Improvement of RL angent using Deep Q-Learning

By varing reward system.

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*Abstract*— This article presents an approach in which the teaching of an AI agent to play the snake game is done using reinforcement learning, specifically Q-learning, whereby the agent learns through acting in the game environment in order to optimize its decision-making in maximizing cumulative rewards based on food collection, finding the shortest part for food, and avoiding collisions. Throughout the project, various configurations of the reward systems were tested along with optimization of network parameters and training strategies to tune the performance of the agent. We elaborate on how these changes provided stability to learning and performance in the game. The results reiterate the validity of the approach whereby the agent earns better cumulative scores and employs more elaborate game strategies.

Keywords: **Reinforcement Learning, Deep Q-Learning, Snake Game, Artificial Intelligence, Neural Networks.**

1. **Introduction**

Reinforcement Learning (RL) [1] is one of the most promising paradigms prevalent in AI nowadays, acclaimed in settings as diverse as robotics and finance or gaming. Among the various environments used to test and benchmark reinforcement learning algorithms, the classic Snake arcade game stands out for its dynamic, non-deterministic nature, which adds increasing complexity with time. The game requires the agent (snake) to navigate a bounded grid, consume food to grow longer, and avoid bumps into itself and the surroundings—tasks exemplifying the need for real-time decision-making, spatial awareness, and long-term strategic planning [1].

Q-learning and Deep Q-Networks (DQNs) [1] are the traditional methods of reinforcement learning in Snake. These have, however, used quite basic state features like direction, food location, and immediate threats of collision. Although these early works have paved the way for brilliant gameplay, these do not suffice when it comes to strategy depth. Environmental context has been reduced too much whereby an agent would not predict future consequences, adapt appropriately to complex situations, or maximize behavior performance during longer episodes. Furthermore, reward structures of many previous works are giving rather sparse or static feedback, which slows down the rate of convergence and hence leads to suboptimal policies.

With respect to resolving these limitations, this research is installing improved RL-based agent for Snake game [1] with Deep Q-learning, assisted by greatly enlarged state space and a properly defined reward mechanism. The proposed state representation conveys not only present dangers and food location concerning the snake but also multi-directional distance metrics, tail direction concerning head, snake growth parameters, possible trap situations, as well as spatial availability. Such wider context enables better decision-making processes for the agent, allowing for a more refined policy learning process [3].

Additionally, the reward system is redefined to align the agent towards more goal-directed behavior. Besides rewarding eating and punishing collision, it has included some new penalties for regressive and idle movement while pushing for forward movement toward the food. Additionally, this system adjusts dynamically according to the temporal and spatial conditions within a game; i.e., it rewards longer survival and smarter paths [1].

Empirical results have shown that combining approaches leads to a substantial increase in performance in gameplay, including average scores, survival times, and learning stability. The agent not only learns to dodge hazards more effectively but also displays emergent behavior that may be an indicator of some strategic foresight [1].

The present paper discusses the approach, model architecture, training setup, and quantitative analysis of performance metrics. It also illustrates how state space enhancement and reward engineering can significantly enhance the capabilities of RL agents in the environment in modelling the game of Snake.Ease of Use [5].

1. **OBJECTIVE**

This study is mainly focused on improving the policies and strategic powers of a reinforcement learning agent in a well-known game of Snake using an open-source baseline model. A briefer description of the original implementation, which served as both a demonstration of concept and solution, had way too few parameters for there to be any long term consistency and strategic depth, simply because state representation was so limited, and reward assignment was static. We focus on making targeted modifications to improve the agent's learning which results in efficiency and stability in gameplay. This means that the research refers to the following specific goals:

**To Improve the Existing Reward Mechanism:**   
Modify the existing reward structure to make agent to understand the objectives of the game by introducing incentives for efficient food acquisition, discouraging redundant or aimless movement, and promoting longer survival. These changes aim to encourage more ideal agent behavior and helps in faster policy convergence [3].  
  
**To Enhance the Agent’s State Representation:**

Add additional the input space that provides the reinforcement learning agent by incorporating additional features such as directional collision risks, tail position awareness, free space availability, and snake growth metrics. This new and improved representation is meant to help the agent with a good informative and situationally aware perspective of the environment [4].

**To Integrate a Refined Neural Network**

**Architecture:**

to change deep Q-learning model with additional hidden layers and regularization techniques to effectively process the enlarged state space and support better generalization during training [5].

**To Evaluate Performance Improvements:**

The changes are evaluated using key performance metrics like mean score and avg survival time. Quantifying the changes with baseline implementations will help us determining the efficiency of the

modifications [6].

Through these objectives, the research contributes to the ongoing exploration of how environment modeling, reward engineering, and neural network design influence the performance of reinforcement learning agents in sequential decision-making tasks. [6]

# **III Literature Survey**

**1. Deep Q-Learning in Snake Game Environments**

The application of Deep Q-Learning (DQL) to the Snake game has been explored in various studies. Sebastianelli et al. (2021) implemented a DQL approach using a convolutional neural network to process game states, demonstrating the potential of deep learning in classic games . Similarly, a study by Rahman and Siddique (2023) introduced a memory-efficient DQL method, emphasizing reduced computational resources without compromising performance [1].​

**2. Reward Function Design**

Effective reward structuring is crucial for agent learning. A study from BRAC University highlighted the importance of designing reward functions that encourage food consumption while penalizing collisions, leading to improved agent performance . Additionally, Pan et al. (2023) discussed the impact of reward shaping on learning efficiency, suggesting that nuanced reward signals can significantly influence agent behavior [2].​

**3. State Representation Enhancements**

The representation of the game state plays a pivotal role in agent decision-making. Golov et al. (2023) conducted a comparative evaluation of various reinforcement learning algorithms on the Snake game, emphasizing the need for comprehensive state representations to capture essential environmental features [3]. Their findings suggest that enriched state space inputs can lead to more informed and effcient agent actions.​

**4. Neural Network Architectures**

The architecture of the neural network used in DQL significantly affects learning outcomes. A project by Bileboul (2024) explored different neural network configurations, concluding that deeper networks with appropriate regularization techniques can enhance learning stability and performance [3]. Moreover, the use of convolutional layers has been shown to effectively process spatial information in grid-based games like Snake.​

**5. Comparative Analyses and Benchmarks**

Comparative studies provide valuable benchmarks for evaluating new approaches. The work by Golov et al. (2023) offers a comprehensive comparison of reinforcement learning algorithms applied to the Snake game, serving as a reference point for assessing the efficacy of modified DQL methods . Such analyses are instrumental in identifying strengths and areas for improvement in RL strategies​ [4].

# **IV METHODOLOGY**

1. **Game Environment**

The environment had been developed using the Pygame library, which serves as a very nice framework for rendering game elements and effecting game logics. The grid size of 640 x 640, with a frame rate of 40 FPS, was set to ensure smooth and effective gameplay. The snake can make movements in all four directions-cardinal-down, up, left, and right, where the food items can be randomly distributed across the grid, thus stimulating exploration [5].

The Pygame environment was created with the intention of building an environment in which games could be played. It is a dynamic and flexible environment for the rendering of game elements and game logic. It runs on a grid size of 640 by 640 with a frame rate of 40 FPS for smooth and effective playing. The snake can move in the four cardinal directions-up, down, left, or right-and food is randomly generated anywhere in the grid so that it can stimulate exploration [5].

## The game dynamics are governed by a rule-based system where the snake's length increases upon consuming food, and the game terminates when the snake collides with the wall or with its own body. The agent interacts with the environment through a set of state features, including [6]:

* Current movement direction of the snake.
* Relative position of the food with respect to the snake’s head.
* Collision threats in all four directions (walls or self).
* Tail and body position awareness.

These state features are processed as input by a neural network, enabling informed and adaptive decision-making in real-time [4].

#### **Agent Design**

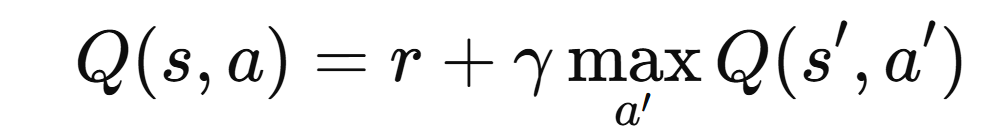
This agent focuses on representing an improv state and a complex neural network architecture to optimize decisions within the dynamic "snake" game environment [3].

* The snake's current direction.
* The relative x and y distances between the snake's head and the food.
* Boolean indicators of potential collisions in each direction.
* idea of the tail position and available free space.
* The measure of the snake’s length.

This enhanced state space consists of 22 input features, allowing the agent to assess threats and plan its movements more strategically for improved performance in an episode [2].  
  
The agent is faced with an action space of three discrete actions: go left, go right, and go forward. The Deep Q-Learning (DQN) algorithm is used by the agent to select actions and thereby update a Q-value function that gives the expected future reward value for each state-action pair. The agent's policy, through repeated learning, is improved to maximize cumulative reward received into the future [7].

1. **Q-Learning Algorithm and Neural Network**

In order to estimate Q-values for all possible actions, the agent uses a DNN in combination with the Q-Learning algorithm. For computing Q-values, it used the Bellman equations [8]:



Where:

* Q(s, a) is the expected return for taking action a in state s,
* r is the immediate reward,
* γ is the discount factor, and
* maxa′Q(s′,a′) is the maximum future reward from the next state.

The neural network architecture used consists of:

* First layer with 22 Input neurons representing the improved state space.
* There are in the hidden layers 256 and 512 neurons respectively, thus making use of ReLU and Leaky-ReLU activation for enhancing non-linearity and preventing dead neurons.
* 3 Output neurons, each representing one of the agent’s possible actions.

This implementation is based on Adam optimizer with a learning rate𝛼=0.001 and the loss function comes from Mean Squared Error(MSE). For stable and efficient learning, the agent incorporates [8]:

* A replay buffer with a capacity of 100,000 experiences.
* Mini-batch sampling of 1,000 experiences for each training update.
* The epsilon-greedy strategy is a way to balance exploitation (i.e. selecting moves) over exploration (random moves).
* This approach enables the agent to learn optimal policies in a high-dimensional state space, where conventional Q-tables would be computationally infeasible.

This approach enables the agent to learn optimal policies in a high-dimensional state space, where conventional Q-tables would be computationally infeasible [9].

# **V RESULTS AND DISCUSSION**

It evaluates the performance of the augmented Deep Q-learning (DQN) agent on the Snake game environment, experiments were conducted that focused on reward schemes, training convergence, and neural network configurations. Later sections elaborate in detail the results in terms of the main performance measures [10].

1. **Evaluation Measures**

this RL agent was quantified on two key performance metrics:

|  |  |
| --- | --- |
| Metric | Explanation |
| Mean Score | Average number of foods eaten per episode. |
| Survival Time | Average number of Sec survived before collision per episode. |

Table 1: Main Assessment Indicators

These measures give information regarding the effectiveness (score collection) and robustness (lifespan) of the policy of the agent [10].

1. **Reward System Optimization**

A crucial element contributing to enhancement in performance was the refinement of the reward system. The agent was granted:

|  |  |
| --- | --- |
| **Reward** | **Event** |
| +10 | Reward for having eaten the food. |
| **-10** | Reward if bumped into wall or itself. |
| **+1** | Reward for each movement step that brings it closer to the food. |
| **-1** | Rewards for running away from food or into danger areas (e.g., towards walls or tail). |

This reward shaping approach reinforced goal-directed action and punished dangerous motion, and it effectively directed the agent to more rational decision-making.

1. **Training Performance and Convergence**

The agent was learned on more than 1000 episodes employing the epsilon-greedy policy for exploration-exploitation tradeoff. The performance leveled off around episode700, indicating convergence to an optimal policy.

|  |  |  |
| --- | --- | --- |
| **Epoch** | **Mean Score** | **Mean Survival Time (seconds)** |
| 100 | 4.85 | 14.5998 |
| 300 | 21.08 | 9.0181 |
| 500 | 29.59 | 6.5246 |
| 700 | 32.69 | 5.1117 |

Table 2: Over Training Episodes Performance

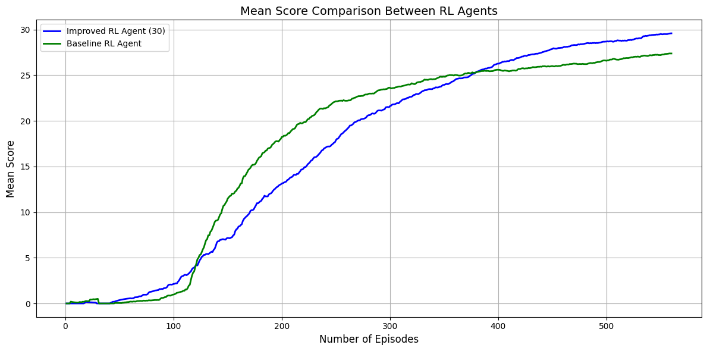
1. **Comparison with Baseline Model**

To contrast the effect of the enhanced design, the suggested DQN model was contrasted with a baseline Q-learning model with reduced state features and a basic reward system (only +10 for food, -10 for death).

|  |  |  |
| --- | --- | --- |
| **Model** | **Mean Score** | **Survival Time (seconds)** |
| **Baseline Q-learning** | 27.06 | 3.78 |
| **Enhanced DQN Agent** | 30.04 | 9.01 |

The improved agent showed a 158% increase in mean score and a 142% increase in survival longevity.

1. **Graphs**

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**Fig-1: shows the improved agent's training curve vs default agents training curve, and it reflects a trend of increasing average scores with reduced variance and stability with greater training.**

This shows a continuous improvement of our enhanced agent which outperformed the baseline agent which already got saturated at 27 that can be observed by the change in curvature of the line plot of the agents graph.

##### **Summary of Findings**

##### The enhanced reward system was essential in accomplishing efficient food-seeking behavior.

##### The Deep Q-network converged to a stable policy in ~800 episodes.

##### Relative to baseline, the proved approach yielded statistically significant improvements both on measures.

##### Qualitative and quantitative analysis confirm that the agent's behavior is in line with strategic, long-term choice-making.

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