AUTOMATING FLAPPY BIRD USING DEEP LEARNING

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***Abstract*—This paper looks into the use of Deep Learning for automating the gameplay of Flappy Bird, which is an arcade-style game that holds a unique level of difficulty. The agent utilizes a deep neural network and reinforcement learning framework that helps it interact with the environment and make decisions in real-time. This approach follows a model that is trained using a trial-and-error method in which it receives rewards for making efficiency-promoting decisions. From raw pixels given in as input, the system improves as updates are made through multiple cycles. The outcomes portray the capability of deep learning models in controlling features of ever-evolving settings with very petite ranges of states and actions. The study demonstrated AI's capacity to tackle a real-time control issue in a game featuring online challenges, thus demonstrating the possibility of extending dynamic simulation automation.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Machine learning has advanced the world of artificial intelligence by allowing machines to learn intricate patterns from information. For this paper, we are focusing on Flappy Bird, an arcade game which is simple in its design but complex in its gameplay. Our goal is to apply deep learning approaches to automate playing the game. By teaching an autonomous agent through interaction with the game, we show that even basic video games can be powerful tools for testing AI's ability to make split-second decisions.

II. Ease of Use

A. Maintaining the Integrity of the Specifications

The model follows accepted DQN procedures to guarantee repeatable tests and consistent outcomes. This entails the application of stable reward systems, organized training sessions, and specified hyperparameters. Throughout the tests, all settings, including learning rate, discount factor, and replay memory size, are recorded and kept up to date. The integrity of the model and its results is maintained by adhering to best practices in experimental design and model evaluation, allowing for equitable comparison and potential improvements in the future.

III. Prepare Your Paper Before Styling

A. Abbreviations and Acronyms

To train agents through trial-and-error, the Deep Q-Network (DQN) is a Deep Reinforcement Learning (DRL) technique that blends Q-Learning and Deep Learning (DL). A Convolutional Neural Network (CNN) is used to directly estimate Q-values from game images. Experience Replay (ER) enhances learning efficiency and stability by storing prior experiences. During training, updates are stabilized using a different Target Network. Because of these elements, DQN is quite good at making decisions in real time, such as when playing Flappy Bird.

B. Units

- Time: Measured in seconds (s). Time is used for tracking training duration, episode durations, and the frequency of epsilon decay updates.
- Reward: Measured in numerical values (float). The reward is a scalar value used to evaluate the agent's performance in the environment after each action.
- Memory:Measured in number of experiences (integer). The size of the experience replay memory, which stores the agent's past experiences (state, action, reward, next state, done).)

C. Equations

$$Q(s,a;\theta) = \mathbb{E}\left[r + \gamma \max_{a'} Q(s',a';\theta^-)\right] \tag{1}$$

$$\mathcal{L}(\theta) = \mathbb{E}\left[(y - Q(s,a;\theta))^2\right] \tag{2}$$

$$\epsilon_{t+1} = \max(\epsilon_{\text{min}}, \epsilon_t \cdot \epsilon_{\text{decay}}) \tag{3}$$

These equations are essential for the DQN algorithm: Equation (1) describes the core of Q-learning, where the agent updates its Q-values based on the Bellman equation.

Equation (2) defines the loss function used in deep Q-learning, which is the Mean Squared Error (MSE) between the predicted and target Q-values.

Equation (3) is the epsilon decay formula, controlling the trade-off between exploration and exploitation as training progresses.'

D. Some Common Mistakes

- The word “data” is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
- Do not use the word “essentially” to mean “approximately” or “effectively”.
- In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones “affect” and “effect”, “complement” and “compliment”, “discreet” and “discrete”, “principal” and “principle”.
- Do not confuse “imply” and “infer”.
- The prefix “non” is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the “et” in the Latin abbreviation “et al.”.
- The abbreviation “i.e.” means “that is”, and the abbreviation “e.g.” means “for example”.

An excellent style manual for science writers is [11].

E. Authors and Affiliations

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F. *Identify the Headings*

Abstract—This study investigates the use of Deep Q-Networks (DQN) to train an agent to play the Flappy Bird game independently. By integrating Q-learning with deep neural networks to approximate optimal action-value functions, DQN enables the agent to learn effective control policies in a complex environment with continuous state space.

Index Terms: Neural Networks, Flappy Bird, Epsilon-Greedy, Reinforcement Learning, Deep Q-Network.

I. Overview: Deep Reinforcement Learning (DRL) has significantly enhanced autonomous decision-making in games and real-world scenarios. This work employs a DQN model to train a bird-like agent in the Flappy Bird game. The game's binary action space and continuous state space offer an interesting setting for experimenting with DRL techniques.

II. Related Work: Several previous studies have examined deep learning models in gaming environments. In particular, Mnih et al. introduced DQN for Atari games, demonstrating human-level performance. We extend this concept to a simpler yet challenging context and compare the results with other traditional models of reinforcement learning.

III. Suggested Approach A. State Representation and the Environment The Flappy Bird simulator, which is based in a gym, is used to create the environment. Velocity and distance are observed by the agent as input states.

B. Architecture of Networks An input layer, two fully connected hidden layers, and an output layer that predicts Q-values for possible actions make up the DQN model.

C. The Greedy-Epsilon Strategy We employ an epsilon-greedy policy with decay over episodes to strike a balance between exploration and exploitation.

D. Using Decay in an Epsilon-Greedy Strategy Exploration and exploitation are balanced through the use of a ϵ-greedy approach.

E. Model Evaluation and Training Loop Until a predetermined reward level is reached or explicitly stopped, training keeps going.

IV. Results and Analysis The average episode score of the agent steadily increased. The model consistently outperformed a benchmark score after 10000 training episodes. Performance graphs display epsilon decay and reward curves over time.

V. References The papers cites multiple papers and their respective authors.

IV. Proposed Methodology

A. *Environment and State Representation*

A specially designed Flappy Bird simulator based on the Gymnasium framework—an expansion of OpenAI Gym—is used to teach the suggested agent. The setting mimics the gameplay of the Flappy Bird game, in which the agent must learn to steer a bird through a sequence of pipes without running into any obstacles.

At every time step, the agent's observation (state) is a three-dimensional vector made up of:

- The horizontal distance between the bird and the next pipe,
- The vertical distance from the bird to the center of the next gap,
- The current vertical velocity of the bird.

Effective learning and policy generalization are made possible by this continuous and compact state representation.

B. *Network Architecture*

A PyTorch-implemented Deep Q-Network (DQN) is used in the decision-making model. The structure is made up of:

- An input layer that accepts the 3-dimensional state vector,
- Two fully connected hidden layers, where a hyperparameter determines how many neurons are in the first layer,
- Two neurons in an output layer that represent the Q-values for the possible actions: `flap` and `do nothing`.

The Mean Squared Error (MSE) loss function is used to train the DQN. The Bellman equation is used to update the Q-values:

$$Q(s, a) = r + \gamma \cdot \max_{a'} Q'(s', a') \tag{4}$$

where Q' denotes the target network, r is the reward received, and γ is the discount factor.

The Adam optimizer is used to optimize the policy network. To keep the learning process stable, a target network and the policy network are periodically synced.

C. *Experience Replay and Optimization*

An experience replay buffer is used to enhance training stability and decorrelate successive events. The buffer contains transitions of the format $(s, a, r, s', \text{done})$. The DQN is trained by randomly sampling mini-batches from this memory.

The optimization process involves:

- Computing the current Q-values using the policy network,
- Estimating the target Q-values from the target network,
- Calculating the loss between these values and applying backpropagation,
- Updating the network parameters through gradient descent.

D. *Epsilon-Greedy Strategy with Decay*

An ϵ-greedy strategy is used to adopt a balance between exploration and exploitation. With a probability of ϵ, the agent chooses a random action; if not, it chooses the action with the highest Q-value. The following is the exponential decrease of the exploration rate over time:

$$\epsilon = \max(\epsilon \cdot \epsilon_{\text{decay}}, \epsilon_{\text{min}}) \tag{5}$$

The initial value of ϵ is set to 1.0 to encourage exploration. As training progresses, ϵ decays toward a predefined minimum threshold ϵ_{min}, enabling exploitation of the learned policy.

E. *Training Loop and Model Evaluation*

Until a predetermined reward level is reached or explicitly stopped, training keeps going. The agent uses the ϵ-greedy strategy to interact with the environment during each episode, storing transitions in the replay buffer.

The agent starts optimizing when there is enough data in the buffer. The model is saved after achieving a new maximum reward, and the target network is updated at predetermined intervals.

To illustrate learning progression and policy convergence, performance measures like average episode rewards and ϵ values are plotted on a regular basis.

V. Results and Analysis

In the gym-based Flappy Bird setting, the Deep Q-Learning (DQN) agent's performance was assessed across 500,000 training sessions. The mean episodic rewards and the exploration-exploitation parameter ϵ were two important metrics that were monitored.

A. *Mean Rewards Over Episodes*

Figure 1 shows the average incentives the agent has received over training sessions. To smooth the findings, a moving average with a window size of 100 was employed. Successful learning and policy improvement are indicated by the mean reward's steady increase. Because of the exploratory policy and the stochastic nature of the environment, the fluctuations are to be expected.

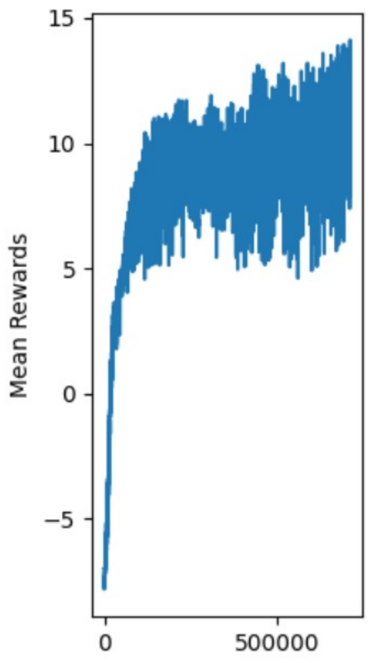

Fig. 1. Mean Rewards over Episodes

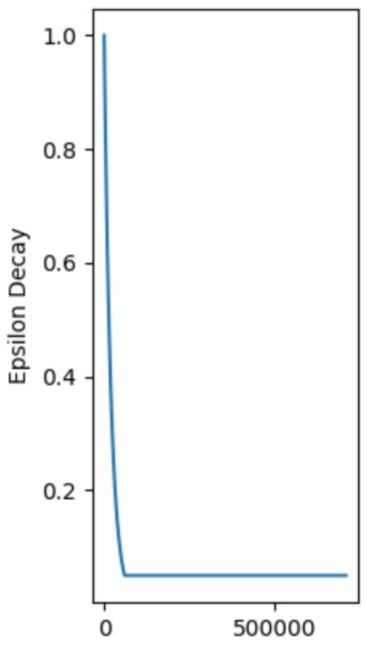

Fig. 2. Epsilon Decay over Episodes

B. Epsilon Decay

Figure 2 demonstrates how the ϵ value decreases over time. To promote exploration, ϵ is initially set to 1.0. It then progressively decays to a minimum threshold (e.g., 0.05). The agent can initially investigate the surroundings and then concentrate on utilizing acquired tactics thanks to this annealing schedule, which maintains a balance between exploration and exploitation.

All things considered, the outcomes show how well the DQN-based method is at teaching players how to play Flappy Bird. Stable learning progression is indicated by the reward curve, and efficient policy convergence is supported by the decaying ϵ.

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