Neuromorphic Solutions to Reinforcement Learning problems

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Introduction

The Neuromorphic Team at Rogues Gallery specializes in neuromorphic, also known as brain-inspired, applications. We're exploring Q-learning and Deep Q-learning models for the Mountain car environment - a classic problem in reinforcement learning provided by the OpenAI gymnasium library to demonstrate the effectiveness of our models. Q-learning provides a simple, yet effective method for the Mountain Car to leverage acceleration and learn the best sequence of actions to reach the goal.

Methodology

Q-Learning

- Method of reinforcement learning that learns to choose the best action in different states by observing the consequences of its actions and estimating the future reward for each potential action.
- Observation space is divided evenly into discrete chunks for the Q-Table, with each chunk representing a cell, and each cell holding different q values for each possible action.
- Values in the Q-Table are randomly initialized, and for each action taken, values begin to update based on the Q-Learning equation.
- Q-Learning equation determines the action that results in the highest reward for the agent at a given position, and updates the entry for it in the Q-Table with a higher value.

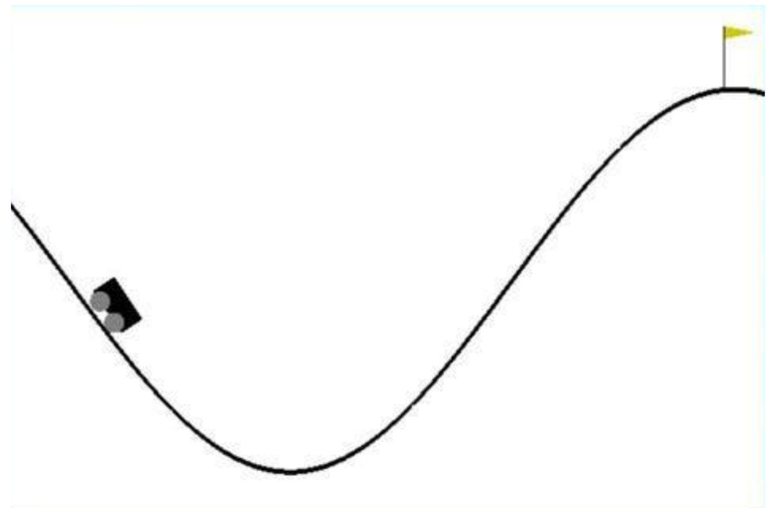
$$Q(s_t,a_t) \leftarrow (1-\alpha)\cdot \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}}\right)}^{\text{learned value}}$$

Q-learning equation

Key Experiments & Results

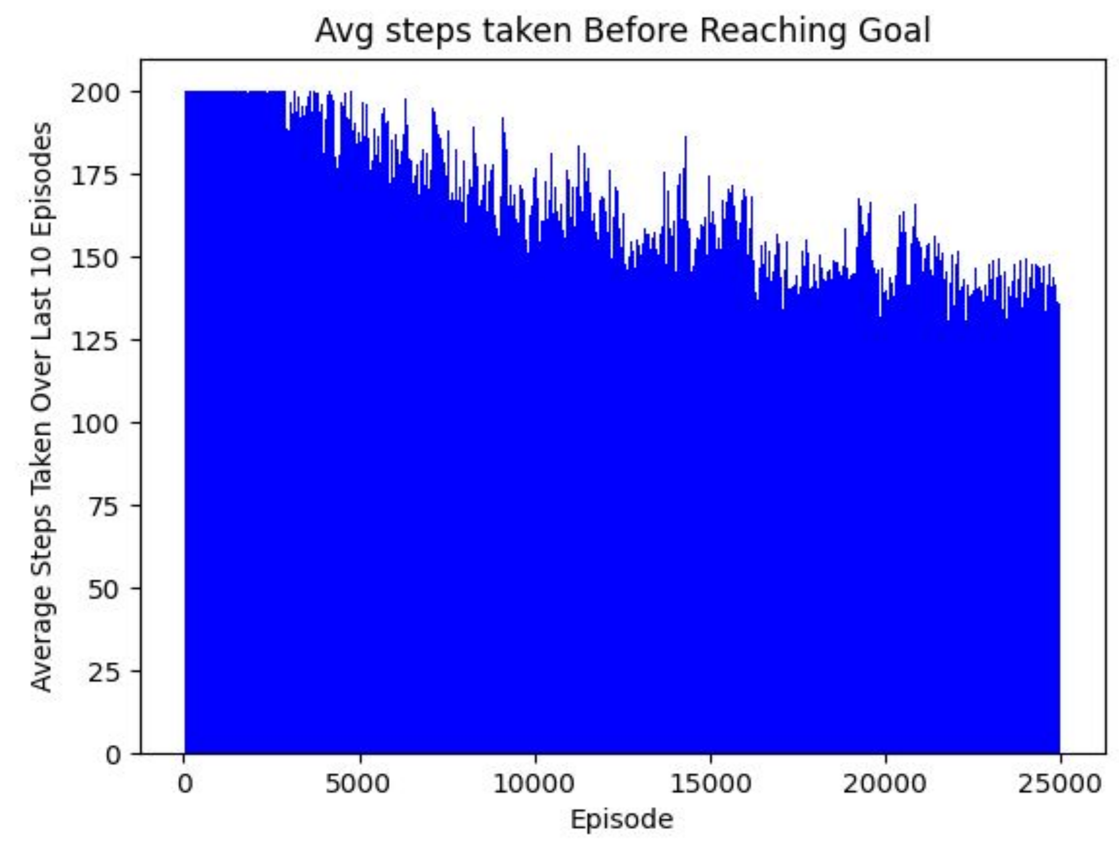
Mountain Car Problem

- The mountain car environment requires a car (agent) with insufficient power to ascend the steep hill to reach the flag.
- The only available actions for the car are accelerations on either directions.
- The car must learn optimal actions to strategically enough momentum and reach the flag placed on top of the right hill.



Hyperparameter Optimization

- Employed grid search over a valid range for learning rate and discount factor to get all combination of values and evaluate the agent's performance over a series of episodes.
- Evaluated average time to reach the goal over a series of episodes as the "score" (primary performance metric).
- Fine-tuned parameters resulted in improved stability and faster convergence of the Q-learning algorithm.



Challenges & Next steps

Challenges

- Encountered difficulties in rendering the environment due to reliance on outdated documentation for the OpenAI Gym framework instead of the updated Gymnasium version.
- Experienced challenges in determining the optimal epsilon value during the hyperparameter tuning phase.

Next steps: Deep Q-Learning

- Conducted an in-depth investigation into the distinctions between Q-learning and Deep Q-learning, focusing on understanding the nuances involved in learning optimal policies.
- Develop a DQL algorithm implementation for the Mountain Car problem, which can handle continuous state spaces, employing a neural network as a Q-function approximator, implementing experience replay, and incorporating a target network.