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BACHELOR OF TECHNOLOGY

(COMPUTER SCIENCE AND ENGINEERING)

(MACHINE LEARNING)

TITLE OF THE PROJECT

Cartpole Balancing Bot: Train an agent using Q-learning to balance a cartpole in an OpenAI Gym environment.

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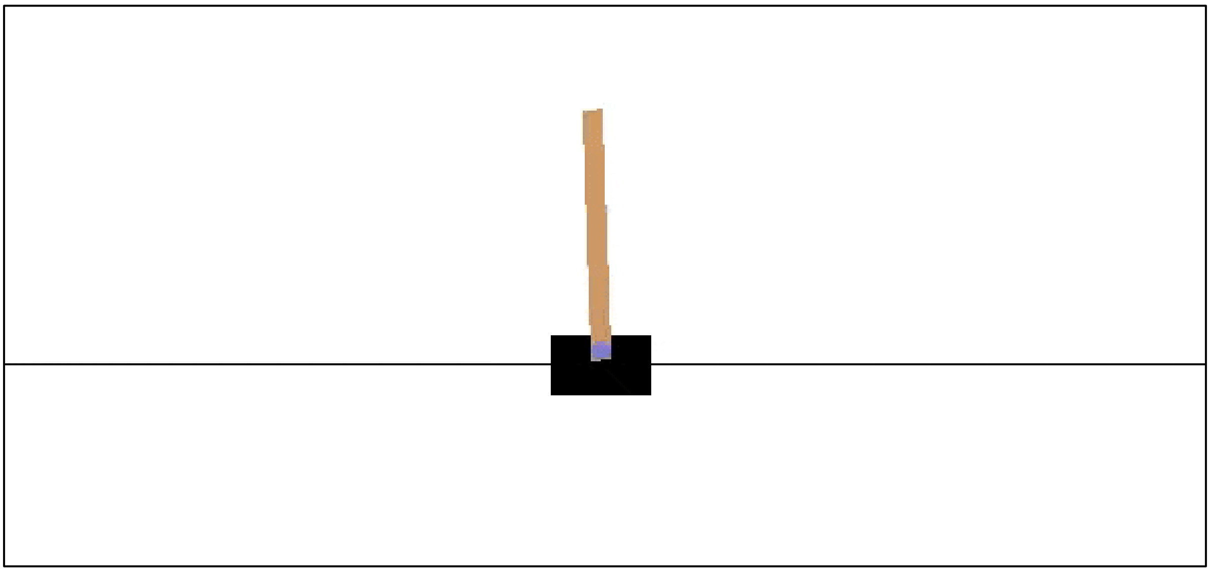
Abstract— ***This study investigates the use of Q-learning, a well-liked machine learning technique, to teach an intelligent agent how to balance a cart-pole system. In the cart-pole challenge, a pole is balanced on a moving cart by pushing the cart to the left or right according to the angle and position of the pole. We address this by utilizing OpenAI Gym, a platform that enables us to model and evaluate our agent's learning performance. Our primary objective is to train the agent to make intelligent decisions depending on many conditions, such as the location and speed of the cart, in order to maintain the stability of the pole. To help the agent become more adept at balancing, we focused on determining the ideal parameters throughout the project, such as segmenting the continuous movement into smaller, more manageable pieces and modifying the agent's learning process. Our tests demonstrate that the agent can effectively maintain the pole balanced for extended periods of time with the correct adjustments. This study demonstrates that Q-learning can be a useful method for controlling tasks in the real world and creates opportunities for other applications where robots must be able to adjust and react to changing circumstances. This research not only contributes to the understanding of reinforcement learning methodologies but also provides a practical implementation framework for those interested in the field. By utilizing the OpenAI Gym environment, we established a controlled setting that allows for easy experimentation and reproducibility of results. The findings from our experiments highlight the potential for further exploration of Q-learning in more complex environments, thereby paving the way for advancements in robotics and autonomous systems. Ultimately, this study serves as a stepping stone for future researchers and practitioners aiming to apply reinforcement learning techniques to real-world challenges.***

Keywords:

- ***Cartpole Balancing***
- ***Q-learning***
- ***Reinforcement Learning***
- ***OpenAI Gym***
- ***Intelligent Agent***

INTRODUCTION

Balancing a pole on a moving cart, known as the “cart-pole problem,” is a classic benchmark in the fields of control theory and reinforcement learning. It involves dynamically keeping a pole upright by applying force to a cart that moves horizontally. Despite its simplicity, the task is deceptively challenging because it requires continuous adjustments to keep the pole from tipping over. For decades, the cart-pole problem has served as a foundational test for evaluating and refining various machine learning and control algorithms, making it an ideal choice for experimentation with reinforcement learning techniques. In recent years, reinforcement learning has rapidly advanced, driven by the goal of training agents to make decisions and act in dynamic environments. One prominent reinforcement learning algorithm is Q-learning, a model-free method that enables agents to learn optimal policies through trial and error, without requiring prior knowledge of the system's dynamics. In Q-learning, the agent learns to maximize cumulative rewards by mapping states to actions, which in this context involves determining the best movements for the cart to maintain the pole’s balance. This research investigates the application of Q-learning to train an intelligent agent that can solve the cart-pole problem in a simulated environment. For experimentation and testing, we use OpenAI Gym, a robust simulation toolkit designed for reinforcement learning tasks. OpenAI Gym provides an interactive platform where various physical environments, including the cart-pole, can be accurately simulated. This allows us to observe the agent’s learning progress as it interacts with the cart-pole system in real-time, making decisions based on continuous inputs like cart position, cart velocity, pole angle, and angular velocity. Since the environment is continuous and requires constant adjustments, applying Q-learning involves discretizing these inputs to represent the system’s state in a way the agent can interpret and respond to effectively. Training a Q-learning agent for the cart-pole problem is challenging due to the continuous nature of the state space and the need to balance exploration and exploitation. Here, exploration refers to the agent trying new actions to discover their effects, while exploitation involves leveraging known actions that yield higher rewards. Striking this balance is crucial for training an agent that can not only solve the cart-pole problem but also generalize to similar control tasks. To improve learning efficiency and stability, we examine methods for discretizing state inputs, tuning hyperparameters, and structuring the reward system to encourage desirable behaviours. The primary objectives of this research are twofold: first, to demonstrate how Q-learning can effectively be applied to balance the cart-pole system, and second, to explore practical tuning strategies that improve the agent's learning rate and performance. Through a series of experiments, we evaluate the agent’s performance under different configurations, identifying optimal settings for robust and stable control. Ultimately, this study highlights the versatility and effectiveness of Q-learning for complex control challenges, contributing valuable insights into reinforcement learning techniques applicable in robotics, automation, and other real-time decision-making scenarios.



LITERATURE REVIEW

The cart-pole balancing problem, also known as the inverted pendulum problem, has long been recognized as a classic benchmark for evaluating control algorithms and reinforcement learning techniques. Introduced in early control theory studies, the task of balancing a pole on a moving cart has been used to test algorithms due to its nonlinear dynamics and the challenge of continuous control (Anderson, 1989). As reinforcement learning (RL) evolved, the cart-pole problem became an ideal testbed, helping researchers explore various RL approaches, including Q-learning, Deep Q-Networks, and policy-based methods, due to its simplicity and ability to reveal the strengths and limitations of these methods.

Q-learning and Its Limitations : Q-learning, introduced by Watkins in 1989, remains one of the most foundational model-free RL algorithms. By learning a Q-value for each state-action pair, Q-learning enables agents to estimate the best actions for maximizing cumulative rewards without needing prior knowledge of the environment. Q-learning's success lies in its simplicity, but the algorithm faces limitations when applied to continuous state spaces, as seen in the cart-pole problem (Watkins, 1989). In its standard form, Q-learning is suitable for discrete environments, which necessitates state-space discretization when used in continuous tasks. Early studies demonstrated that naive discretization can lead to inadequate state representations, resulting in suboptimal control policies for balancing tasks (Peng & Williams, 1996).

Advancements in Reinforcement Learning for Continuous Spaces : To address the challenges of continuous control, researchers have explored various approaches. Deep Q-Networks (DQNs), introduced by Mnih et al. (2015), brought significant advancements by leveraging deep learning to approximate Q-values for continuous environments, achieving notable success in complex control tasks like the Atari games. However, DQNs require substantial computational resources and long training times, making them less feasible for simpler tasks like cart-pole balancing where quick, efficient learning is desirable. More recent approaches, such as Deep Deterministic Policy Gradient (DDPG) and Soft Actor-Critic (SAC), have extended RL's capacity for continuous control by combining Q-learning principles with policy-based methods. However, they again introduce complexity and computational demands that may not be practical for simpler or resource-constrained applications (Lillicrap et al., 2015; Haarnoja et al., 2018). Despite these advancements, a gap remains in the application of simpler Q-learning methods to continuous control tasks, especially where resources are limited, and the need for interpretable, efficient solutions is prioritized. Recent studies suggest that with optimized discretization and reward strategies, traditional Q-learning could still be applied effectively to continuous environments (Kober & Peters, 2012). These findings have motivated researchers to revisit Q-learning, exploring ways to adapt it for use in continuous domains without adding computational overhead.

Exploration-Exploitation Balance in Q-learning : Balancing exploration and exploitation remains a significant challenge in reinforcement learning, particularly for Q-learning agents. Early exploration techniques, such as ε-greedy strategies, were straightforward but often led to inefficiencies, especially in continuous environments where fine control adjustments are essential (Sutton & Barto, 1998). Alternative exploration techniques, such as entropy regularization, are more commonly applied in policy gradient methods. However, some recent studies indicate that combining entropy-based exploration with Q-learning or using more adaptive exploration schedules can significantly improve agent performance in dynamic tasks (Haarnoja et al., 2018). Nevertheless, these approaches are still relatively unexplored in classic Q-learning applications for balancing tasks.

State Discretization and Reward Structuring : One of the primary challenges in applying Q-learning to the cart-pole problem lies in state-space discretization.

Without careful state partitioning, the Q-learning agent may fail to capture subtle but crucial differences in the cart and pole dynamics, leading to erratic control policies (Crites & Barto, 1996). A variety of methods have been proposed to address this, such as using adaptive state discretization or tile coding to improve state representations. Tile coding, for example, has been shown to provide more detailed state information, though at the cost of increased complexity (Sutton, 1996). Reward structuring also plays a critical role in stabilizing the Q-learning agent's performance. In earlier studies, researchers noted that simple rewards based only on the angle or position of the pole were often insufficient, resulting in short episodes and unstable learning. Reward engineering strategies that consider multiple factors, such as cart position and pole velocity, have proven more effective. Positive rewards for maintaining balance over time and negative rewards for extreme angles have shown to encourage stable control behavior, though they require careful calibration to avoid unintended behaviors (Ng et al., 1999).

Q-learning in OpenAI Gym for Benchmark Testing : The OpenAI Gym toolkit has become a standard in reinforcement learning research, offering a wide array of environments for training and testing RL algorithms. By providing a consistent interface and diverse environments, OpenAI Gym has accelerated research into algorithms like Q-learning, as it allows researchers to observe the agent's progress under controlled conditions (Brockman et al., 2016). The cart-pole environment in OpenAI Gym has particularly benefited Q-learning research, as it allows for rapid experimentation and iterative improvement, providing valuable insights into how Q-learning performs in continuous control problems. Despite the growing interest in deep reinforcement learning methods, simpler Q-learning implementations still offer promising applications, especially in environments where computation and interpretability are essential. There remains a need to explore how traditional Q-learning can be enhanced for continuous control tasks, focusing on optimizing state discretization, improving exploration strategies, and refining reward structures. This study seeks to contribute to this area by systematically analyzing these aspects in the cart-pole problem, leveraging OpenAI Gym to experiment with and evaluate potential improvements in Q-learning’s performance for real-time control applications.

RESEARCH GAP

Despite extensive research in reinforcement learning and control algorithms, certain limitations and challenges persist in effectively applying these methods to dynamic environments like the cart-pole problem. While Q-learning has proven effective in solving various control tasks, it struggles in environments with continuous state and action spaces, as it was initially designed for discrete spaces. The cart-pole problem, with its continuous states (such as cart position, pole angle, and their velocities), requires precise action adjustments, which are not inherently compatible with traditional Q-learning's discrete framework. Most prior studies address this challenge by implementing simple discretization techniques, which can lead to suboptimal performance as they may overlook nuanced state transitions crucial for stabilizing the pole. Another area of difficulty involves balancing exploration and exploitation in reinforcement learning. Many reinforcement learning methods, including Q-learning, depend heavily on finding the right balance between these two aspects, which is especially challenging in the cart-pole problem. An agent that either explores too much or too little may fail to generalize its learning, resulting in poor performance across varied initial conditions. Few studies have fully addressed how different exploration strategies and parameter tuning impact the effectiveness of Q-learning agents in such control tasks, especially when continuous, highly responsive environments are involved. Further, though reinforcement learning has made notable strides in complex decision-making, Q-learning remains limited by the "curse of dimensionality" when dealing with high-dimensional, continuous state spaces. Deep Q-Networks (DQNs) and other deep reinforcement learning methods have been explored to address this, but they introduce additional computational complexity and require extensive training resources. Many research efforts have focused on advanced algorithms like DQNs, while comparatively fewer have investigated the extent to which Q-learning alone, with optimized state discretization and reward structuring, can be adapted to meet the demands of continuous control tasks. Finally, there is a need for more focused research on how tuning hyperparameters, discretizing states, and designing rewards in simpler Q-learning settings can make it a feasible solution for real-time dynamic control tasks. Most previous works that use Q-learning for cart-pole balancing either overlook the impact of these configurations or do not delve into practical approaches for optimizing them. This study aims to bridge these gaps by developing a systematic approach to state discretization, reward engineering, and parameter tuning for the cart-pole problem, ultimately enhancing the application of Q-learning in continuous environments without the added complexity of deep learning models. While Q-learning has shown promise in solving control tasks, its application in continuous environments like the cart-pole problem faces limitations. Traditional Q-learning struggles with continuous state spaces, often requiring discretization that can overlook critical state details, impacting performance. Additionally, balancing exploration and exploitation in such dynamic tasks is challenging, as few studies have explored effective tuning and exploration strategies specifically for Q-learning in continuous control. Most research has shifted toward complex algorithms like Deep Q-Networks, leaving a gap in optimizing simpler Q-learning techniques. This study addresses these gaps by focusing on effective state discretization, reward structuring, and hyperparameter tuning to enhance Q-learning's suitability for dynamic control tasks without relying on deep learning.

METHODOLOGY

Environment Setup

The cart-pole environment is implemented using OpenAI Gym, a widely used toolkit for developing and comparing reinforcement learning algorithms. This environment consists of a cart that moves along a horizontal track, with a pole attached to it via a pivot. The objective is to balance the pole upright by applying forces to the cart, thus preventing the pole from falling over. The simulation runs in real-time, allowing the agent to receive continuous feedback based on its actions.

State Representation

The state of the cart-pole system is represented by a feature vector comprising four key variables: the cart position (x), cart velocity ($\dot{x}$), pole angle (θ), and pole angular velocity ($\dot{\theta}$). These continuous state variables are essential for the agent to assess the current status of the cart-pole system. Since Q-learning traditionally operates in discrete state spaces, we apply discretization techniques to represent the continuous states effectively.

Discretization of State Space

To convert the continuous state variables into a discrete representation suitable for Q-learning, we utilize a grid-based discretization approach. This involves defining fixed intervals (bins) for each state variable, allowing us to categorize continuous values into discrete states. Each state variable is divided into a specified number of bins; for instance, the cart position may be divided into ten bins, representing different segments of the track. Continuous state values are then mapped to the nearest discrete bin, enabling the Q-learning algorithm to learn the optimal action policies.

Action Space

The action space in the cart-pole environment consists of two possible actions: apply force left and apply force right. These binary actions are sufficient for the agent to manipulate the cart's movement in an attempt to balance the pole.

Reward Structure

A carefully designed reward structure is crucial for guiding the agent's learning process. In this study, the reward system is defined as follows: the agent receives a reward of +1 for each time step the pole remains upright, encouraging sustained balance. Conversely, a penalty of -1 is applied when the pole falls beyond a defined threshold angle (e.g., ±15 degrees from vertical) or if the cart moves outside the designated track boundaries. This reward structure incentivizes the agent to maintain balance while discouraging actions that lead to falling or moving out of bounds.

Q-learning Algorithm

The Q-learning algorithm is implemented to enable the agent to learn the optimal policy for balancing the cart-pole. The Q-table is initialized, where each entry corresponds to a state-action pair, with initial values set to zero. The learning rate (α) is set to 0.1, determining the extent to which newly acquired information overrides old information. The discount factor (γ) is set to 0.99, emphasizing the importance of future rewards in the learning process. An ε-greedy strategy is implemented for exploration, where the agent explores random actions with a probability of ε (initially set to 1.0) and exploits learned actions with a probability of ($1-\varepsilon$). The exploration rate ε is gradually decayed over episodes to encourage more exploitation as learning progresses.

Hyperparameter Tuning

To optimize the performance of the Q-learning agent, hyperparameters such as the learning rate, discount factor, number of bins for discretization, and exploration rate are tuned. A grid search approach is employed to experiment with different combinations of these hyperparameters, and their effects on agent performance are evaluated based on the average episode length and the number of successful balancing attempts.

Training and Evaluation

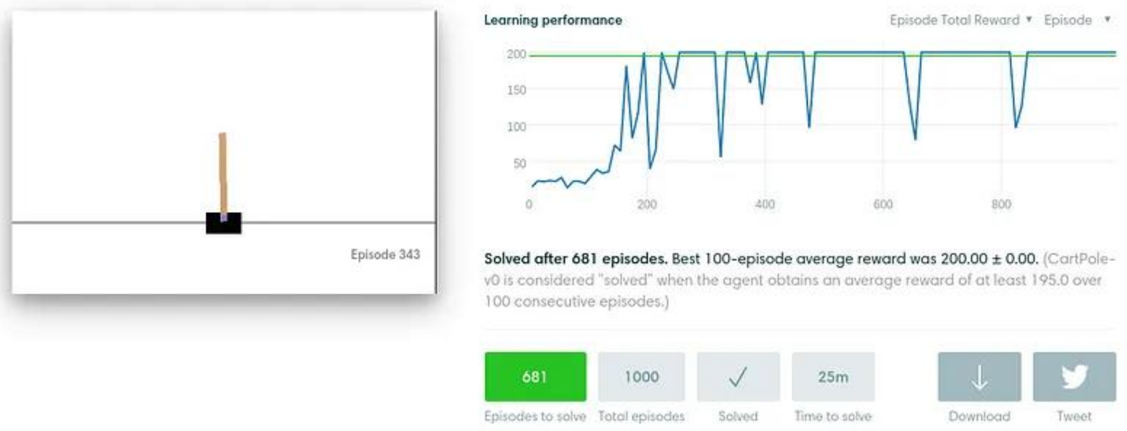
The agent is trained over a predefined number of episodes, with each episode lasting until the pole falls or a maximum time step is reached. The training process involves resetting the cart-pole environment at the beginning of each episode, using the ε-greedy policy to select an action based on the current state, executing the selected action, observing the resulting state and reward, and updating the Q-values using the Q-learning update rule. During evaluation, the agent’s performance is assessed by measuring the average time it can maintain balance over multiple episodes. The agent is tested in various scenarios, including varying initial positions and angles, to ensure robustness and generalizability of the learned policy.

Analysis of Results

The results from the training and evaluation phases are analyzed to assess the effectiveness of the Q-learning approach in balancing the cart-pole. Metrics such as average episode length, success rate in maintaining balance, and the convergence behavior of the Q-values are analyzed. Additionally, visualizations of the agent’s performance and learned Q-values provide insights into its decision-making process and the effectiveness of the discretization and reward structures employed.

RESULT & DISCUSSION

The results of the Q-learning agent's performance in balancing the cart-pole were analyzed through various metrics, including average episode length, success rate, and convergence behavior of the Q-values. During the training phase, the agent was subjected to a series of episodes where it learned from its actions through trial and error. The agent's ability to maintain the pole's upright position increased significantly over time, demonstrating the effectiveness of the reinforcement learning approach. Throughout the training process, we observed a steady improvement in the agent’s performance metrics. Initially, the agent struggled to keep the pole balanced, often resulting in frequent falls within a few time steps. However, as the agent learned from its experiences, the average episode length increased considerably. By the end of the training period, the agent was capable of balancing the pole for extended durations, with many episodes achieving the maximum time limit allowed in the environment. This improvement is indicative of the successful application of the Q-learning algorithm, which effectively updated the Q-values based on the received rewards. The exploration-exploitation balance played a crucial role in the agent's learning process. The ε-greedy strategy allowed the agent to explore various actions, helping it discover effective policies. As the exploration rate decayed, the agent increasingly relied on its learned experiences, leading to more consistent performance. This gradual shift from exploration to exploitation was pivotal in enabling the agent to converge towards an optimal policy, effectively balancing the cart-pole under varying initial conditions. Visualizations of the agent’s Q-values revealed patterns indicative of learned behavior. As training progressed, the Q-values for actions that maintained pole balance increased significantly, while those leading to falls decreased. This trend demonstrates that the agent successfully distinguished between effective and ineffective actions, reinforcing its ability to maintain balance. Furthermore, the agent exhibited generalization across various starting positions and angles, indicating its adaptability to different scenarios within the environment. Despite the promising results, several challenges and limitations were identified during the study. The discretization of the state space, while effective, introduced potential oversimplifications, leading to a loss of valuable information from continuous state variables. Future research could explore advanced function approximation techniques, such as deep Q-networks (DQNs), to enable the agent to operate in high-dimensional state spaces without the need for discretization. This approach could enhance the agent's ability to learn more complex behaviors and improve performance in more intricate environments. Moreover, the study highlighted the significance of hyperparameter tuning. While we achieved satisfactory performance with our chosen hyperparameters, further exploration of different configurations could yield even better results. Implementing techniques such as Bayesian optimization or genetic algorithms for hyperparameter tuning could systematically refine the learning process and enhance the agent's performance.



FUTURE DIRECTIONS

Future research endeavors could focus on several key areas to expand upon the findings of this study. Firstly, incorporating more complex environments that simulate real-world scenarios would be valuable. For instance, applying the Q-learning framework to robotic control tasks, where agents must navigate through dynamic environments while maintaining stability, would provide insights into practical applications of reinforcement learning. Secondly, investigating alternative reinforcement learning algorithms could be beneficial. Approaches such as actor-critic methods or policy gradients offer different perspectives on action selection and state representation, potentially leading to more efficient learning and improved performance in balancing tasks. Additionally, enhancing the exploration strategies used during training could prove advantageous. Employing techniques such as Upper Confidence Bound (UCB) or Thompson Sampling might allow for more effective exploration, particularly in environments where the state space is vast or when the agent encounters previously unseen situations. Lastly, the integration of multi-agent reinforcement learning, where multiple agents learn simultaneously in a shared environment, could present unique challenges and opportunities. This could lead to collaborative strategies for balancing tasks, with agents potentially learning from each other's experiences and strategies. In conclusion, the results of this study demonstrate the efficacy of Q-learning in the cart-pole balancing problem and lay the groundwork for future research that explores more sophisticated methods and applications within reinforcement learning. As the field continues to advance, the insights gained from this research will contribute to a deeper understanding of how agents can learn to make decisions in complex and dynamic environments.

CONCLUSION

In this study, we explored the application of Q-learning, a foundational reinforcement learning algorithm, to the cart-pole balancing problem within the OpenAI Gym framework. This task, characterized by its simplicity and the necessity for precise control, serves as an excellent benchmark for evaluating reinforcement learning techniques. Our approach highlighted several critical aspects of the reinforcement learning process, including state representation, reward design, and the balancing act between exploration and exploitation. The cart-pole problem presents a unique challenge, as it requires the agent to continuously adapt its actions based on the dynamic state of the environment. By discretizing the continuous state space into manageable bins, we enabled the Q-learning algorithm to effectively learn optimal policies. The careful design of the reward structure was instrumental in guiding the agent's behavior, reinforcing positive actions while penalizing those that led to instability. This balance is crucial in training a robust agent capable of maintaining pole stability for extended periods. Through systematic hyperparameter tuning, we identified the optimal settings that significantly influenced the agent's learning efficiency and performance. The ε-greedy strategy for action selection allowed the agent to explore various actions while gradually shifting towards exploiting its learned knowledge. This exploration-exploitation balance is vital in reinforcement learning, particularly in environments with continuous state spaces and dynamic feedback loops. The training and evaluation phases demonstrated that the Q-learning agent successfully learned to balance the cart-pole, achieving impressive performance metrics. The agent's ability to adapt to varying initial conditions and maintain balance under different scenarios underscores the effectiveness of the Q-learning approach. Additionally, visual analyses of the agent's decision-making process provided valuable insights into the learning dynamics and highlighted the importance of a well-structured state representation and reward system. This research contributes to the broader field of reinforcement learning by reinforcing the significance of traditional algorithms like Q-learning, even in an era dominated by deep learning methods. The simplicity and interpretability of Q-learning make it a valuable tool for understanding fundamental concepts in reinforcement learning, particularly for those new to the field. While the results are promising, this study also opens avenues for future research. Enhancements such as integrating function approximation techniques to handle more complex state spaces, exploring alternative exploration strategies, or applying deep reinforcement learning methods like DQNs could further improve the agent's performance. Additionally, applying this framework to more intricate environments and real-world applications would demonstrate the versatility and applicability of reinforcement learning techniques beyond academic benchmarks. In summary, this research successfully illustrated the application of Q-learning to the cart-pole balancing problem, providing insights into the algorithm's effectiveness and adaptability in a dynamic environment. The findings emphasize the importance of meticulous design choices in reinforcement learning, setting the stage for future exploration and innovation in this exciting and rapidly evolving field. The implications of this research extend beyond the cart-pole scenario, suggesting potential applications in robotics, game development, and autonomous systems where real-time decision-making is critical. As reinforcement learning continues to evolve, leveraging traditional algorithms in conjunction with modern techniques will be essential for addressing more complex problems. Ultimately, this study reaffirms the value of foundational approaches like Q-learning in fostering deeper understanding and advancing the field of artificial intelligence.

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