**Designing a Snake Game Agent with Reinforcement Learning and Curriculum Learning**

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**Abstract**

*This project aims to design a reinforcement learning (RL)-based agent capable of playing the classic Snake Game. At the initial stage, we will employ Deep Q-Networks (DQN) to establish the baseline training framework. Later, we plan to integrate* ***Curriculum Learning****, which allows the agent to train progressively from simpler to more complex environments. This approach is expected to accelerate convergence and enhance the stability of learning. The anticipated result is an agent that gradually improves its gameplay performance while demonstrating the advantage of curriculum-based training compared to traditional reinforcement learning methods.*

# **Introduction**

Game AI research has been a critical component of artificial intelligence, and the Snake Game serves as an ideal platform for reinforcement learning experiments. Despite its simple rules, Snake presents significant challenges due to its dynamic and expanding state space as the snake grows. Building an RL agent for Snake not only tests reinforcement learning in a controlled environment but also provides insights into how advanced training strategies, such as curriculum learning, can enhance performance.

In the Snake Game, the agent must decide its actions (up, down, left, right) based on the current state, which includes the snake’s position, the food’s location, and potential danger directions. The objective is to maximize survival time and score. However, the problem has several challenges: (1) The state space grows rapidly as the snake becomes longer. (2) Reinforcement learning models often converge slowly or fail to learn effective strategies. (3) Directly applying DQN on the full Snake environment usually leads to suboptimal performance.

Existing approaches include heuristic-based methods, which rely on simple rules such as moving toward food and avoiding collisions. While effective in specific cases, these methods lack adaptability. Deep reinforcement learning methods such as DQN (Mnih et al., 2015) have achieved breakthrough results in Atari games and been applied to Snake. Community-driven projects (e.g., Snake-RL) demonstrated feasibility but also highlighted limitations in convergence and generalization. Curriculum Learning has been proposed as a solution, where training tasks gradually increase in complexity. The CurriculumSnake project demonstrates this staged approach and motivates our design.

Our project will first establish a DQN-based Snake agent as the baseline. To overcome the limitations of direct training, we plan to incorporate Curriculum Learning, starting with simplified tasks and gradually transitioning to the full Snake environment. This progressive approach is expected to enhance both learning speed and stability.

# **Method**

We propose a DQN-based framework enhanced with curriculum learning. The algorithm design includes:  
1. Base Algorithm: Deep Q-Network (DQN).  
2. State Representation: snake head position, relative food location, danger indicators (wall and body collision risks), and snake length.  
3. Action Space: four possible moves (up, down, left, right).  
4. Policy: ε-greedy for exploration and exploitation balance.  
  
Reward function:  
+10 for eating food.  
 -10 for collisions (wall or self).  
 -0.1 for each step (to discourage endless loops).  
  
Training strategy:  
1. Experience Replay to break correlations between consecutive samples.  
2. Target Network to stabilize Q-value updates.  
3. Curriculum Learning:  
 - Stage 1: Small grid to learn basic survival.  
 - Stage 2: Medium grid, focusing on food collection.  
 - Stage 3: Full Snake environment requiring long-term planning.  
  
This staged training ensures the agent masters simpler behaviors before tackling complex environments.

# **Expected Results**

We expect the following outcomes:  
1. The agent will learn basic survival strategies and avoid immediate collisions.  
2. The agent will improve its ability to locate and consume food as training progresses.  
3. Curriculum Learning will accelerate convergence compared to plain DQN.  
4. Learning curves will show step-wise improvements with temporary drops at the beginning of each new curriculum stage.  
5. Gameplay screenshots will demonstrate the agent navigating toward food and surviving longer.

# **References**

1. V. Mnih, K. Kavukcuoglu, D. Silver, et al., “Human-level control through deep reinforcement learning,” *Nature*, vol. 518, pp. 529–533, 2015.
2. R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA: MIT Press, 2018.
3. Y. Bengio, J. Louradour, R. Collobert, and J. Weston, “Curriculum learning,” in *Proc. Int. Conf. Machine Learning (ICML)*, 2009, pp. 41–48.
4. Greerviau, “Snake-RL,” GitHub repository. [Online]. Available: <https://github.com/greerviau/Snake-RL>