Optimization of Flappy Bird using NEAT

SUBMITTED TO Prof. Amiya Kumar Dash

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Source Code

Agenda

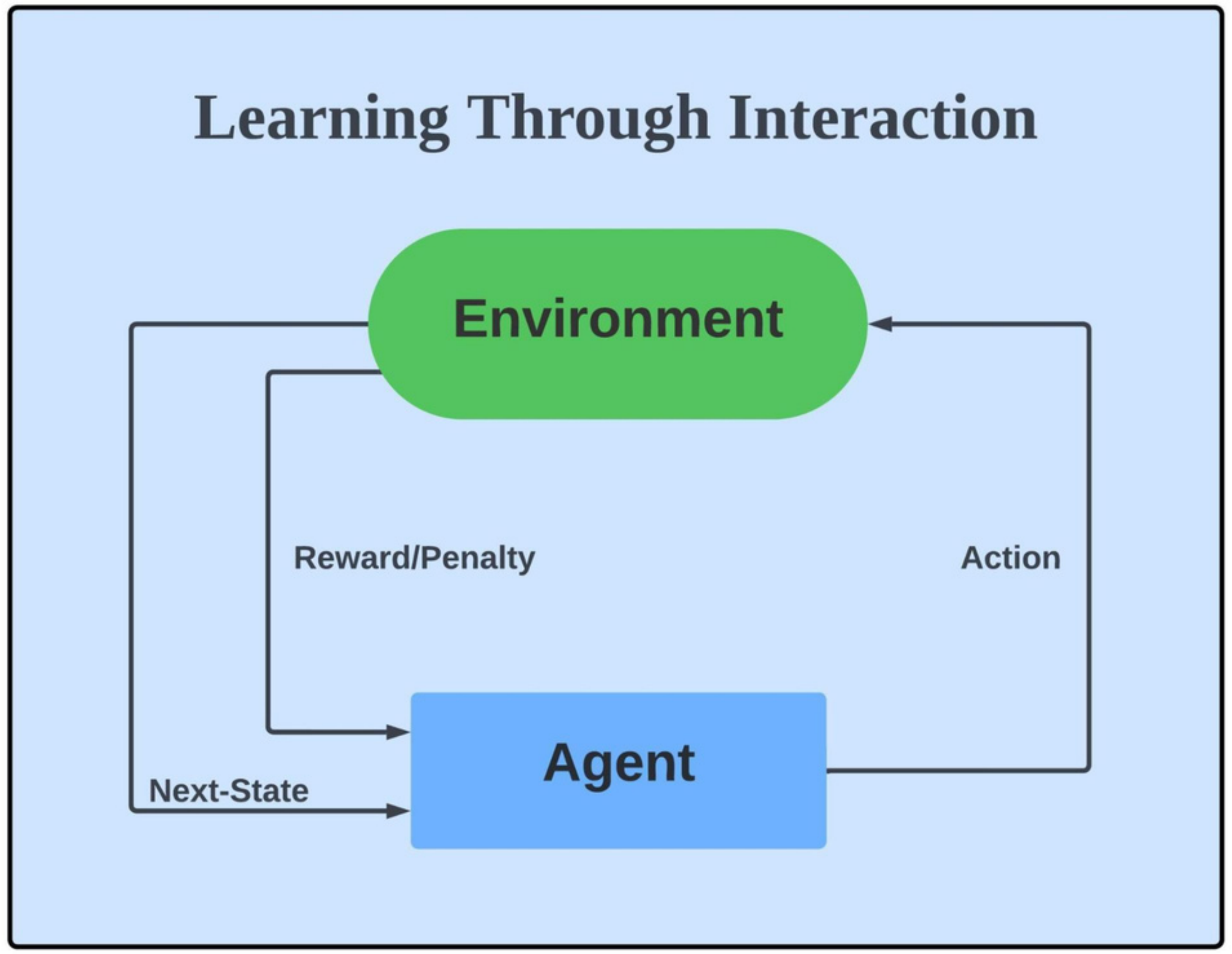
Abstract

Game learning is currently one of the most popular topics being researched in the field of artificial intelligence. AlphaGo, Agent57 and DecodeChess are some AI agents which even defeated human players. These AI agents need to go through a training phase. In this project, we propose a minimal training strategy to develop an Artificial Intelligence agent using the NeuroEvolution of Augmenting Topologies (NEAT) algorithm to play the Flappy Bird Game. The agent was not provided any prior information about the surroundings and in order to play the well-known "Flappy Bird" game as best it can, our agent learns how to carefully avoid all of the obstacles and flap its way through them.

Neuroevolution—the process of evolving artificial neural networks using genetic algorithms, leverages evolutionary principles to automatically develop the structure and connection weights of neural networks. It automatically designs the structure and connections during training, making it useful for complex tasks where traditional ANNs struggle.

***Keywords**: Artificial Intelligence; Artificial Neural network; Genetic algorithm; Flappy bird; Neuro-Evolution.*

Introduction



An intelligent agent is anything that can detect its surroundings, act independently to accomplish goals, and learn from experience or use knowledge to execute tasks better. The method is a general one, capable of being applied to an extremely wide range of problems. One such approach is NEAT algorithms which are numerical optimization algorithms inspired by both natural selection and natural genetics.

What is NEAT?

NeuroEvolution of Augmenting Topologies (NEAT) is **a genetic algorithm that generates artificial neural networks (ANNs) through evolution**. It combines network weight search with network structure complexity. It keeps a population of individual genomes, each with two sets of genes that describe how to build an ANN:

- **Node genes**: Each gene specifies a single neuron
- **Connection genes**: Each gene specifies a single connection between neurons.

Why Flappy Bird?

- Simple Ruleset and Environment
- Clear Fitness Function
- Continuous Action Space
- Visually Engaging and Accessible

Problem Statement

To optimize the Flappy Bird Game in y-axis to produce a much better result along with scores which are the highest ever recorded by any human user on this game.

Scope of the study

This project will investigate the effectiveness of NeuroEvolution of Augmenting Topologies (NEAT) in training an artificial intelligence (AI) agent to play the Flappy Bird game. The focus will be on developing a NEAT algorithm that can autonomously learn the game's mechanics, navigate obstacles, and achieve high scores.

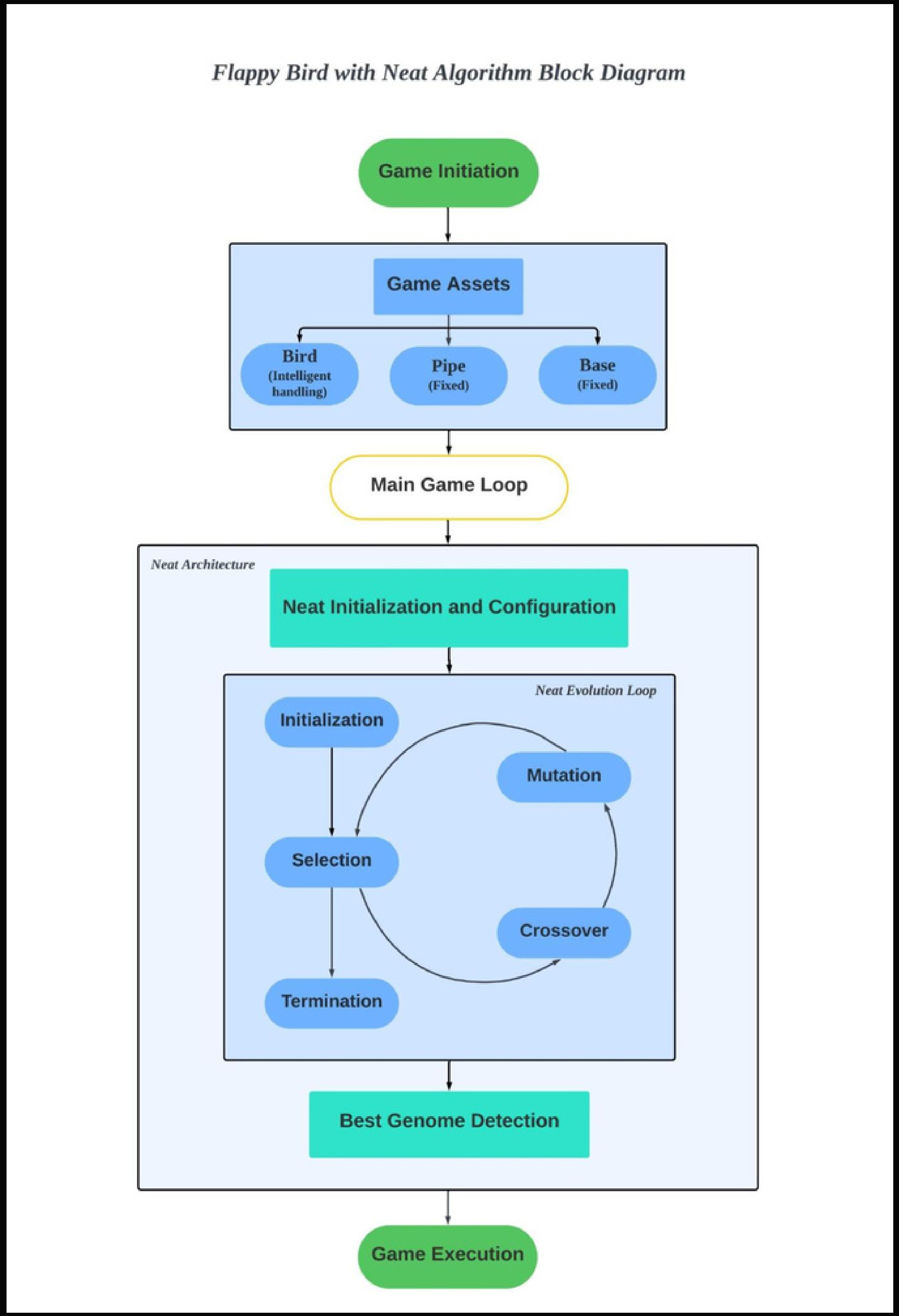
Relevance of the study

- **Understanding NEAT**: By applying NEAT to Flappy Bird, we gain insights into its capabilities for evolving neural networks in a dynamic environment.
- **AI in Games**: The project contributes to the field of AI in games by exploring a novel approach to training game-playing agents.
- **Benchmarking**: The results can serve as a benchmark for comparing NEAT to other AI techniques for similar tasks.

Research Questions

- Can a NEAT-based AI agent effectively learn to play Flappy Bird?
- What NEAT configuration parameters lead to the best performance in this game?
- How complex does the evolved neural network become to achieve high scores?

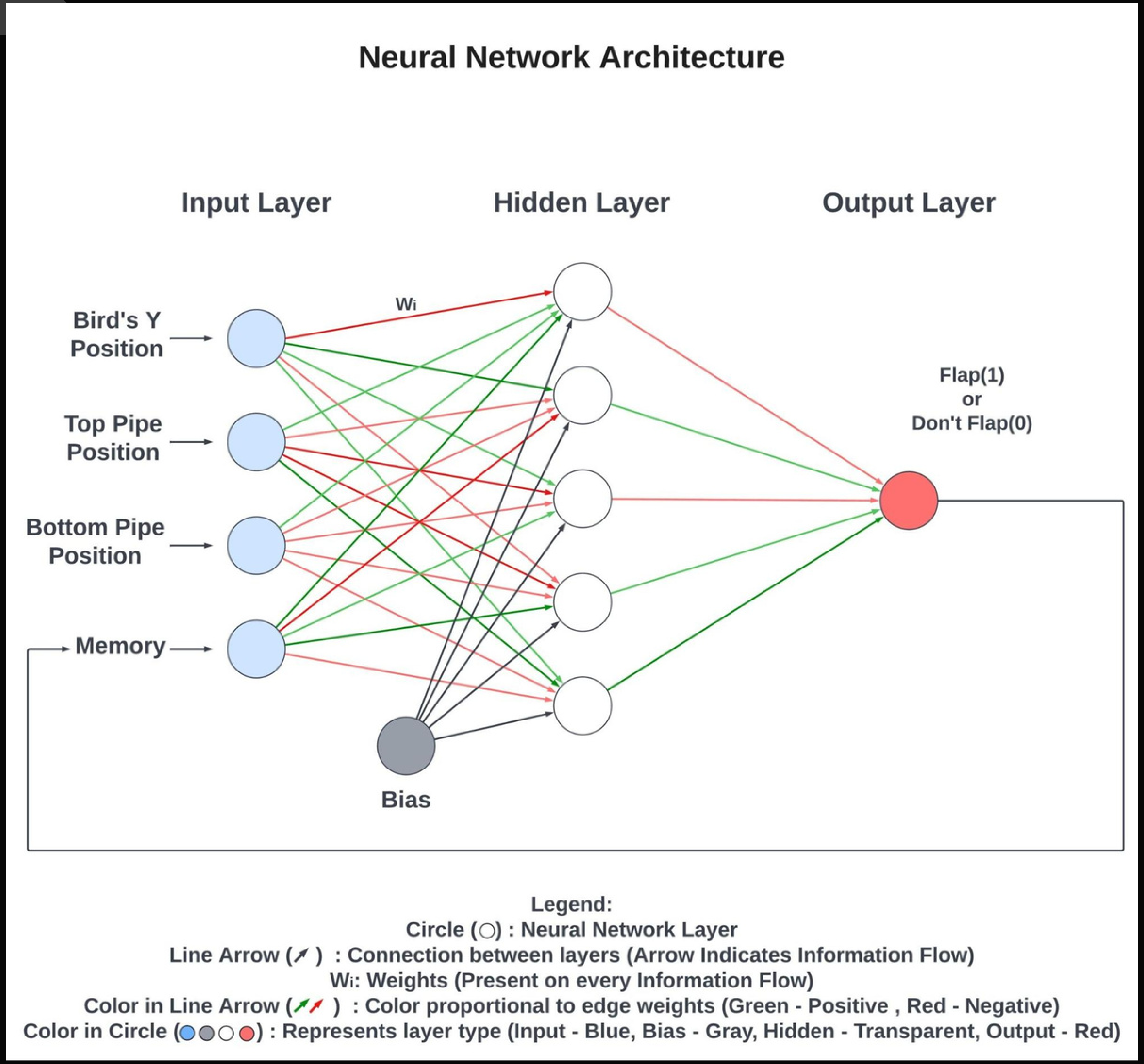
Methodology



- This diagram serves as a comprehensive roadmap for understanding the intricacies of our project, showcasing how NEAT facilitates the training of a neural network to excel at playing Flappy Bird.

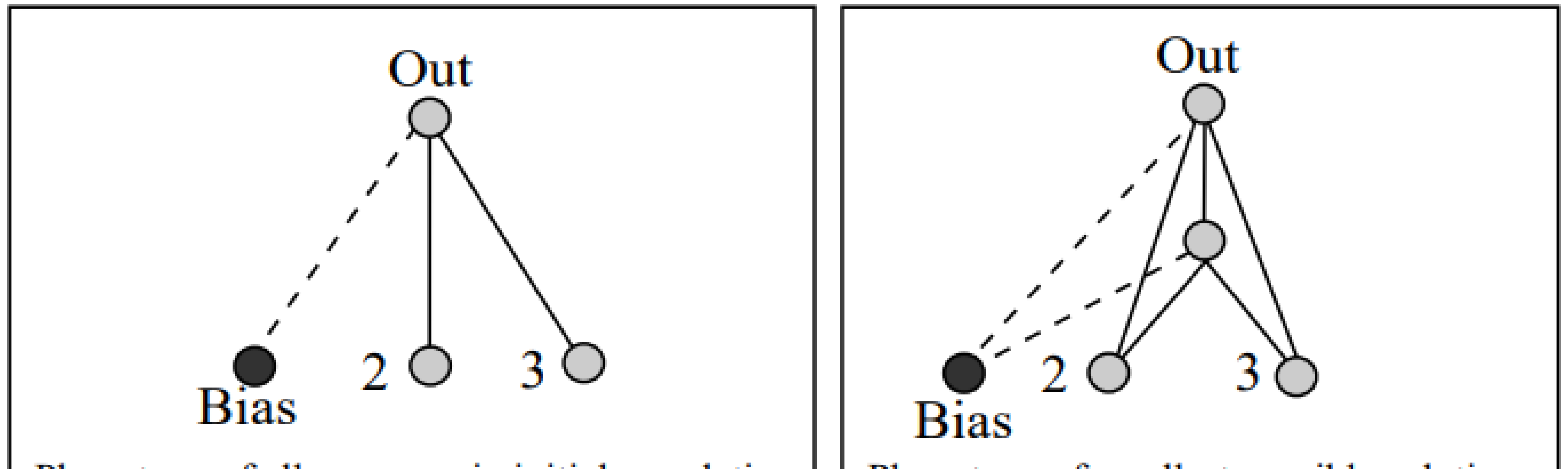
- It shows the steps of the game, including game initiation, game settings, game assets, game execution, and game termination.

Neural Network Architecture
Fitness & XOR Parameters



Fitness Parameters

- Crashing : -1
- Moving : +0.1
- Pipe Passed : +5

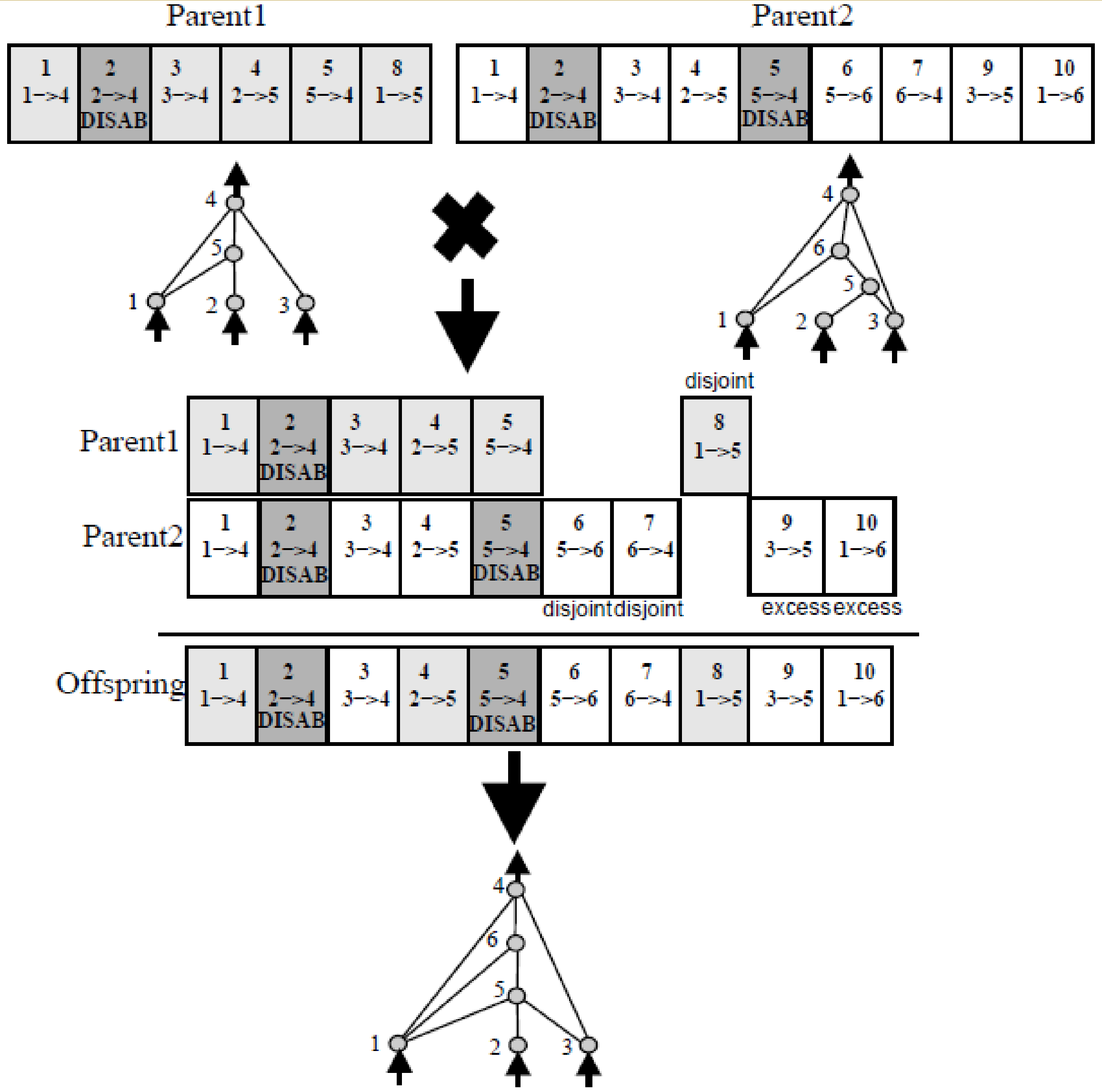


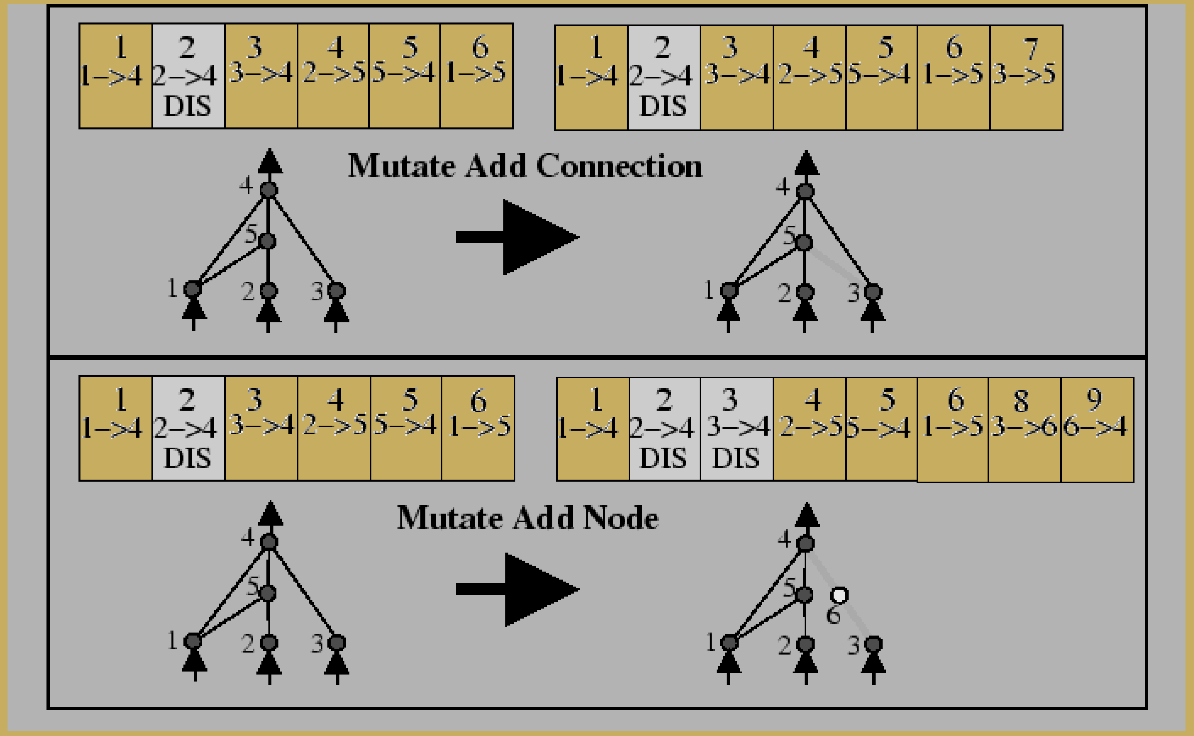
Phenotype of all genomes in initial population (No hidden nodes)

(a)

Phenotype of smallest possible solution

(b)





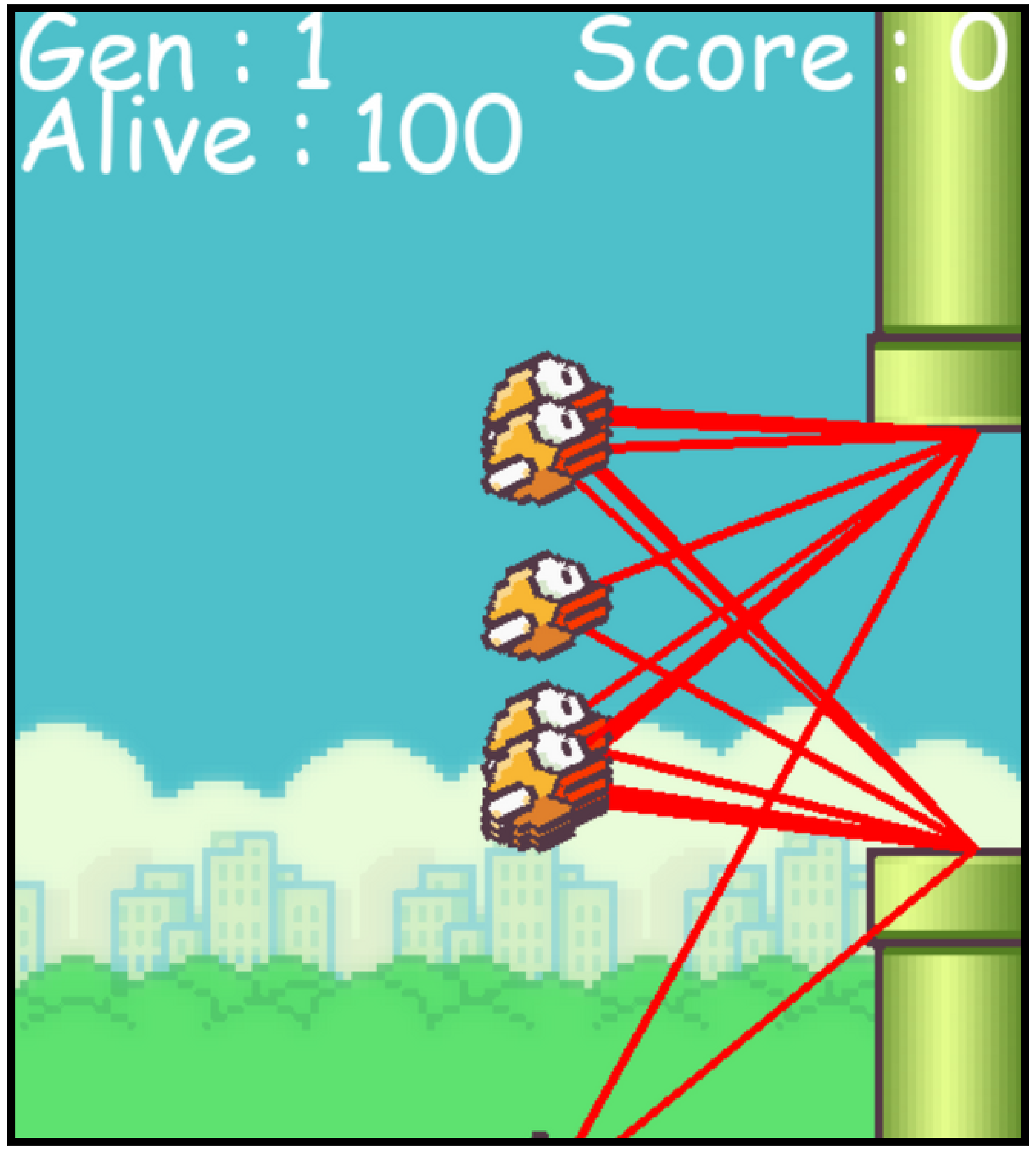
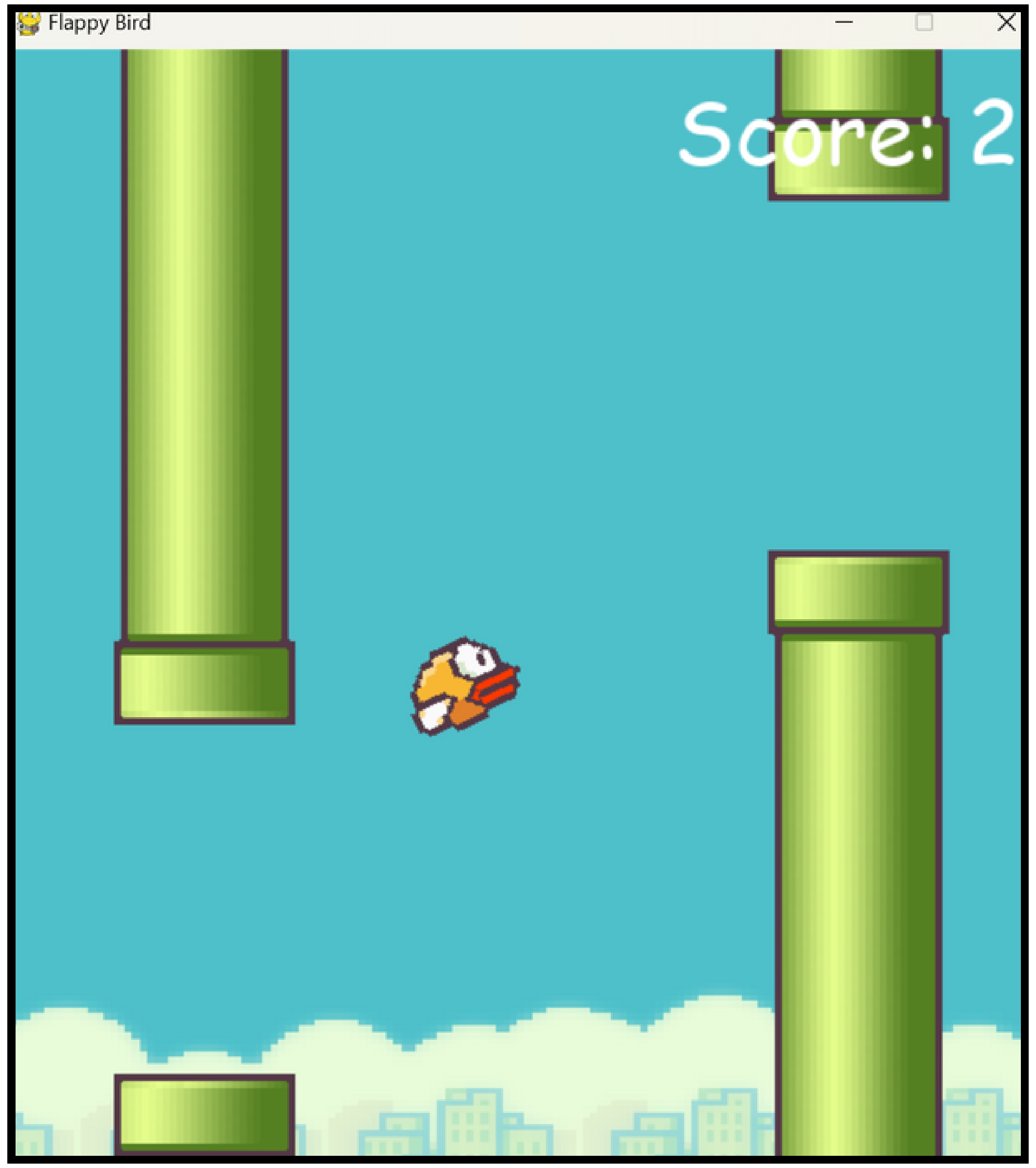
Distance Calculation & Adaptive Decision Making

$$\Delta SF = SF_{bird} - SF_{passage}$$

$$FF = \alpha \times DC_s + \beta \times Score_s - \gamma \times \Delta SF_s$$

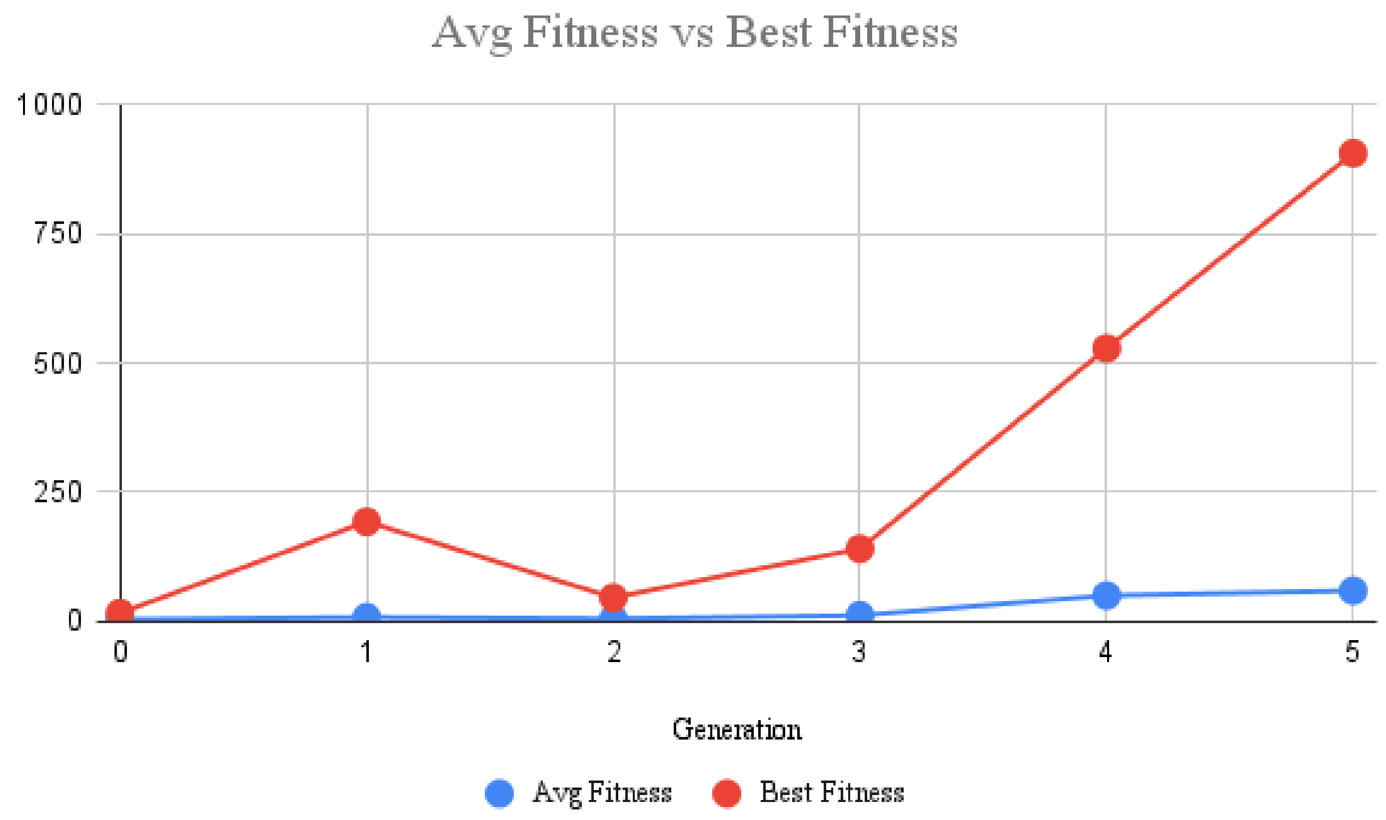
$$FF_{Agent} = \frac{\sum_{i=1}^{Tw} (w_i \times FF_i)}{\sum_{i=1}^{Tw} w_i}$$

Environment

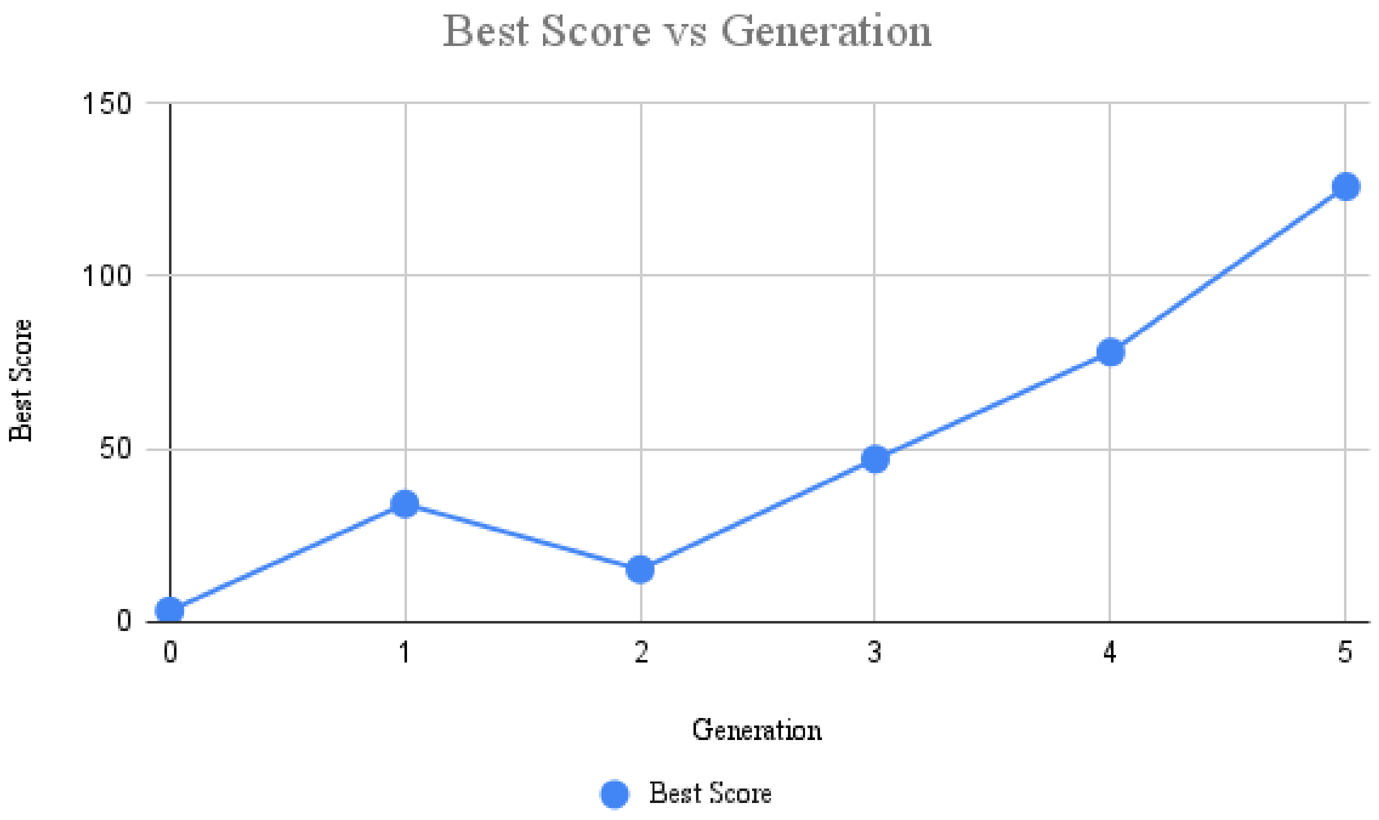
Training		Testing	
	In the training environment, the process begins with an initial population of 100 birds, each represented by a genome. The training process involves multiple generations of birds evolving and learning through finding the optimal point to cross the gap between the pipes. Each generation aims to improve upon the performance of the previous one.	In the testing environment the best-performing genome from the training phase is saved. By focusing on the best-performing genome, the testing environment provides a targeted evaluation of the learned behaviors and the agent's ability to play Flappy Bird with precision and skill.	

Result Analysis

Figure: Sample Result



This Figure represents the Fitness results. The x-axis of the chart corresponds to generations, from the beginning going up to only 5, while the y-axis corresponds to the average fitness (blue line) and the best fitness (red line) on every generation.



This Figure is quite similar to the Fitness Chart but instead of Fitness it showcases the actual Maximum Score achieved by a single genome (bird) at each generation.

Conclusion

This project demonstrated the potential of NEAT in training AI agents to play Flappy Bird. The NEAT algorithm successfully evolved neural networks that could navigate the game environment with increasing skill. The project also explores the potential applications of NEAT-based training for various real-world scenarios. By addressing the challenges of data collection, scalability, and safety, NEAT showcases to be a valuable tool for developing intelligentand adaptable AI systems.

Future Scope

- Flappy Bird requires decisions based on visual information and precise actions, similar to real-world problems in the y-axis only.
- Integrating movement along the horizontal axis (x-axis) and introducing multiple obstacles, varying their positions on both axes, and potentially including dynamic obstacles (moving cars, pedestrians) would create a richer training environment for autonomous vehicle control.
- Extending the training space to a third dimension (z-axis) could unlock the potential for training algorithms for autonomous flight. By incorporating vertical movement and obstacles in a simulated airspace, the training could encompass scenarios relevant to drone navigation or robot navigation.

Acknowledgements

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