Evolution of Brain Complexity in Artificial Life Environments

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Abstract

This study investigates how artificial neural network (ANN) complexity evolves in response to varying environmental parameters within artificial life (A-life) simulations. By systematically evolving grid-world environments that include agents, predators, and resource constraints, we aim to identify specific environmental factors that maximize neural network complexity, measured by the number of network weights. Using a meta-evolution approach (`gaSpecs`), we optimize environments across two criteria: maximizing agent survival time and a combination of agent survival time and neural network complexity. Results from extensive simulations indicate distinct environmental parameter sets significantly influencing ANN complexity and agent survival, providing insights into how environmental pressures drive neural complexity in artificial systems.

1 Introduction

Understanding how environmental factors influence the evolution of neural complexity is essential for both evolutionary biology and artificial intelligence research. A fundamental question in evolutionary biology and artificial intelligence is how environmental factors shape the complexity of neural systems. Previous research has highlighted that changes in environmental conditions can significantly impact the evolution of neural architectures. However, the exact environmental pressures that foster more complex neural systems remain unclear.

In this study, we use artificial life (A-life) environments to investigate how varying environmental parameters influence the complexity of artificial neural networks (ANNs) controlling simulated agents. By evolving environments to incorporate factors such as predators, resource limitations, and reproductive dynamics, we aim to identify the environmental conditions most conducive to increased neural complexity. Our findings aim to enhance understanding of how complex neural architectures evolve, offering insights applicable to both artificial and biological systems.

2 Problem Formulation

To perform our analysis, we use an extended version of Vadim Bulitko's artificial life (A-life) testbed with the addition of predators. The environment is a grid map where each grid tile represents a different terrain. This terrain includes grass tiles that agents can feed from and wall tiles that agents and predators cannot occupy. The world progresses in discrete time steps in which grass regrows and every agent and predator on the map performs an action simultaneously.

Each agent has several actions available to them, including moving left, up, right, down, or staying in place. Agents stay alive by feeding on grass tiles to increase their energy to a maximum value of one and die if their energy reaches zero. Every agent has an ANN, which acts as their brain and determines the action an agent takes. The environment is initialized with a population of agents whose ANN structures are randomly chosen. These networks are composed of an input layer, 0-2 convolution layers each followed by a batch normalization layer and a ReLU layer, 0-2 fully connected layers each followed by a ReLU layered, and finally, a fully connected layer followed by a softmax function. During an A-life trial, agents can give birth to offspring who have a chance to inherit the same ANN structure with weights randomly changed or to inherit a new randomly generated structure and weights.

As an extension to the A-life testbed, we implemented predators that serve as a hazard to agents. Like agents, predators have energy that decreases over time. Instead of eating grass to replenish their energy, predators must kill agents. At every time step, each predator calculates the Euclidean distance to all agents and moves toward the closest one. How many tiles a predator moves is determined by the environmental predator speed. If a predator occupies the same tile as an agent, the agent is killed immediately, and the predator's energy increases.

We define the complexity of an agent's network $C(N)$ as the number of weights in the network N. The goal of this study is to determine how environment parameters P outlined in Table 1 interact to affect network complexity and, more specifically, how they can be tuned to maximize complexity. Formally, we aim to find

$$\max_{P} \frac{1}{T} \sum_{i=1}^{T} C(N_i)$$

where T is the number of networks tested in an environment.

3 Related Work

The evolution of complex behaviour in artificial agents has been explored through various frameworks. One foundational contribution is by Gomez and Miikkulainen (1997), who introduced an incremental learning approach where agents first learn to solve simpler tasks, increasing task difficulty over time. They proposed delta coding, a technique that improves the transfer of learned knowledge between tasks during evolution. However, their framework does not address dynamically changing environments and does not explore how specific environmental parameters can influence the complexity of evolved ANNs—an essential gap our work aims to fill.

Calvin (2002) proposed a biological theory linking abrupt climate change to increased brain complexity in humans. While the work provides a valuable conceptual framework, it does not include a computational model to test the relationship experimentally. This study builds on that foundation by extending a controlled artificial life simulation, allowing for manipulation of environmental conditions and direct observation of their effects on neural network complexity in evolving agents.

4 Proposed Approach

To investigate how environmental factors influence agent brain complexity, we extended the artificial life (A-life) testbed with a predator-prey model. Each agent is controlled by an artificial neural network (ANN), whose complexity is measured by the total number of weights. Agents with larger networks consume more energy per decision step, encouraging selective pressure against unnecessarily large architectures.

To study the effects of environmental variation, we manipulated a set of environmental parameters that direct agent behaviour and survival. These include mutation chance, movement energy cost, and reproduction age. These parameters were chosen based on their potential to affect both selective pressure and population dynamics (as detailed in Table 1).

We used the `gaSpecs` meta-evolution framework to evolve environments by optimizing a fitness function. We tested three optimization objectives:

1. **Extinction time**, promoting environments where agents survive longer.
2. **Neural network complexity**, to encourage larger ANN architectures.
3. **A combination of extinction time and network complexity**.

While all three were explored, the complexity-only objective frequently led to unstable populations that died off early, limiting meaningful comparisons. Consequently, we excluded this condition from our formal evaluation and focused on the extinction-only and combined objectives. For each evolved environment, we conducted 64 trials and recorded extinction times and ANN statistics, enabling us to assess how different parameter configurations influence agent survival and brain complexity.

5 Theoretical Analysis

We define the brain complexity of an agent as the total number of weights in its artificial neural network (ANN). Formally, for a network N, the complexity is given by:

$$C(N) = \sum_{l \in L} \text{weights}(l)$$

where L is the set of layers in the network. This definition captures both the size and structure of the ANN.

To study how environmental conditions affect this complexity, we optimize a set of environment parameters P using a meta-evolutionary algorithm. The goal is to find the environment configurations that maximize one of the following fitness objectives:

(1) Extinction Time:

$$\max_P E(A)$$

where $E(A)$ is the average extinction time of a population of agents in environment P.

(2) ANN Complexity:

$$\max_P \frac{1}{T} \sum_{i=1}^{T} C(N_i)$$

where T is the number of trials and N_i is the ANN of the i-th agent.

(3) Combined Objective:

$$\max_P E(A) + \frac{1}{T} \sum_{i=1}^{T} C(N_i)$$

These objectives are used to evolve different environments and evaluate their effect on an agent's brain complexity. We hypothesize that environments optimized for extinction time will favor more adaptive behaviour and longer survival, while those optimized for complexity may favor larger networks. However, as observed in our experiments, optimizing for complexity alone can destabilize populations, suggesting a potential trade-off between complexity and survival.

Due to the stochastic nature of agent interactions and reproduction, closed-form theoretical analysis is not sufficient to predict the outcomes of environmental changes. Therefore, we rely on empirical evaluation to observe how these optimization criteria influence ANN evolution in practice.

6 Empirical Evaluation

Figure 1 shows the evolution of agent brain complexity under two different environments. The first is optimized for extinction time, and the second is optimized for a combination of extinction time and ANN complexity. In the combined environment, we observe a larger mean ANN size when compared with the extinction-optimized environment. This indicates that agents in the combined environment are more complex on average, though the underlying reason for this is unclear. From the same figure, we can see that on average, populations in the combined environment survived longer than the extinction-only environment. This could indicate that the environment itself is easier or that more complex agents are better equipped to survive for longer.

Figure 2 shows the same environments and trials as Figure 1, but only includes agents that lived for longer than 20 time steps. This is done in an effort to remove extraneous data from poorly performing agents, in this case those that lived for only 20 time steps or less, to not skew the mean ANN size. After removing these agents we can see that the difference in mean ANN size between the two environments is roughly halved. The reduced difference in mean complexity indicates that more complex ANNs do not survive as long as ANNs with less complex networks. As a result, we can infer that the environment itself is easier. This, in addition to our observations from Figure 1, shows that more complex networks do not offer any additional benefit and could be harmful.

Examining Table 1 offers additional insight into why the combined environment has a longer extinction time and more complex agents. Some differences between parameters are the structure mutation chance, move energy, max bite, min reproduction energy, and mutations.

We see that the move energy is lower and the max bite is higher in the combined environment. This means that agents can eat more grass to replenish energy and lose less energy when moving, indicating that the environment is easier to survive in. Since agents with more complex networks use additional energy to make decisions, we believe that these easier conditions are more favourable for the survival of complex networks. The lower mean complexity in the seemingly more difficult extinction environment can then be attributed to the energy costs of complex networks outweighing the additional computing power they provide. This result is contrary to our expectations, and more work needs to be done to determine what conditions necessitate complex networks.

Looking at other parameter differences, such as the lower min reproduction energy, higher structure mutation chance, and higher mutation count in the combined environment, allows us to infer why this environment has higher mean complexity. The lower min reproduction energy means that agents can reproduce even when they are close to death, which is

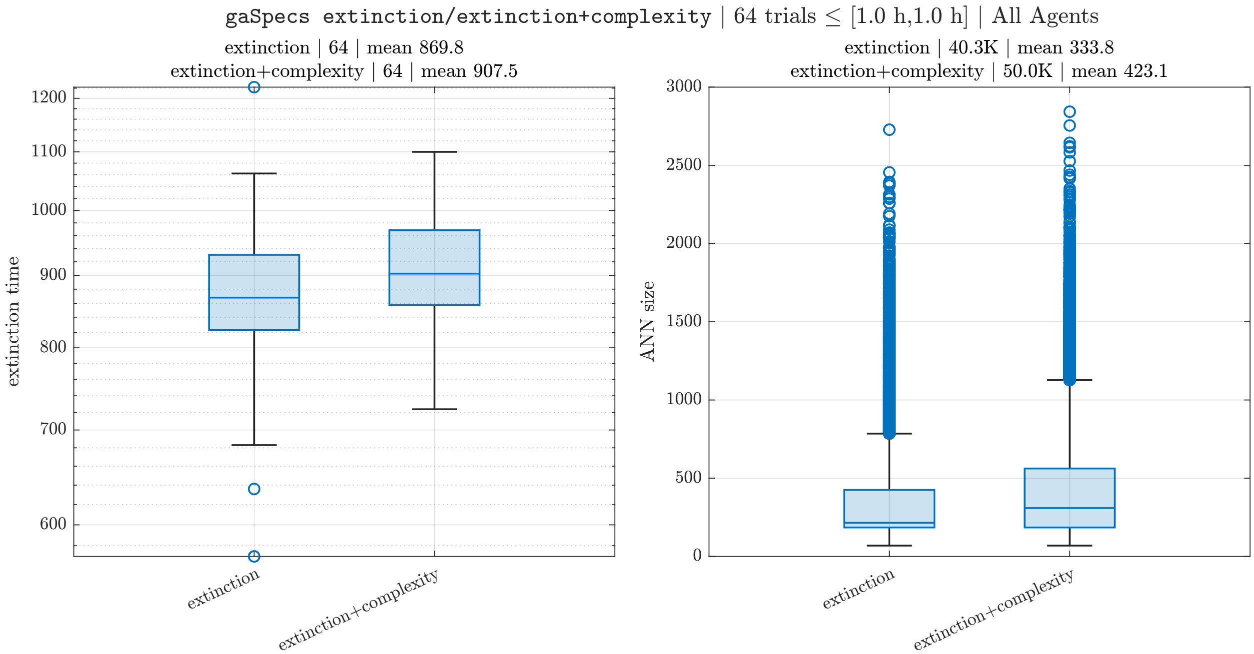

Figure 1: Comparison between environments evolved to promote long trial extinction times and a combination of long trial extinction times plus network complexity. The extinction time of each trial is on the left, while the ANN sizes of agents measured as the number of weights is on the right. Data includes all agents in all trials regardless of age at death.

beneficial to more complex agents who use more energy. The higher structure mutation chance means that less complex agents are more likely to give birth to complex agents rather than replicating their own structure. This ability to reproduce more often and create different structures is likely the reason for the higher mean complexity. The results from Figure 2 indicate that high-complexity structures often die before reproduction age, so less complex agents birthing more complex ones increases mean complexity.

7 Discussion

Our experiments show that the environment parameters used during evolution influence both the survival and neural network complexity of agents. When environments were evolved using a combined objective (extinction time and ANN complexity), we observed higher average network sizes compared to extinction-focused environments. This supports the idea that encouraging both survival and complex behaviour can lead to larger networks.

Environments optimized only for complexity led to unstable populations. Agents often failed to survive long enough to develop meaningful changes, highlighting a limitation of using complexity as the sole fitness signal. This trade-off between network size and survival suggests that complexity must be paired with some form of performance-based feedback to be useful in evolution.

We also observed differences in complexity across environments, but the reasons for these differences remain unclear. Since we only measured the number of network weights, our current metric may not capture other important aspects of brain function, such as learning ability or behavioural diversity.

These results suggest that environmental design plays an important role in shaping the evolution of neural architectures, but further analysis is needed to understand the underlying dynamics.

8 Future Work

There are several directions we plan to explore in future work. First, we aim to run longer trials with more generations and a wider range of parameter settings. This may help us observe more stable patterns in complexity growth and better understand long-

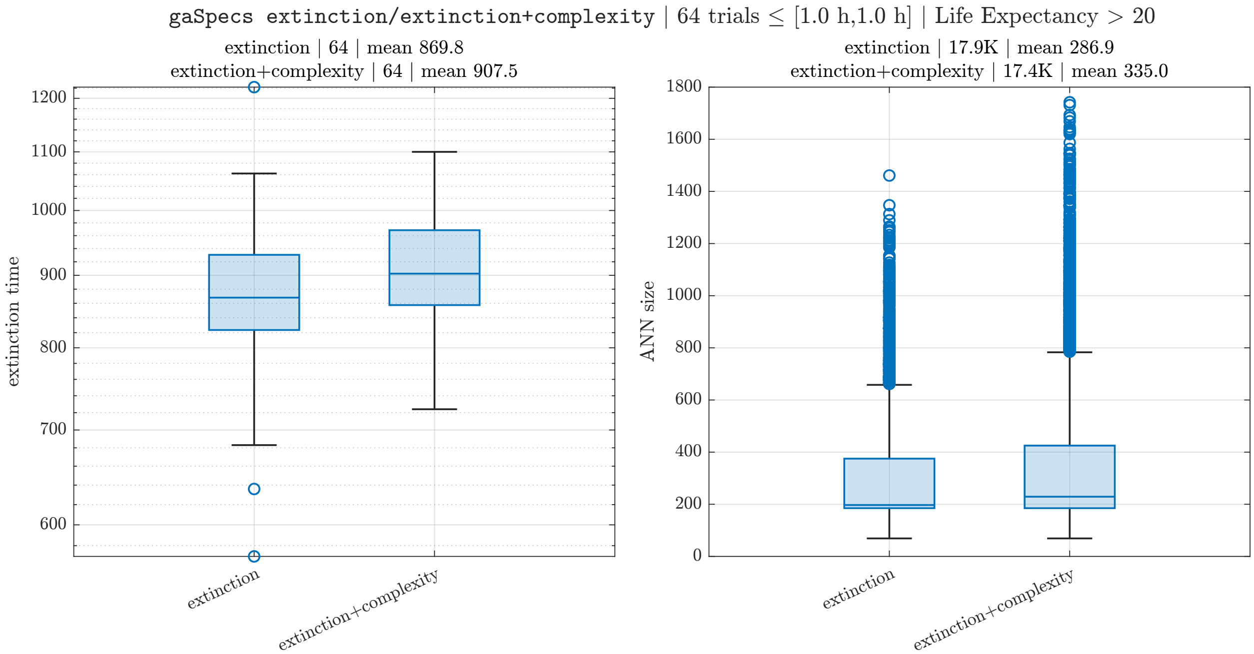

Figure 2: Comparison between environments evolved to promote long trial extinction times and a combination of long trial extinction times plus network complexity. The extinction time of each trial is on the left, while the ANN sizes of agents measured as the number of weights is on the right. Data includes only agents with an age greater than 20 at death.

term evolutionary dynamics.

Second, we plan to expand the ANN search space to include deeper and more varied network architectures. Allowing more layers could enable the evolution of more sophisticated behaviours.

Third, we intend to add communication capabilities to agents. This could involve creating a new output channel for communication or introducing a separate communication-specific network. Studying how communication affects group behaviour and neural complexity may reveal new forms of emergent behaviours.

Finally, we plan to explore new ways to measure complexity beyond just the number of weights. These could offer a more complete view of how complex and adaptive the evolved agents truly are.

9 Conclusions

In this project, we studied how the complexity of an agent's brain, represented by its neural network, changes in response to different types of environments. Our goal was to understand whether certain environmental conditions encourage the evolution of more complex brains.

We used an extended A-life simulation with predators and evolving environmental parameters. By testing different fitness objectives, we found that environments optimized for both survival and brain complexity tended to produce agents with more complex neural networks.

Overall, our results show that environmental factors play an important role in how neural networks evolve. Encouraging both survival and complexity appears to support the development of more complex agent behavior.

Acknowledgments

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Table 1: Environment parameters evolved for Extinction and Extinction+Complexity environments

Environment	**Extinction**	**Extinction+Complexity**
Grass Growth	0.0333	0.0333
Grass Decay	0.996	0.996
Structure Mutation Chance	0.1533	0.3744
Channels	3	3
Radius	1	1
Move Energy	0.0446	0.0333
Live Energy	0.1	0.1
Power Coefficient	0.0001	0.0001
Max Bite	0.2309	0.2702
Min Reproduction Energy	0.5432	0.2080
Min Reproduction Age	20	20
Initial Agents	14	15
Max Agents	20	20
Mutations	32	49
predator count	0	0
predator speed	3	2

References

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