Combining Conway's Game of Life with Reinforcement Learning and Evolutionary Algorithms for Anti-fragile Emergent Complexity

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Introduction:

Cellular automata, first introduced by John von Neumann and popularized by mathematician John Conway's Game of Life, are discrete, grid-based computational models that evolve over time based on a set of simple rules.[1] The Game of Life, as a simple yet powerful model, has been widely studied due to its ability to generate complex patterns and behaviors from a minimal set of rules. These properties have led researchers to investigate the potential of cellular automata in various fields, including cryptography, communication systems, and fault-tolerant computing.

One of the challenges in studying cellular automata, particularly in the context of the Game of Life, is the discovery of emergent complexity and the identification of patterns that exhibit anti-fragile or noise-resistant characteristics. Anti-fragile systems, as introduced by Nassim Nicholas Taleb, are those that not only withstand external perturbations but also thrive and improve under such conditions.[2] In the case of cellular automata, noise resistance refers to the ability of a pattern to maintain its overall structure and functionality despite the presence of random disturbances.

This project aims to explore the potential for anti-fragile emergent complexity in cellular automata by combining Conway's Game of Life with reinforcement learning and evolutionary algorithms. By leveraging a Deep Q-Network (DQN) agent,[3] we seek to discover noise-resistant cellular automata patterns and evaluate AI's role in knowledge extension and code generation.

Our research design employs an evolutionary algorithm, DQN integration, and parallelization to enhance the search for noise-resistant patterns, building upon Kuhn's concept of interdisciplinary knowledge extension.[4] Through this investigation, we hope to uncover and visualize fascinating macro patterns, contribute to our understanding of complex pattern formation in cellular automata, and shed light on AI's role in extending knowledge. The role of which will have broader implications for the future of scientific discovery and technological innovation.

Specific Aims:

I. Developing noise resistance in a Game of Life environment for biological systems.

Our primary objective is to create noise-resistant patterns within a Game of Life environment, which simulates biological life by implementing rules and parameters that mimic living organisms' behaviors. By leveraging reinforcement learning,[5,6,7,8] which mirrors evolution where successful reproduction is rewarded, and evolutionary algorithms, we aim to discover cellular automata patterns that exhibit anti-fragile emergent complexity. These patterns should withstand and adapt to noise introduced into the system, much like how chaotic agents contribute to evolutionary variation and selection in biological systems, demonstrating resilience and robustness in the face of perturbations.

• Integrate the Game of Life with a DQN agent and evolutionary algorithms, structured by purpose, functions, and environment.[8]

• Investigate the impact of varying levels and types of noise on cellular automata patterns.

• Identify patterns that demonstrate robustness and adaptability to noise. (Most DQN patterns won't be resistant and therefore won't persist against noise.)

• Analyze the characteristics of these noise-resistant patterns and their potential applications in biological systems.

Regarding feasibility, we have access to a high-performance computing cluster for research, enabling us to run large programs. Additionally, the smaller search space provided by the DQN method increases the likelihood of finding a solution to noise resistance. To maximize our compute window of eight hours, we have parallelized our algorithm to run simulations across 128 CPUs. Furthermore, we estimated the maximal number of generations feasible based on the time difference between two smaller generation run-time tests. Using this method going forward, we will maximize our compute time and number of generations to arrive at more interesting patterns with varying sizes or degrees of complexity during tuning.

II. Investigating the role of AI in knowledge extension and code generation for biological research. As a standalone idea, we aim to explore the extent and potential of AI as a tool for knowledge extension and code generation in biological research. By utilizing AI-generated code and examining the relationship between our prompts and the resulting outputs, we hope to gain insights into the effectiveness of AI in guiding our research and the direction of our subsequent questions.

- Utilize AI-generated code in the development and implementation of our framework for biological systems.
- Analyze the relationship between prompts given to the AI and the resulting code output
- Evaluate the effectiveness of AI-generated code in achieving our research objectives in biological contexts.
- Investigate the role of AI in shaping the direction of our research and the generation of new questions related to biological systems.[9]
- It would also be curious to assess how these models can relate to machine learning methods more so, as well as the extent that these techniques can enhance existing AI models, specifically in large language models used to generate much of the code for this project.[9-12]

By addressing these two aims, we hope to contribute to the understanding of emergent complexity in cellular automata for biological systems and explore the potential of AI as a valuable tool in interdisciplinary research and knowledge extension.[13-20]

Background and Significance:

Our research project incorporates three main concepts: John Conway's Game of Life as a template and visual aid, reinforcement learning to create emergent complexity, and the role of AI in knowledge extension. We will discuss each of these concepts in detail, their significance to our research, and how they relate to biological systems.

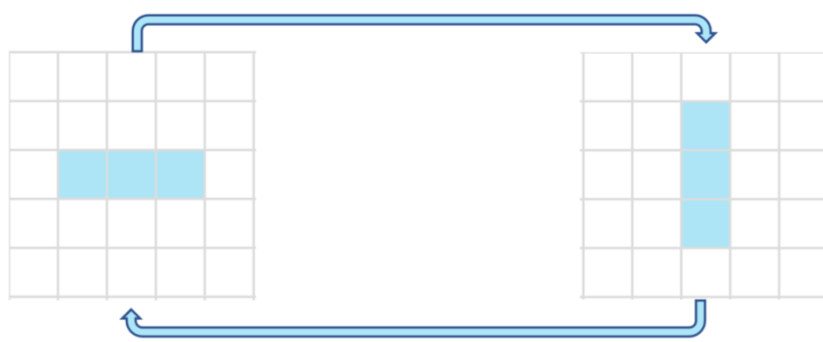
John Conway's Game of Life and Anti-fragile Emergent Complexity in Biological Systems:

The Game of Life is a cellular automaton and mathematical model that simulates the behavior of a set of cells evolving according to a specific set of rules, similar to the interactions seen in biological organisms. Played on a two-dimensional grid, each cell has two possible states: alive or dead. The behavior of each cell is dictated by the state of its eight neighboring cells, following simple rules that determine whether a cell will live, die, or be born in the next generation. Despite its simplicity, the Game of Life can produce incredibly complex and dynamic patterns that have captivated mathematicians, computer scientists, and enthusiasts for decades.

In a standard game of life, cycles exist which when unperturbed by outside forces continue indefinitely. The original Game of Life consists of three simple rules:

1. A live cell with fewer than two live neighbors dies (underpopulation).
2. A live cell with two or three live neighbors lives on to the next generation (survival).
3. A live cell with more than three live neighbors dies (overpopulation).

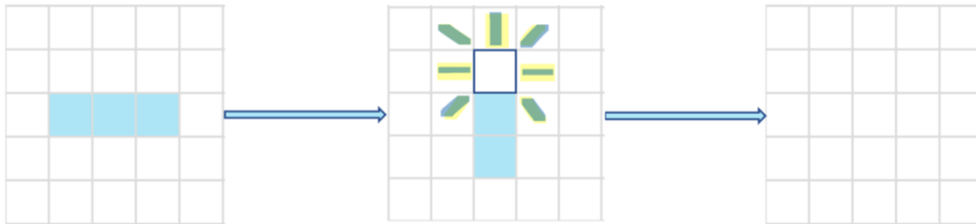
∞ Cycle



A standard game of life event that can result in an endless simulation.

However, in our research we have modified the Game of Life to include a fourth rule that minimizes the probability of repeated patterns through the addition of chaotic noise. This noise has a biproduct of reducing the runtime of a game from endless to just a few seconds. The success of an instance of a game is measured against other instances relative to the time or duration that the simulation persists.

Finite game



A modified game with negative noise that eliminates cycles over time to enable selection.

In this way, the fourth rule makes the simulations more like biological life, which is subject to random events, disturbances, and games that end. Through a selection method, we plan to find instances of emergent complexity that are noise-resistant and therefore don't end, by modifying games that do not persist as measured against time. The resulting system, if found, would be robust to noise and exemplify anti-fragile emergent complexity akin to those found in biological systems.

Reinforcement Learning and Deep Q-Networks in Biological Contexts:

Using an evolutionary algorithm to make minute changes is a slow process, especially when we can make inferences like symmetrical patterns as being preferable to non-symmetrical pattens in terms of longevity against noise. Therefore, another method to bolster evolutionary selection was implemented to exhibit the desired emergent complexity in a reasonable time. Specifically, we implemented a reinforcement learning algorithm on small sections of the 2D Game of Life grid. By splitting up the board into smaller pieces and evolving those, the search space effectively reduces to the size of these smaller boards. Moreover, these bite-sized boards can be strung together again after the selective process and tested against noise.

This board splitting technique enables two things. One is room for parallelization across many CPUs to all run at once. Two, it enables the possibility of using only one bite-sized board repeatedly to form a larger macro template from the copies. This would inherently have a pattern within it which may have other emergent properties while the template patterns combine during the simulation. All of this is done via a specific instance of reinforcement learning called a Deep Q-Network (DQN), that acts as a selective agent within the evolutionary algorithm. Introduced by Volodymyr Mnih and colleagues at DeepMind in 2013,[3] DQN combines the strengths of deep neural networks with Q-learning, enabling control policies to be learned directly from high-dimensional sensory input using reinforcement learning. In the context of our research, control policies represent the strategies used by the DQN agent to modify cellular automata patterns in the Game of Life, with the goal of identifying noise-resistant patterns. The agent learns these control policies through interactions with the environment, using the feedback it receives in the form of rewards to improve its decision-making process. By learning effective control policies, the DQN agent is better equipped to navigate the search space and identify cellular automata patterns that demonstrate robustness and adaptability to noise.

In our project, the DQN agent is responsible for choosing actions that modify cellular automata patterns in the Game of Life, helping to identify patterns that demonstrate robustness and adaptability to noise. This process mirrors the role of natural selection in biological evolution, where individuals with favorable traits are more likely to reproduce and pass on their genetic material. The integration of a DQN agent not only assists in discovering noise-resistant cellular automata patterns but also explores AI as a tool for knowledge extension in biological research.

The Role of AI in Knowledge Extension for Biological Research:

Building upon the interdisciplinary approach exemplified in Thomas Kuhn's work on knowledge extension, our project seeks to understand the extent to which AI can facilitate a similar process in the context of biological research. By integrating Conway's Game of Life with reinforcement learning and evolutionary algorithms, our project potentially leads to new discoveries and applications in the fields of artificial life, complex systems, and computational design related to biological systems. Moreover, within this framework, we seek to understand the extent to which AI, specifically ChatGPT or its equivalent, can replicate a similar process through a verifiable environment like a programming language. Largely, this project will record instances of its use case and report back on the efficacy of this technique as a model to build evidence-based arguments in the future.

Research Design:

Our research design, can be described in the following stages:

1. Initialization: We generate an initial population of cellular automata templates with random patterns, determining the population size, grid size, and number of generations according to the desired computational capacity and optimization goals.
2. Evolutionary Optimization: We use an evolutionary algorithm to refine the cellular automata patterns iteratively, involving the evaluation of fitness scores, selection of top-performing templates, reproduction and mutation, and generation advancement. The fitness function computes the number of iterations before a pattern dies out in a noisy environment, with higher scores indicating greater noise resistance. This process parallels natural selection in biological systems, where successful reproduction is rewarded.

3. Integration of DQN Agent: We incorporate a DQN agent into the optimization process to enhance the search capabilities of the evolutionary algorithm. The agent is trained to select actions that potentially improve the noise resistance of the patterns, expediting the search for optimal solutions. This mirrors the role of evolution in biological systems, where noise contributes to variation and selection.
4. Evaluation and Analysis: We monitor the performance of the algorithm by tracking the fitness scores of the templates, analyzing the convergence properties of the algorithm, and identifying non-linear jumps in performance that may signify the discovery of particularly noise-resistant patterns.
5. Visualization and Reporting: After the optimization process, we visualize and save the best cellular automata pattern found, along with its corresponding fitness score, to gain insights into the effectiveness of our approach and the types of patterns that exhibit higher noise resistance in biological systems.

Potential Extensions and Preliminary Results:

Preliminary results show the progression toward noise resistance from a micro-template perspective, where a Game of Life grid is composed of micro-boards that together constitute the main board. Each micro-board hosts a cellular automata pattern that exists simultaneously with other patterns on the main board. As the evolutionary algorithm progresses, the micro-board patterns interact with each other within the larger environment, potentially developing noise-resistant characteristics like those observed in biological systems.

Expected results:

Optimal outcome:

- The model converges quickly and discovers high-quality macro patterns in the Game of Life.
- Non-linear jumps in the total reward are observed during training, indicating that the agent learns to create increasingly complex and interesting patterns.
- The best board discovered by the agent has a high total reward.
- The final macro patterns generated by the algorithm are visually appealing, showcasing intricate and dynamic behavior.

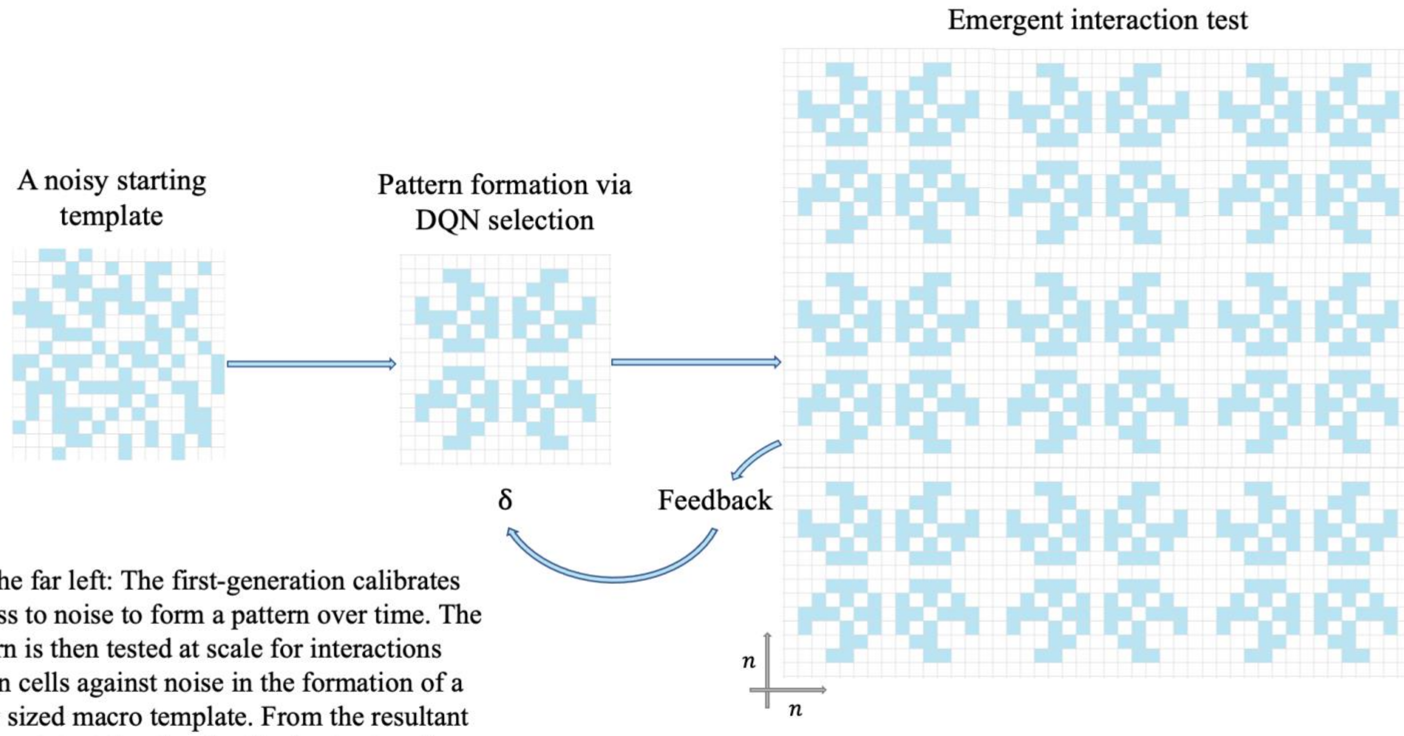
Non-optimal outcome:

- The model struggles to converge, taking a long time to learn or not learning at all.
- No significant non-linear jumps in the total reward are observed during training, suggesting that the agent fails to find high-quality macro patterns.
- The best board discovered by the agent has a low total reward.
- The final macro patterns generated by the algorithm are visually uninteresting or static, failing to exhibit complex behavior.

Most likely outcome:

- The model converges at a reasonable pace, discovering some high-quality macro patterns in the Game of Life.
- A few non-linear jumps in the total reward are observed during training, indicating that the agent learns to create some interesting patterns.
- The best board discovered by the agent has a moderate total reward.

- The final macro patterns generated by the algorithm show a mix of interesting and less interesting behavior, with some room for improvement.



From the far left: The first-generation calibrates robustness to noise to form a pattern over time. The pattern is then tested at scale for interactions between cells against noise in the formation of a flexibly sized macro template. From the resultant noise resistant duration feedback, step two is repeated. Portions of the micro template patten change, as does the probability of the emergent pattern's robustness.

Potential Extensions

In our pursuit of understanding anti-fragile emergent complexity in cellular automata and reinforcement learning, we have identified several promising directions for further exploration. These potential avenues aim to enhance our approach and expand its applicability across various domains.

Firstly, we recognize that the current DQN model's architecture is relatively simple. To improve pattern recognition and generation, we could experiment with more complex architectures such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs).

Secondly, while our implementation relies on a DQN agent, exploring alternative reinforcement learning algorithms such as Proximal Policy Optimization (PPO)[22] or Deep Deterministic Policy Gradient (DDPG)[23] could potentially yield better performance.

Thirdly, our approach could benefit from incorporating multi-agent systems. Instead of using a single agent to discover macro patterns, employing multiple agents in a collaborative or competitive setting could foster richer and more diverse pattern generation.

Furthermore, our current research focuses on the Game of Life, but there is potential to extend the approach to other cellular automata or even more general pattern formation problems, thereby expanding the problem domain.

In addition, refining our fitness function could lead to more accurate pattern evaluation. Currently, the fitness function only considers the number of ticks a pattern persists. Future work could involve developing a more sophisticated fitness function accounting for pattern complexity, diversity, and other desirable properties.

Lastly, incorporating human feedback could provide valuable insights. By integrating preferences or evaluations from human observers into the learning process, we could guide the agent towards patterns that are not only mathematically interesting but also visually appealing.

By pursuing these avenues, we aim to contribute to the broader landscape of interdisciplinary knowledge extension and AI-assisted code generation while further refining our understanding of anti-fragile emergent complexity in cellular automata.

Future Directions

To further improve the approach, several future directions can be pursued:

Within the existing architecture, a parallelized version of the algorithm can be run on the discovery cluster to enable the exploration of a larger search space more quickly. This parallelization of the simulation across more computers simultaneously has a higher chance to uncover more complex and interesting patterns and yield noise resistance.

There's also work to be done on the visualization aspect of this project which can showcase the resulting macro board and focus on the patterns relating to noise resistance. This would provide a better understanding of the properties and characteristics of noise-resistant patterns, which could have implications for real-world applications in fields such as complex biological systems, cryptography, communication systems, and fault-tolerant computing.

There is reflective work to be done on the role that AI has had on the code generation for the project. This includes the prompts we gave, the intentions we had with our code functions and goals, as well as an assessment of the resulting output. Reflecting on how AI can accelerate knowledge extension and assess the extent to which current AI is able to do so independently would involve analyzing the role of AI in automating the discovery process, generating new patterns in the code itself, and verifying their properties without errors automatically.

Moreover, alternative fitness functions can be investigated to explore different selection criteria, which may also work towards multiple evolutionary objectives besides noise resistance. These investigations would likely shed light on the trade-offs involved in noise-resistant cellular automata in biological systems. We can also leverage pre-trained DQN agents pre-trained on related goals from related tasks, which may accelerate the training process and enhance the algorithm's capacity to identify noise-resistant patterns. Specifically, we can adapt this broad optimization process to real-world scenarios in cellular and molecular biology, studies on emergence. Utilizing related fields could demonstrate the practical value of noise-resistant cellular automata patterns and their potential impact on various industries.

Preliminary results from the current implementation illustrate the potential of our approach in discovering interesting and noise-resistant patterns. As we move forward, refining optimization techniques and examining real-world applications of noise-resistant cellular automata patterns will be the primary focus. By combining the power of reinforcement learning, evolutionary algorithms, and parallelization, we hope to uncover fascinating macro patterns and contribute to our understanding of complex pattern formation in cellular automata. Furthermore, our research will shed light on AI's role in extending knowledge and generating code, which has broader implications for the future of scientific discovery and technological innovation.

Summary

This interdisciplinary project explores the potential of anti-fragile emergent complexity by combining Conway's Game of Life with reinforcement learning and evolutionary algorithms. Utilizing a Deep Q-Network (DQN) agent, our objective is to discover noise-resistant cellular automata patterns and assess AI's role in facilitating knowledge extension and improving code generation. Building upon Kuhn's concept of interdisciplinary knowledge extension, our research design employs an evolutionary algorithm, DQN integration, and parallelization to enhance the search for noise-resistant patterns.

Our preliminary results demonstrate the potential of our approach in discovering captivating, dynamic noise-resistant patterns. These findings have significant implications for various domains, including biology, cryptography, communication systems, and fault-tolerant

computing. By combining these disciplines, our research aims to capitalize on the power of AI to advance our understanding of complex pattern formation in cellular automata and beyond.

In the future, we will focus on refining optimization techniques and examining real-world applications of noise-resistant cellular automata patterns. Leveraging reinforcement learning, evolutionary algorithms, and parallelization, we hope to uncover enthralling macro patterns and contribute to the growing body of knowledge on complex pattern formation in cellular automata. Furthermore, our research will shed light on AI's role in extending knowledge and generating code, which has broader implications for the future of scientific discovery and technological innovation.

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