Deep Q-Learning for Flappy Bird: Implementation and Evaluation

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Abstract

This report presents the implementation and evaluation of a Deep Q-Learning (DQN) agent trained to play Flappy Bird using PyTorch and Gymnasium. The report details the neural network architecture, hyperparameter settings, and experimental results. Various training runs were conducted to evaluate the performance of the agent under different configurations. The best-performing agent achieved a maximum score of **763** across multiple runs.

1 Introduction

Flappy Bird is a challenging and fast-paced game, making it an ideal testbed for reinforcement learning algorithms. This project leverages the Deep Q-Learning algorithm with experience replay and a convolutional neural network (CNN) to approximate Q-values. The goal is to train an agent capable of achieving a high score consistently.

2 Methodology

2.1 Agent Architecture

The DQN agent consists of two main components:

1. **Neural Network (NN)**: The network is designed to approximate Q-values for each action using convolutional and fully connected layers:
   - **Input Layer**: Grayscale image of size 84×84.
   - **Convolutional Layers**:
     - Layer 1: $1 \rightarrow 32$ channels, kernel size 3×3, stride 1, padding 1.
     - Layer 2: $32 \rightarrow 64$ channels, kernel size 3×3, stride 1, padding 1.
     - Layer 3: $64 \rightarrow 128$ channels, kernel size 3×3, stride 1, padding 1.
     - Layer 4: $128 \rightarrow 256$ channels, kernel size 3×3, stride 1, padding 1.
   - **Fully Connected Layers**:
     - Flatten layer: Output from convolutional layers flattened to $256 \times 5 \times 5$.
     - Dense Layer 1: $256 \times 5 \times 5 \rightarrow 512$ units.

- Output Layer: $512 \rightarrow 2$ (Q-values for actions).

2. **Replay Buffer**: A fixed-size replay buffer stores past experiences for sampling during training.

2.2 Hyperparameters

The training hyperparameters used for the DQN agent are summarized in Table 1.

Parameter	**Value**
Learning Rate (η)	1×10^{-5}
Discount Factor (γ)	0.99
Epsilon (ϵ)	$0.1 \rightarrow 0.0001$ (decay 0.995)
Batch Size	32
Replay Buffer Capacity	50,000
Training Start Threshold	5,000 experiences
Number of Epochs	2,000

Table 1: Hyperparameters for training the DQN agent.

2.3 Explanation of Hyperparameters

The hyperparameters used in training the DQN agent play a crucial role in determining its performance. Below is a detailed explanation of each parameter:

- **Learning Rate (η)**: A small learning rate of 1×10^{-5} ensures that the updates to the neural network weights are gradual, reducing the risk of overshooting the optimal values during training.
- **Discount Factor (γ)**: The discount factor of 0.99 prioritizes long-term rewards, helping the agent to plan strategies over multiple steps instead of focusing solely on immediate gains.
- **Epsilon (ϵ)**: Initially set to 0.1, epsilon facilitates exploration by encouraging the agent to take random actions. Over time, it decays to 0.0001 with a decay rate of 0.995, shifting the agent's behavior towards exploitation of its learned policy.
- **Batch Size**: A batch size of 32 ensures computational efficiency while maintaining sufficient diversity in the training samples, improving the robustness of updates to the neural network.
- **Replay Buffer Capacity**: The replay buffer holds up to 50,000 experiences, providing a diverse set of past interactions for training. This helps to reduce temporal correlations in the data, stabilizing the learning process.
- **Training Threshold**: The agent begins training only after 5,000 experiences are collected in the replay buffer. This ensures a diverse set of data is available, preventing premature updates that could hinder learning.

- **Number of Epochs**: Training the agent over 2,000 epochs allows sufficient iterations for the neural network to learn and adapt to the environment, achieving stable performance.

These carefully chosen hyperparameters ensure that the agent learns effectively while balancing exploration and exploitation. The use of a replay buffer and batch sampling further contributes to stable and efficient training.

2.4 Preprocessing

The input images undergo the following preprocessing steps:

1. Crop the bottom 110 pixels to remove irrelevant information.
2. Convert the cropped image to grayscale.
3. Resize to 84×84 pixels.
4. Normalize pixel values to $[0, 1]$ and convert to tensors.

2.5 Training Procedure

The training process consists of:

1. Epsilon-greedy action selection.
2. Experience replay with randomly sampled mini-batches.
3. Q-value updates using the Bellman equation.
4. Saving model checkpoints every 100 epochs.

3 Implementation Details

3.1 Q-Learning Algorithm

The Q-learning algorithm uses the Bellman equation:

$$Q(s, a) \leftarrow Q(s, a) + \alpha\Big(r + \gamma \max_{a'} Q(s', a') - Q(s, a)\Big)$$

Here, s and s' are the current and next states, a and a' are the actions, r is the reward, α is the learning rate, and γ is the discount factor.

3.2 Neural Network Implementation

The neural network was implemented in PyTorch, and the Adam optimizer was used for gradient descent. The Mean Squared Error loss was employed to minimize the difference between predicted Q-values and target Q-values.

4 Experiments and Results

4.1 Experimentation

Multiple training runs were conducted with varying seeds. The performance was evaluated based on:

- **Game Scores**: Average and maximum scores achieved in the Flappy Bird environment.

4.2 Results

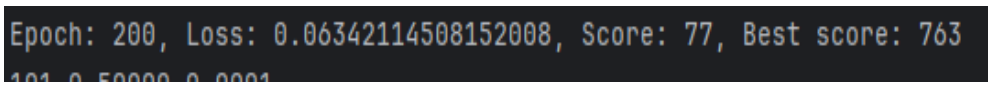
The performance of the agent is summarized in Table 2.

Epoch	Average Score	Best Score
1000	1	3
2000	10	27
2020	25	73
2030	43	98
2070	50	115
2120	55	122
2230	70	159
2290	85	219
2340	75	219
2550	78	225
2585	84	308
2600	93	308
2620	102	323
2670	114	371
2870	167	408
2900	223	578
3040	265	578
3100	311	675
3250	355	763

Table 2: The agent's performance during training, showing both the average score (indicating consistency) and the best score (representing peak performance) at various epochs.

5 Conclusion

The DQN agent successfully learned to play Flappy Bird, achieving a maximum score of **763**. Training on pixel data proved challenging but effective after extensive preprocessing and hyperparameter tuning. Future improvements include exploring advanced RL techniques like Double DQN or Prioritized Experience Replay.



References

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