Pacman-NEAT: Exploring the Power of Evolutionary Algorithms in Game Playing

A Case Study with NEAT and Pacman

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Introduction

The Challenge: Can a Neural Network Play Pac-Man?

The goal of this project is to train an artificial neural network to master the classic arcade game, Pac-Man. This non-trivial task requires the agent to develop complex strategies for:

- Efficient maze navigation
- Dynamic evasion of multiple, intelligent opponents (ghosts)
- Strategic use of resources (power-ups)
- Long-term planning to clear the entire level

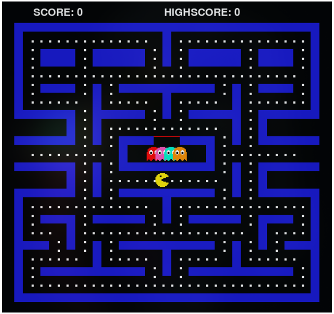


Figure 1: Pac-Man environment

Instead of traditional programming, we use an evolutionary approach to **discover** these strategies automatically.

Our Tool: NeuroEvolution of Augmenting Topologies

We use **NEAT** [3], a powerful algorithm that evolves both the **weights** and the **structure (topology)** of neural networks.

Key features of NEAT:

- **Complexification:** Starts with simple networks and gradually adds nodes and connections.
- **Innovation Numbers:** Tracks the historical origin of genes to solve the "competing conventions problem" during crossover.
- **Speciation:** Groups similar networks to protect new innovations until they're ready to compete.

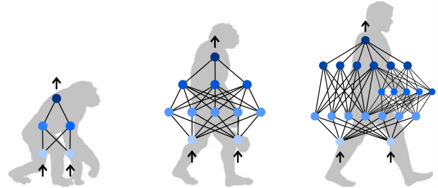


Figure 2: NEAT increases network complexity over time [2].

Project Architecture

The project integrates the NEAT algorithm with a custom Pac-Man game environment.

Pac-Man Game Engine

- Adapted from the *PyPacman* repository.
- Refactored game state management for stability and performance in a machine learning context.
- Core logic encapsulated in a Gym-like environment.

NEAT Framework

- `trainer.py`: Manages the evolutionary loop, population, and checkpoints.
- **Parallel Evaluation:** Uses Python's multiprocessing to evaluate hundreds of genomes simultaneously, drastically reducing training time.

NEAT → trainer.py → game_env.py → Pac-Man

Figure 3: High-level interaction between NEAT and the game environment.

Choosing a Game Environment

To train and evaluate NEAT agents, a reliable Pac-Man environment was essential. After surveying available options, I selected the *PyPacman* repository [1] for its simplicity and open-source nature.

Advantages:

- Lightweight and easy to understand
- Fully open-source and modifiable
- Minimal dependencies

Why this matters:

- Fast simulation of thousands of games per generation
- Easy integration with custom agent logic

Limitations:

- Contained several bugs and inconsistencies
- Not optimized for large-scale, automated runs

Actions Taken:

- Refactored core game logic for stability and speed
- Added a Gym-like interface for agent-environment interaction

The repository provided a solid foundation, but required several changes to meet the needs of this project.

Problem Formulation

How Does Pac-Man "See"? The Observation Model

For the neural network to make a decision, it needs a numerical representation of the game state. This is the **observation vector**.

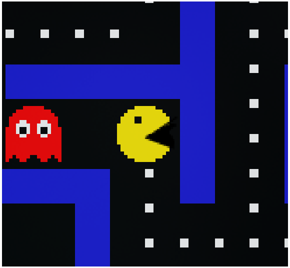
Vectorial Observation Vector (26 inputs):

Feature	Description	# items
Ghost Relative Positions	(x, y) for each ghost	8
Ghost Scared Status	1 bit per ghost	4
Closest Dot Vector	(x, y) to nearest dot	2
Closest Power-up Vector	(x, y) to nearest power-up	2
Remaining Dots	Number of dots left	1
Wall Distances	Distance in 4 directions	4
Power-up Active	1 if power-up is active	1
Last Action	One-hot, previous move	4

Table 1: Total: 26 elements. *Limitation: lacks spatial context.*

Minimap Observation Vector (64 inputs):

The observation shown above was soon found to be ineffective. To give more awareness of the environment, I implemented an 8x8 minimap centered on Pac-Man.



$$\begin{bmatrix} 0.5 & 0.5 & 0.5 & 0 & 0 & -1 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0.5 & 0 \\ -1 & -1 & -1 & -1 & -1 & -1 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0.5 & 0 \\ -0.75 & 0 & 0 & 0 & 0 & -1 & 0.5 & 0 \\ -1 & -1 & -1 & 0.5 & 0 & -1 & 0.5 & 0 \\ 0 & 0 & -1 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0 & 0 & -1 & 0.5 & 0 & 0 & 0.5 & 0 \end{bmatrix}$$

It encodes the positions of walls (-1), dots (0.5), and ghosts (-0.75). The four central cells represent the current Pac-Man position.

The final observation vector is the concatenation of the vectorial observation and the minimap observation, for a total of **90 elements**.

How Does Pac-Man "Learn"? The Reward Function

The agent's goal is to maximize its cumulative **reward**. The design of the reward function—*reward shaping*—is critical to guide its behavior.

A naive approach is insufficient:

- *Reward only for points?* The agent might learn to get stuck in a safe corner, doing nothing.
- *Reward only for survival?* The agent might learn to run in circles and never eat dots.

The Challenge: How do we design a task that is simple enough to be learned, yet complex enough to lead to intelligent behavior?

Early Issues: Unintended Behaviors

Initial experiments with complex environments and reward functions led to classic AI failures:

Reward Hacking

The agent found loopholes in the reward function. For instance:

- If the reward function penalizes being stuck, the agent learns to oscillate between two positions.
- If there is no cost of life, the agent learns to run in circles.

Premature Complexity

- Starting with the full game was overwhelming.
- The agent couldn't learn basic evasion while also needing to manage power-ups and complex ghost behaviors.
- This led to a very slow or stalled learning process.

These challenges motivated a structured approach:

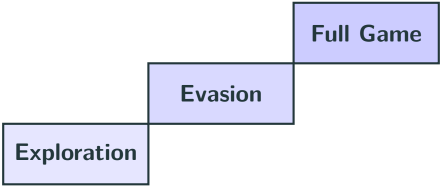
Curriculum Learning

Curriculum Learning

The Concept of Curriculum Learning

Curriculum Learning is a training strategy where the agent is exposed to tasks of increasing difficulty, much like a human student.

Instead of tackling the final, complex problem from the start, we break it down into a sequence of simpler sub-tasks.



The hypothesis is that by mastering fundamental skills first (like exploration), the agent can build upon that knowledge to solve more complex problems (like evasion, power-up usage, etc.).

Our Pac-Man Curriculum

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- **Phase 1: Exploration Training (Gen 0-999)**
  - **Goal:** Master map exploration.
  - **Setup:** No power-ups, no ghosts, only dots.
  - **Reward:** Simple function rewarding dot collection and penalizing time.
  - **Key Tweak (Gen 500):** Switched from Feed-Forward to **Recurrent Networks** to enable memory.

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- **Phase 2: Evasion Training (Gen 1000-1999)**
  - **Goal:** Ghosts are introduced.
  - **Setup:** Only dots and ghosts. Still no power-ups.
  - **Reward:** The same simple reward function.
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- **Phase 3: Full Game Mastery (Gen 2000+)**
  - **Goal:** Master the complete game.
  - **Setup:** The full game, including power-ups.
  - **Reward:** A highly-shaped, complex reward function is activated.

The Advanced Reward Function (Phase 3)

To encourage mastery, the final reward function included several components:

- **Dynamic Point Multiplier:** `SCORE_MULTIPLIER` increases as more dots are eaten, incentivizing level completion.
- **Event Bonuses:** Large, distinct rewards for eating dots, power-ups, and scared ghosts.
- **Ghost Proximity Shaping:**
  - Small **penalty** for being near a dangerous ghost.
  - Small **reward** for chasing a scared ghost.
- **Exploration Bonus:**
  - A small **reward** for visiting a new tile for the first time.
  - A large **penalty** for revisiting the same tile.
- **Penalties:**
  - Getting stuck against a wall.
  - Taking too long to eat the next dot (anti-stalling).
  - A large penalty for dying.

GitHub - AnandSrikumar/PyPacman: Pacman clone written in python — github.com.
`https://github.com/AnandSrikumar/PyPacman.git`.

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Thank You!