Adaptive Ecosystem Simulation with Evolutionary AI and Reinforcement Learning

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Introduction

Abstract

Artificial life research aims to model complex, adaptive behaviors. However, most simulations treat long-term evolution and short-term learning as mutually exclusive. This project introduces a hybrid framework that synergistically combines Evolutionary Algorithms (EA) and Reinforcement Learning (RL) to create autonomous agents that adapt both within their lifetimes and across generations. Our results demonstrate that this hybrid approach significantly outperforms EA-only and RL-only baselines, yielding agents with higher fitness, faster convergence, and richer, emergent social behaviors like resource stewardship and kin-based cooperation.

Problem Statement & Research Question

Our Core Question:

«Can artificial agents simultaneously learn within a lifetime (via RL) and evolve across generations (via EA)? If so, does this hybrid strategy produce measurably more adaptive and resilient behaviors than either mechanism alone?»

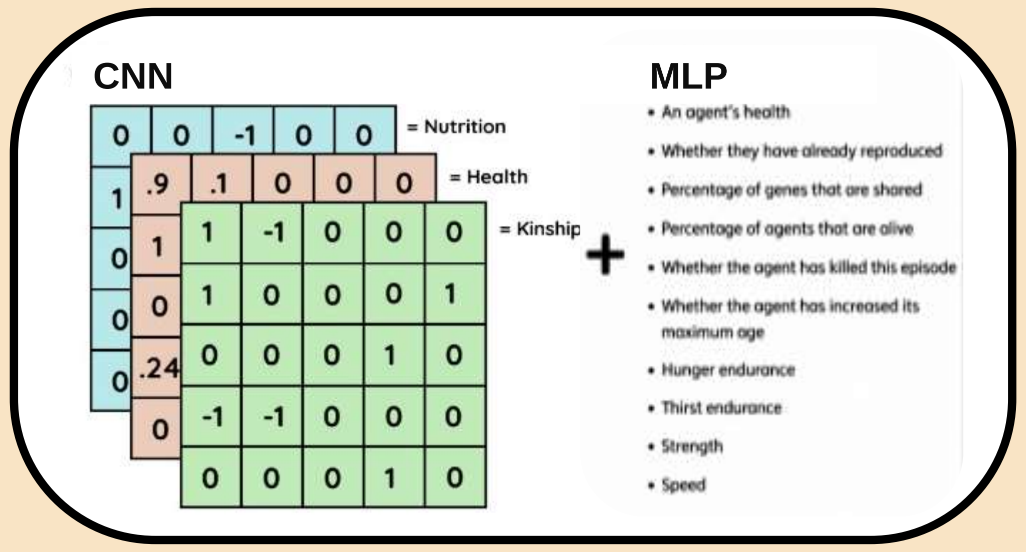
Existing agent-based models often struggle with a fundamental trade-off:

- Evolutionary Algorithms (EA): Excel at global, generational search but produce brittle agents that cannot adapt to rapid environmental changes within a lifetime.
- Reinforcement Learning (RL): Enables rapid, intra-lifetime adaptation but can get stuck in local optima, lacks behavioral diversity, and struggles in sparse-reward environments.

Research

The Hybrid Evolutionary Reinforcement Learning (ERL) Framework

We developed a multi-agent simulation where each agent's behavior is governed by a hybrid neural architecture trained with both RL and EA.



Agent Perception: Dual-Stream Input

Spatial (CNN): A Convolutional Neural Network processes a k x k grid of local sensory data across multiple channels (Nutrition, Hazards, Kinship). This enables spatial reasoning.

Internal (MLP): A Multi-Layer Perceptron processes a vector of scalar states (e.g., Health, Hunger, Reproductive Status, Population Stats). This provides internal and contextual awareness.

Decision Making: Q-Learning

The fused output from the CNN and MLP is fed into a Q-network that estimates the value of discrete actions (move, forage, flee, mate).

During an episode, agents use an ε-greedy policy, and the network is updated using the Bellman equation.

Evolution: Genetic Algorithm

At the end of each episode (a "lifetime"), a fitness score is calculated for each agent:

$F = \alpha \cdot Survival + \beta \cdot Reproduction - \gamma \cdot Energy$

The highest-fitness agents are selected via roulette-wheel selection.

New agents are generated for the next generation through simulated crossover and Gaussian mutation of their "genes" (e.g., neural network weights, speed, endurance).

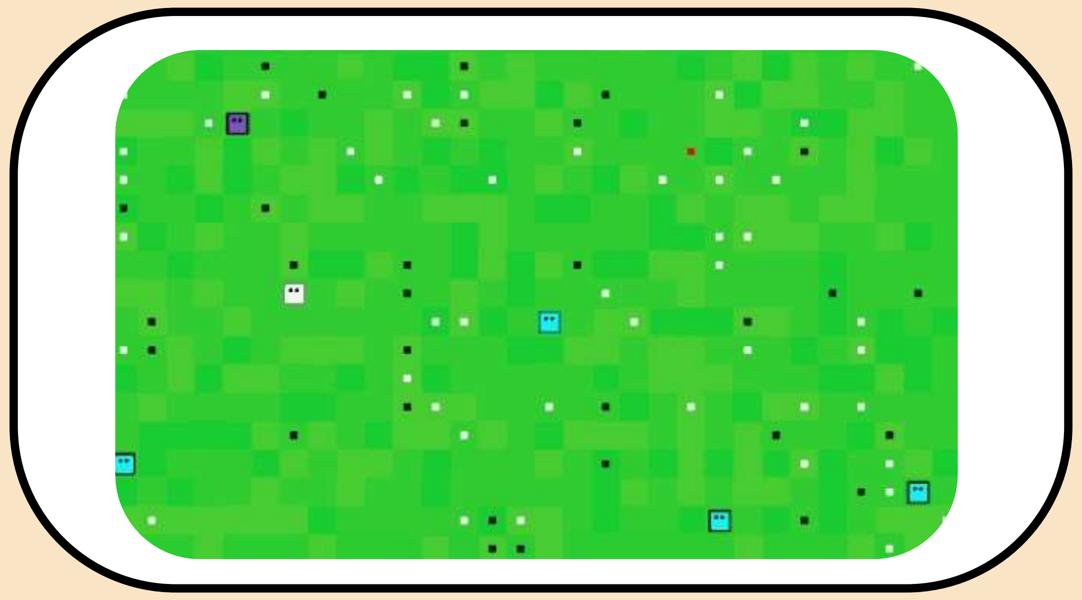
Experimental Setup: Ablation Study

To validate our primary hypothesis, we compared three distinct models under identical environmental conditions (20x20 grid, 50 agents, renewable resources, and hazards):

GA-only: Agents evolve across generations but do not perform RL updates within their lifetime.

RL-only: Agents are initialized with random weights each generation and learn only via RL. There is no genetic inheritance.

Hybrid (GA+RL): The proposed model, combining both mechanisms.



Conclusion

Key Results

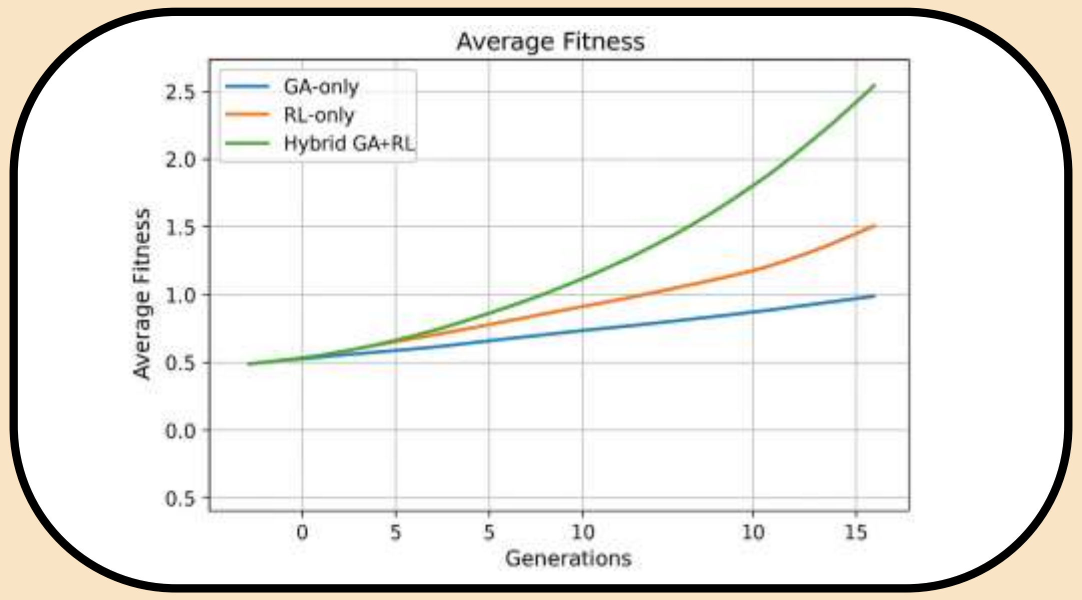
Our primary finding shows that the hybrid model dramatically outperforms both baselines. The genetic algorithm provides a robust starting point for each generation, which reinforcement learning then rapidly fine-tunes.

Emergent Social & Behavioral Dynamics

The hybrid model produced qualitatively richer behaviors not seen in the baselines:

Kin-Based Alliances: Agents with high genetic similarity (kinship) exhibited cooperative behaviors, such as avoiding conflict and jointly guarding resource zones from non-kin.

Behavioral Specialization: Over generations, distinct genetic lineages (kins) evolved different survival strategies. Some became more aggressive (high strength_bonus), while others specialized in endurance and efficiency (high max_health_bonus).



Conclusion & Future Directions

This work successfully demonstrates that a hybrid of evolutionary algorithms and reinforcement learning creates a powerful and robust framework for simulating adaptive ecosystems. By integrating generational evolution with lifetime learning, our agents develop complex, emergent strategies that are unattainable by either method in isolation.