisions in the early stages of training. As the learning progresses, the Q-table converges to more accurate estimates of state-action values, but occasional fluctuations may still occur. The learning rate also plays a crucial role in the stability of the learning process. A high learning rate may cause the agent to overfit to recent experiences, leading to instability in performance, while a low learning rate might slow down the learning process, causing the agent to take longer to find the optimal policy. Balancing these factors is essential for achieving stable and optimal learning outcomes in reinforcement learning tasks such as the cart-pole problem.

Although there were fluctuations in the minimum and maximum scores, the overall trend indicates a successful implementation of Q-learning in solving the cart-pole problem.

5 Github Link

This is our Github Link: `https://github.com/s821y9/Comp562-Final-Report`

Reference:

- Wikipedia contributors. (2023). Q-learning. *Wikipedia*.
  `https://en.wikipedia.org/wiki/Q-learning`
- Paul, S. (2023). An introduction to Q-Learning: Reinforcement Learning.*FloydHub Blog*.
  `https://blog.floydhub.com/an-introduction-to-q-learning-reinforcement-learning/`
- Awan, A. A. (2022). An Introduction to Q-Learning: A Tutorial For Beginners.
  `https://www.datacamp.com/tutorial/introduction-q-learning-beginner-tutorial`
- Shyalika, C. (2021, December 12). A Beginners Guide to Q-Learning - Towards Data Science. *Medium*.
  `https://towardsdatascience.com/a-beginners-guide-to-q-learning-c3e2a30a653c`