

AI Generating Algorithms Using Self-Organizing Neural Cellular Automata

Sanyam Jain (sanyamjaincs@gmail.com);
spv. Stefano Nichele

Dept of Computer Science and Communication

Østfold University College



Table of Contents

1 Introduction

Evolution, Life and
Emergence
Artificial Life
Research Questions

2 Background Work

Cellular Automata
Neural CA

3 Proposed Methods

Neural CA

Evaluation Metrics

4 Results and Discussions

Experimental Results
Discussing Research
Questions

5 Conclusion & Scope of Improvement

Conclusion
Scope of Improvement

6 References

Introduction: Motivation from Origins & Artificial Life

- Evolution: Uni-cellular to Multi-cellular;
- (1) recombination of genes and (2) mutation via *random* perturbation;
- Life, a cell?

Cells are the language of life, filled with millions of complex structures of proteins and simpler molecules like water. Complex and continuous self-replicating processes happen within cells. Work done by cells explained by Philip, in [Ball, 2023], towards cellular developmental agency, includes:

- Cells attaching to one another;
- Assembly via swarms;
- Complex behavior through growth and multiplication;
- Self-replication or the generation of a clone through algorithmic repetition.

Life via Cellular Communication (3)

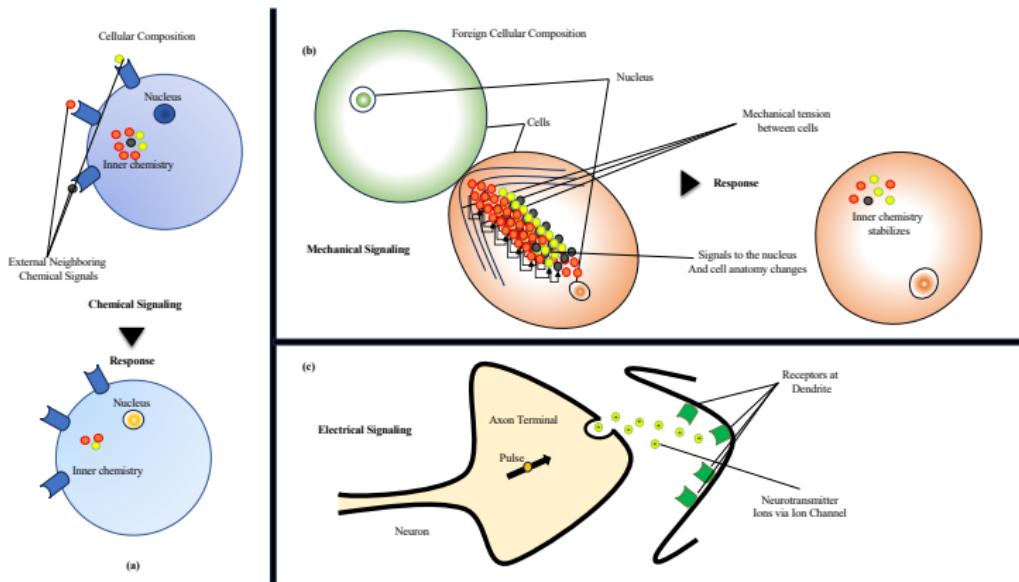


Figure: Intra-cellular communication via three signals types. (a) Chemical Signals, (b) Mechanical Signals and (c) Bio-electrical Signals

- Communication, maintain itself;
- Cells combine, cooperate, and specialize to respond to one another over time to develop into more complex structures;
- Final question: how do dumb individual cells know what to do? Cells communicate with their neighboring cells via chemical information and then decide what to do;
- Emergence of intelligence.

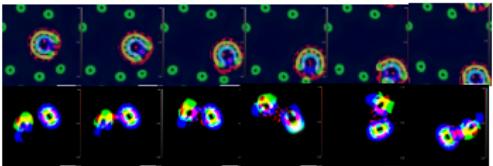
- ALife understands and mimic fundamental principles of biological systems and intelligence;
- Open-endedness [Stanley et al., 2017] is the ability of a system to perpetually generate an infinite variety of novel and meaningful outcomes, thriving on evolution, adaptation, and the emergence of unpredictable behaviors;
- Unlike the more task-centric focus of traditional AI, ALife loosely resembling AGI, envisions a broader, long term novelty driven goals;
- Open-ended ALife systems exhibit autonomy and self-organization, i.e., entities organizing themselves into diverse higher-order structures within their environment, giving rise to complex patterns and behaviors.

- Should be non-trivial reproducing criteria;
- New individuals should be *interesting* and unpredictable;
- Individuals interact within an environment autonomously;
- Promoting endless variation, no fixed complexity, otherwise all interestingness would exhaust;

ALife frameworks (3)

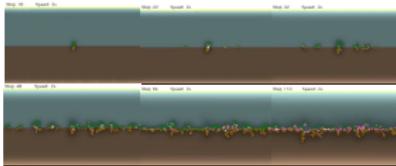
Cellular Development Agency

(1)



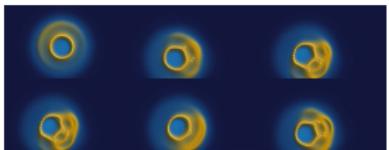
Sensorimotor Lenia (Hamon et al. 2022) uses partial asynchronous updates to make agents robust within environment where they show behavior of attaching to one another. Cells adhering to one another is a fundamental aspect of cellular interactions and is crucial for the formation and maintenance of tissues and organs.

(3)



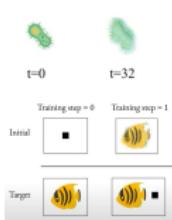
Biomaker CA (Randazzo et al. 2023) demonstrates complex behaviors analogous to biology through its cellular nature (utilizing CA) to simulate the growth, reproduction, multiplication and evolution of plant-like organisms in diverse environments where nutrients are in budget.

(2)



The assembly of swarms, whether in biology or ALife, refers to the collective organization and coordination of individual entities into a larger, coherent structure or group. In the context of biology, this concept often pertains to the aggregation or grouping of cells to form tissues, organs, or larger structures within an organism. In ALife, it can be a fundamental principle for simulating emergent behaviors and complex patterns through the interaction and cooperation of individual agents as shown in Particle Lens (Mordvinstev et al. 2022).

(4)



In Self-Replication, Spontaneous Mutations, and Exponential Genetic Drift in Neural Cellular Automata (Sinapayen 2023) The goal is to understand and replicate the self-organizing behavior observed in the development of multicellular organisms, starting from a single cell.

Figure: ALife Frameworks

- **RQ1:** Speciation: emerge, survive, reproduce and becomes extinct (dead) within substrate?
- **RQ2:** Genotypic Diversity Quantification?
- **RQ3:** What is the impact of the self-replication and self-maintenance processes, characteristic of autopoiesis, on the genetic makeup on substrate?
- **RQ4:** What contributes to diversity?
- **RQ5:** Sensitivity to initial conditions and its effect on PD and GD?

Background Work: Cellular Automata

Discrete Cellular Automata (CA)

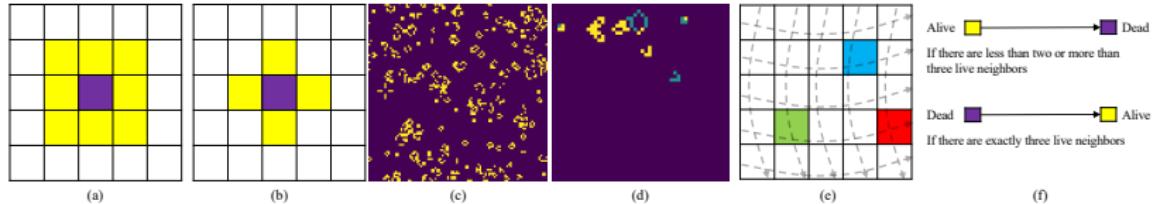
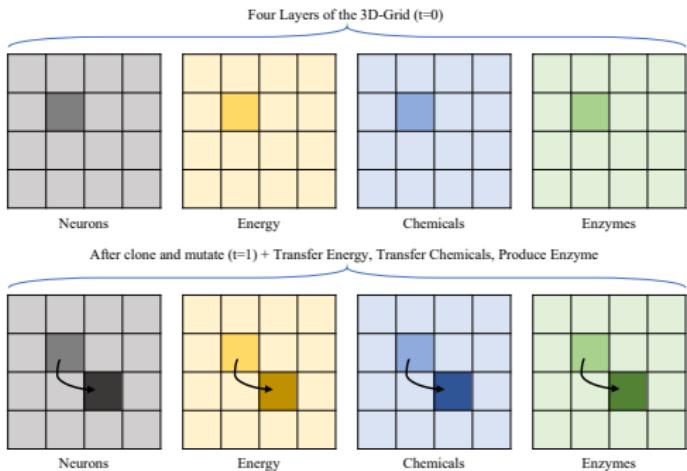


Figure: Summary of working of 2D CA. (a) Moore neighborhood (b) Von Neumann neighborhood (c) GoL in action (d) Glider Gun in action (e) Wrap around conditions in CA environments, also CA grid is initialised with three different states (also called as MNCA [Slackermanz, 2021]) (f) GoL rule conditions

Neural CA



In this system, a physics component is introduced, involving energy fields and fields of various chemicals at each grid location, where cells can manipulate these quantities in multiple directions at an energy cost, engaging in interactions and potentially dying if energy falls below a threshold, and cells also produce enzymes controlling sequential reactions with associated energy costs, exemplified by maximizing energy through enzyme, with cells having a maximum lifetime and a need for non-trivial actions. While noting that in the implementation, elements can autonomously self-replicate.

Figure: A simple illustration of Neural CA introduced in literature
[Gregor and Besse, 2021, Mordvintsev et al., 2020]

Comparisons

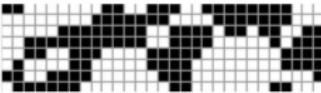
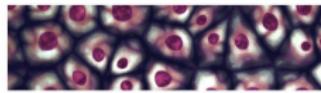
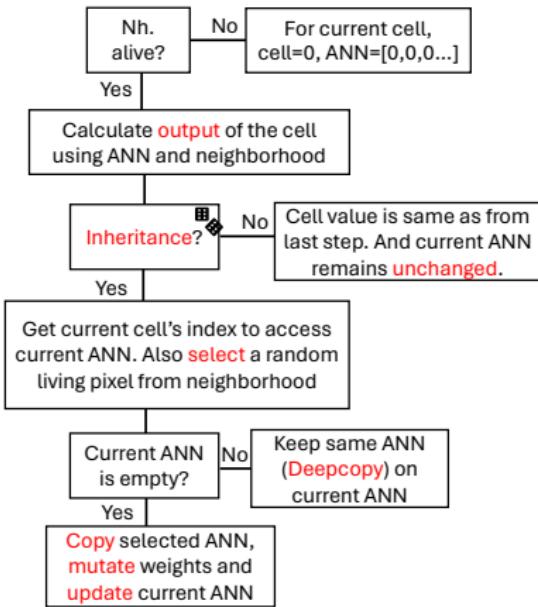
Cellular automata	Neural cellular automata	Biological cells
		
- Two cell states: dead or alive	- Many possible cell states	- Many possible cell states
- Simple, hand-picked growth rules	- Complex growth rules determined by a neural network	- Complex growth rules determined by genes and morphogens
- Local interactions produce global structure	- Local interactions produce specific global structure (with 10^4 cells)	- Local interactions produce specific global structure (with 10^{13} cells)
- No objective	- Objective is to grow a shape that resembles the target image	- Objective is to grow an organism that fits its ecological niche

Figure: Brief comparisons [Greydanus, 2022]

Proposed Methods: (1) Neural CA, (2) Evaluation Metrics

Working of Proposed Neural CA (NCA) (1)



Fate of the current cell. Alive or dead?

There could be a situation where a cell is not alive but still permits entering a routine to become alive in the next generation. Even if all neighboring cells are dead and only this cell is alive, it still counts as fulfilling the condition of having a living neighbor, as a cell is considered its own neighbor. If any cell in the neighborhood is alive, the cell calculates the output based on its neighbors and weights, even if that output is 0 (indicating the cell is dead). If the cell cannot enter the inheritance loop, it uses the most recent cell output value and retains the current weights, leaving them unchanged. If the cell was dead, it remains in the death state. If the cell was alive, it continues to live with the same weights, but the cell value is the output of the weights. If the cell hits the "rolling dice" condition, it enters the inheritance loop. First, the cell's position and weights are identified. Second, a random living neighbor, its position, and its weights are selected. The routine checks whether the cell's weights are empty. If the cell is found to be dead, it becomes alive by inheriting and mutating the DNA of the randomly selected living neighbor, updating its weights. This allows the cell to have its own value in the next generation. If the cell is already alive, the routine keeps the same weights. Therefore, only dead cells are given the opportunity to acquire new weights, DNA, or agency through inheritance.

Figure: How NCA works as functionality. Life-cycle of a cell and update method

Rules for Living Cell (2)

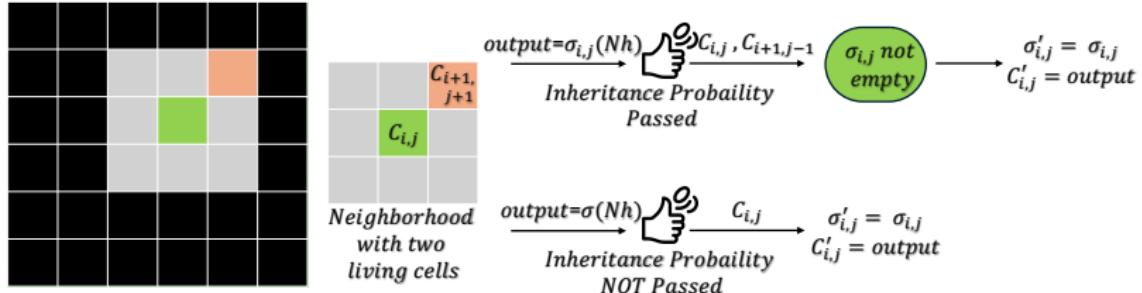


Figure: Fate of a living cell

Rules for Dead Cell (3)

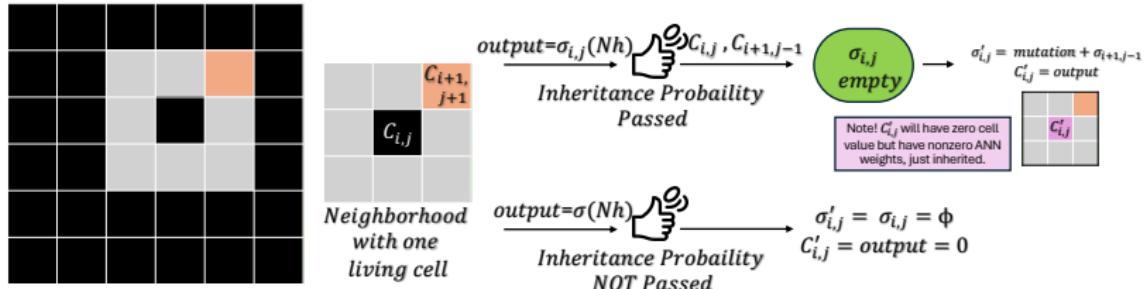


Figure: Fate of a dead cell

Inheritance Mechanism (4)

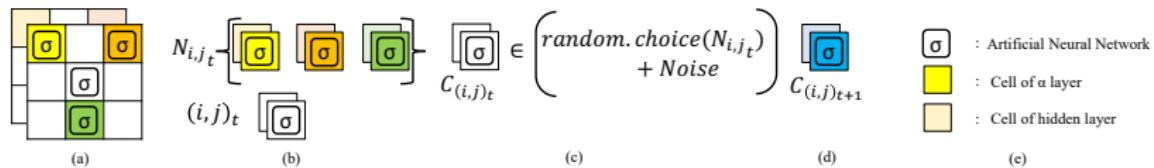


Figure: A simple illustration of the proposed NCA inheritance framework. (a) 3×3 grid of Moore neighbors of the current cell, showing cells (and agents) that are active while all white cells are dead. (b) List of all living neighbors at time t for the current cell at position (i, j) . (c) Current cell undergoes inheritance and mutation using a Noise vector. (d) Cell at time $t + 1$ shows the resulting value from the agent (σ). (e) Representation for the rest of the diagram.

We discuss how Evaluation Metrics work? Following tools are mostly inspired from [Medernach et al., 2013] with little modifications to adjust it for Neural CA:

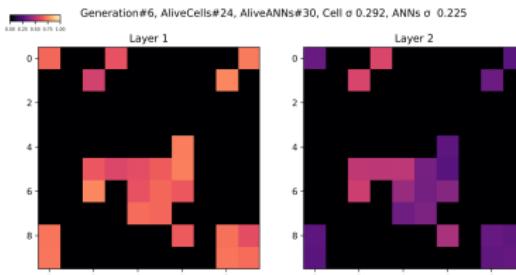
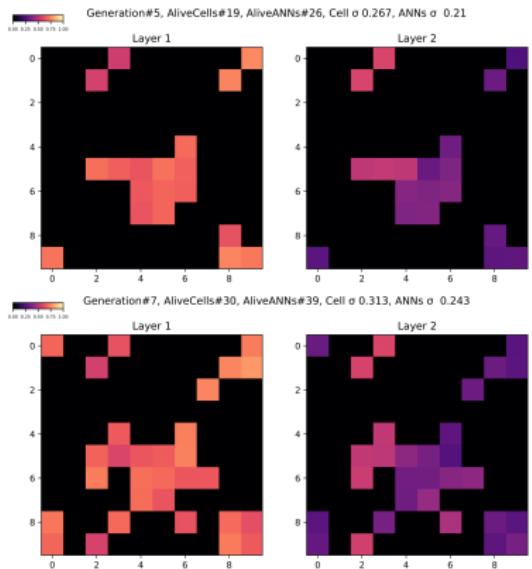
- Cellular Type Frequency Plot (CTFP)
- Global Entropy Plot (GEP)
- Gross Cell Variance Plot (GCVP)
- Cell Local Organisation Global Variance (CLOGV)

Genotypic Diversity (GD) (2)

We discuss how Evaluation Metrics work? Following are Genotypic Diversity (GD) tools mostly inspired and modified from respective references:

- Random Weight Selection Plot (RWSP)
[Gregor and Besse, 2021]
- Genotype Hash Coloring (GHC)
[McCaskill and Packard, 2019]
- Unique Color Count Plot (Combined)

Demo of NCA framework (3.1)



NCA as substrate for α and chemistry channels.

Figure: Neural CA Overview (for intermediate generations)

Demo of PD (3.2)

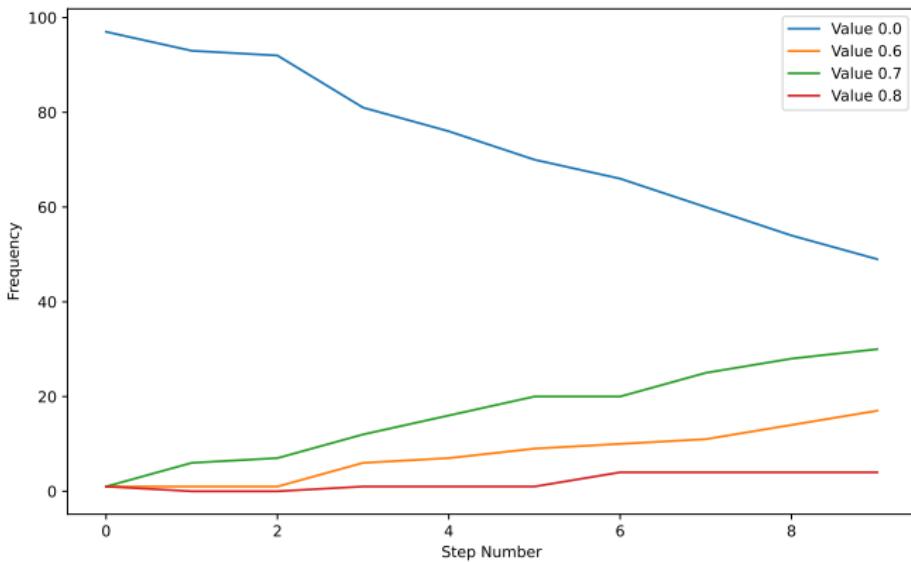


Figure: Phenotypic Diversity Overview

Demo of GD(3.3)

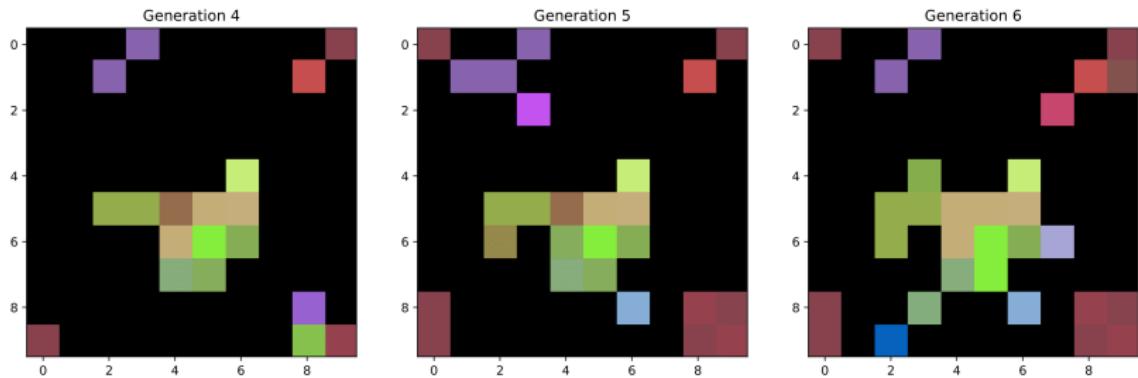


Figure: Genotypic Diversity Overview

A note and about upcoming discussions:

- It is advised to refer the technicalities in thesis, including mathematical formulations of each PD and GD tool;
- We see NCA example simulation next;
- Analyse each of the PD and GD tools after the simulation;
- Summarising research questions;
- Conclusions and future usage and scope of improvement.

Results & Discussions and Research Questions

All Results - Exp 1 to 4

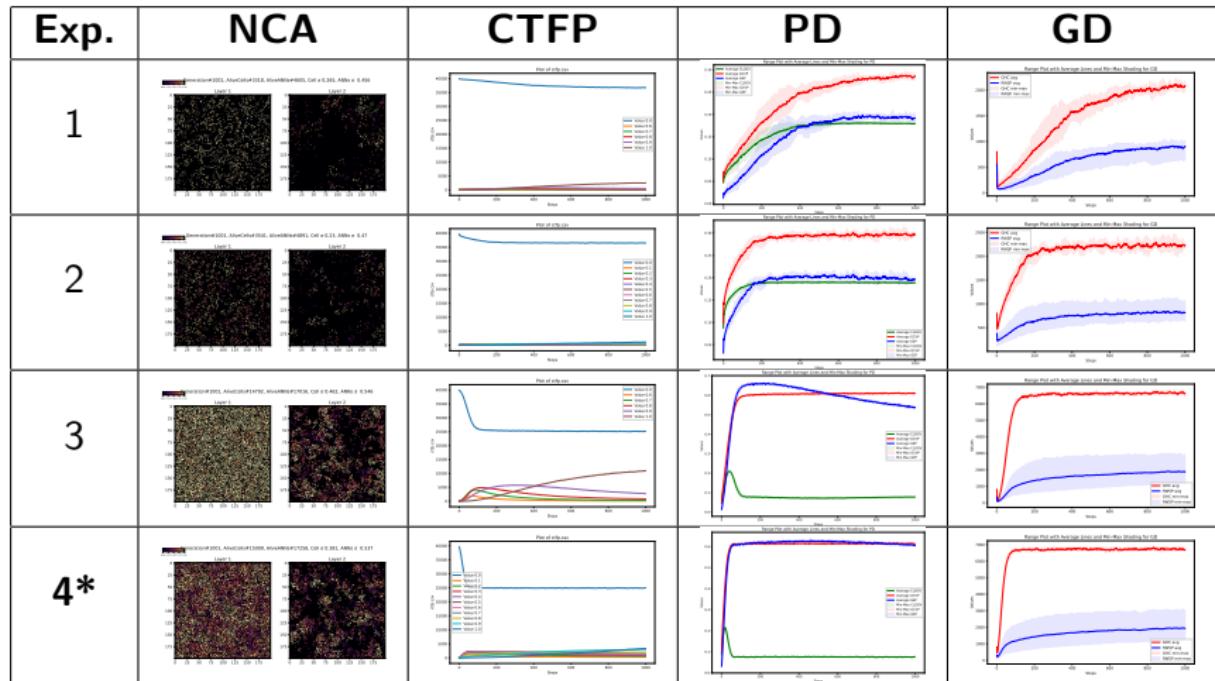


Table: Exps 1 to 4

All Results - Exp 5 to 8

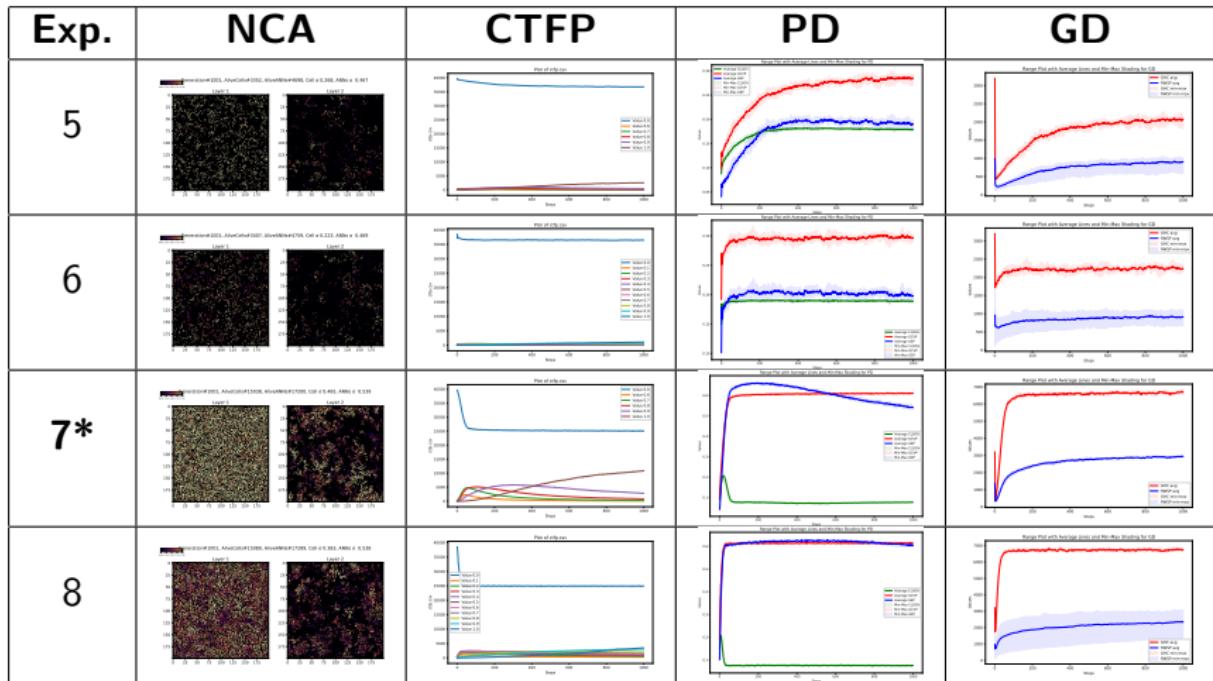


Table: Exps 5 to 8

All Results - Exp 9 to 12

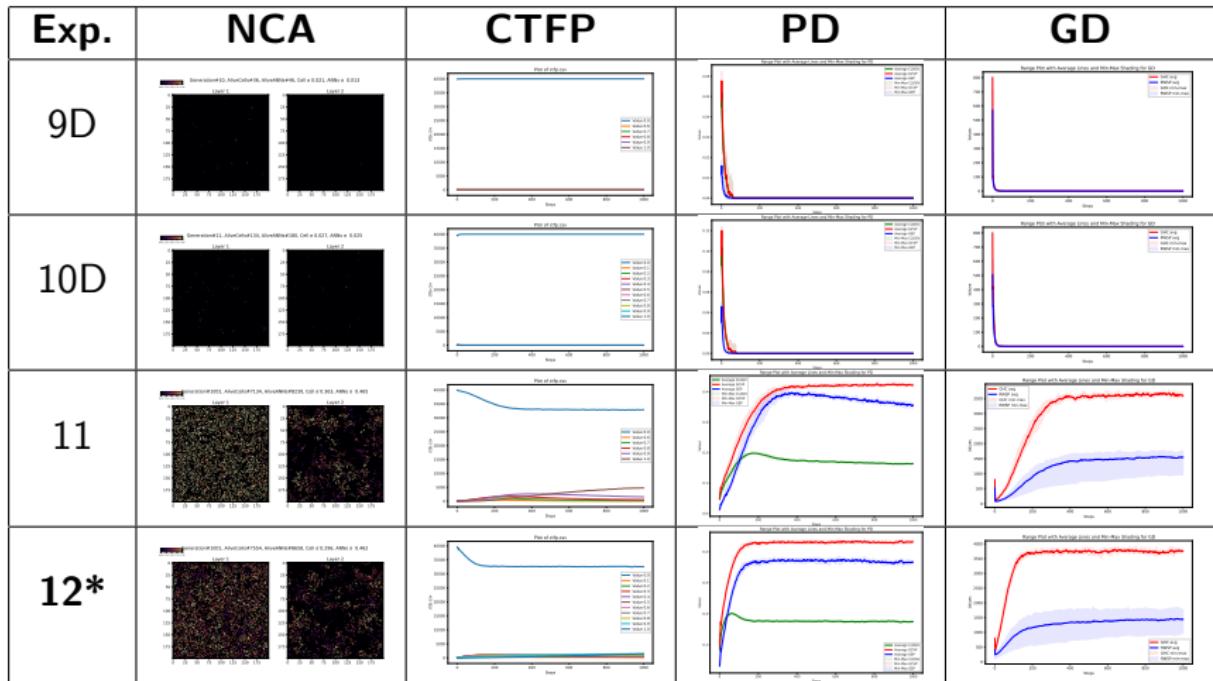


Table: Exps 9 to 12

All Results - Exp 13 to 16

Exp.	NCA	CTFP	PD	GD
13D	 	 	 	
14D	 	 	 	
15	 	 	 	
16*	 	 	 	

Table: Exps 13 to 16

All Results - Exp 17 to 20

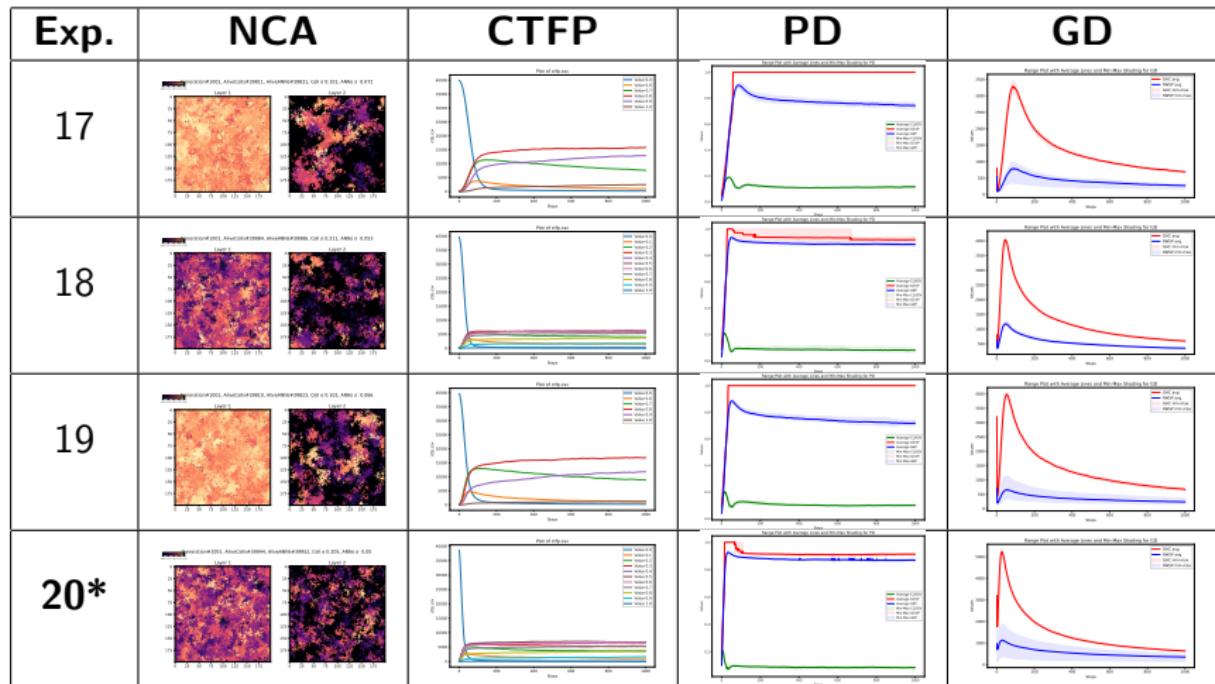


Table: Exps 17 to 20

All Results - Exp 21 to 24

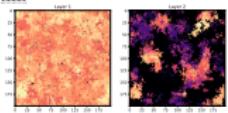
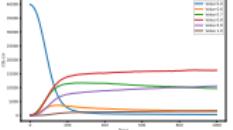
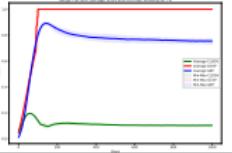
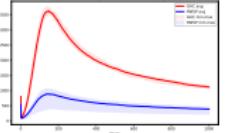
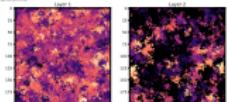
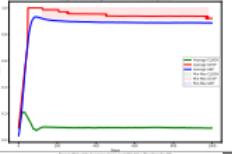
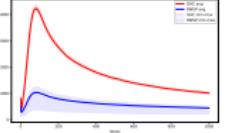
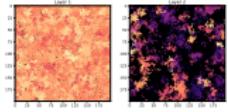
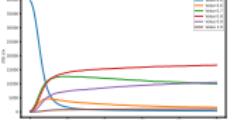
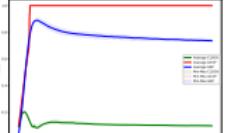
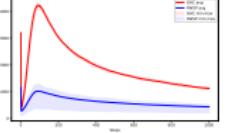
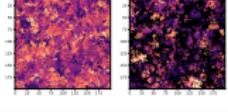
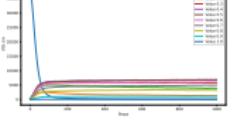
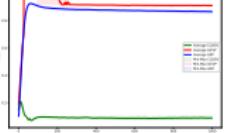
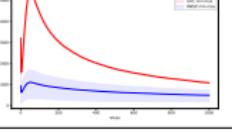
Exp.	NCA	CTFP	PD	GD
21*				
22				
23*				
24				

Table: Exps 21 to 24

RQ1: Speciation: emerge, survive, reproduce and becomes extinct (dead) within substrate? (1)

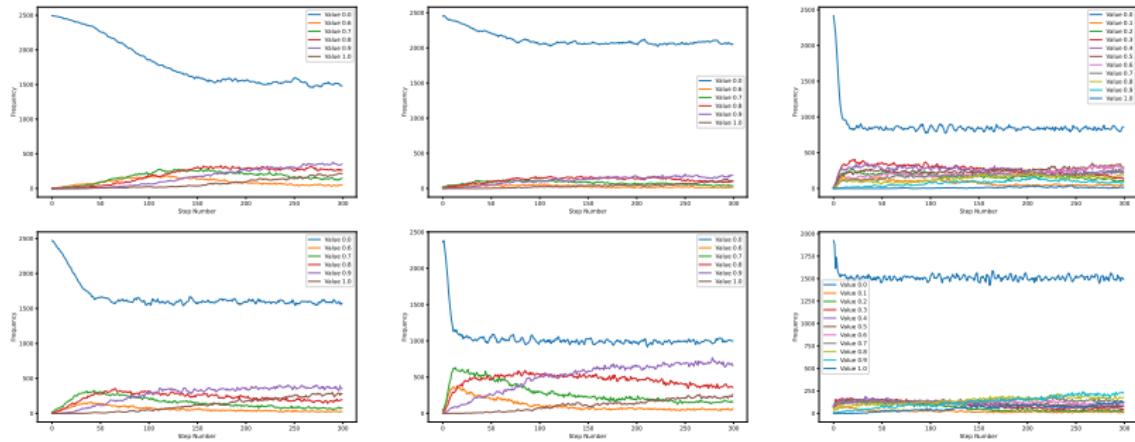
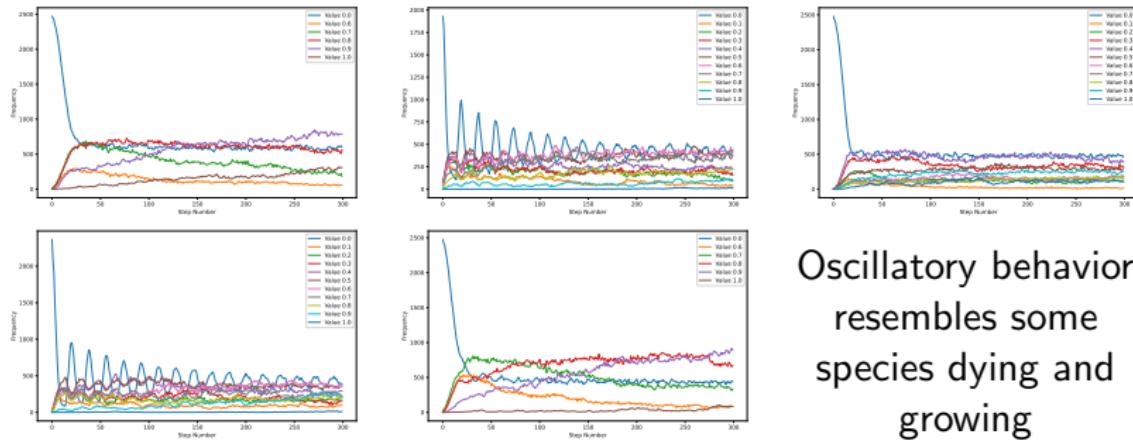


Figure: Coexistence of Species

RQ1: Speciation: emerge, survive, reproduce and becomes extinct (dead) within substrate? (2)



Oscillatory behavior
resembles some
species dying and
growing

Figure: Species consumes all space to coexist

RQ1: Speciation: emerge, survive, reproduce and becomes extinct (dead) within substrate? (3)

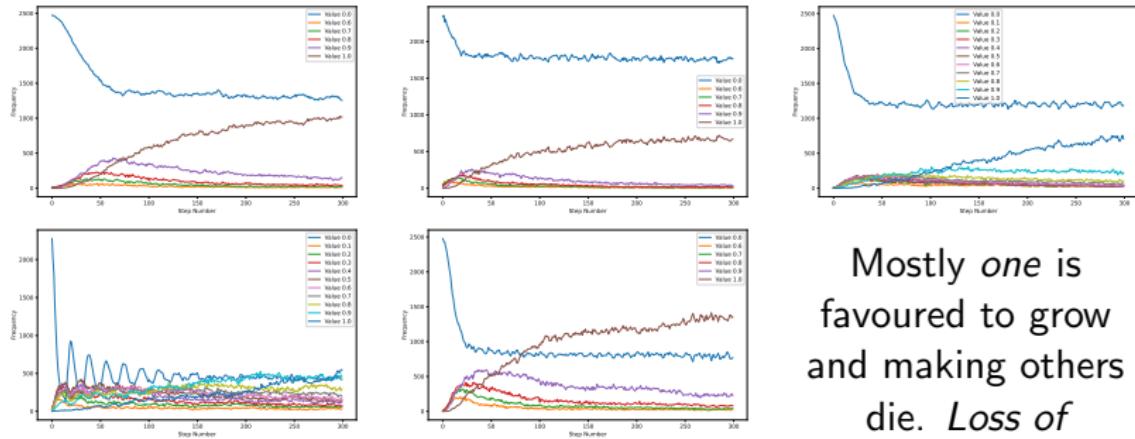


Figure: One species dominate

Mostly *one* is
favoured to grow
and making others
die. *Loss of
diversity*

RQ2: Genotypic Diversity Quantification? (1)

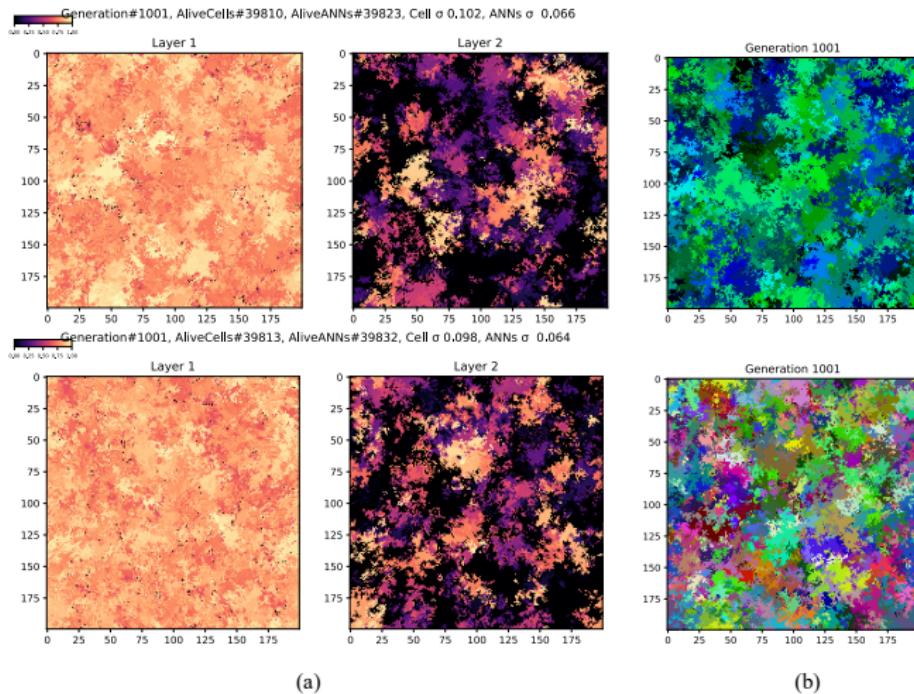


Figure: (a) Evolved NCA biome (b) Corresponding GD

RQ2: Genotypic Diversity Quantification? (2)

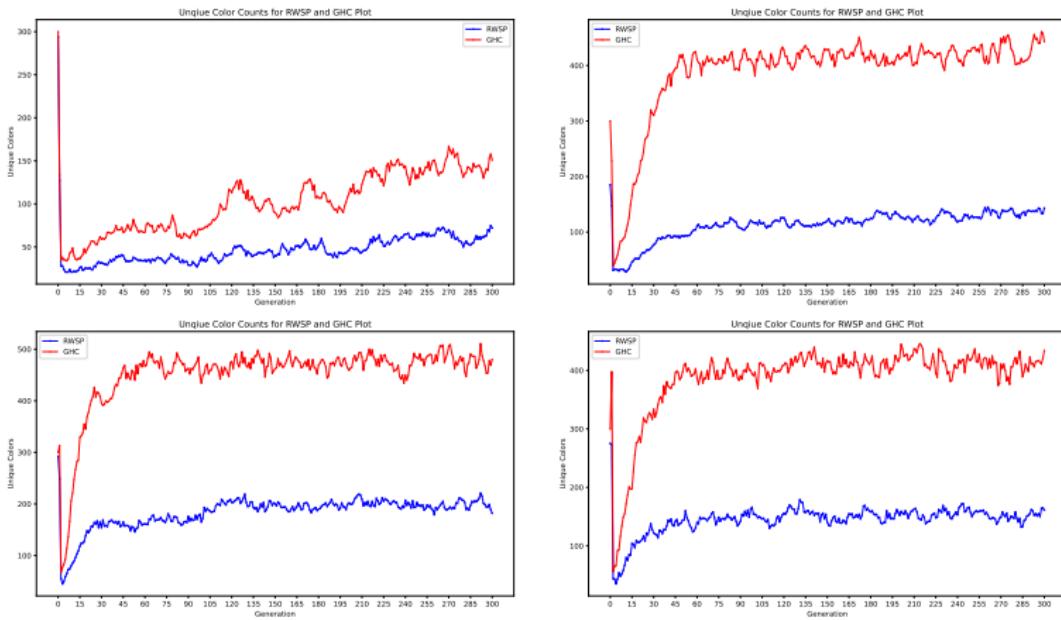


Figure: Unique Color Count Plots of RWSP and GHC for effect of inheritance probability on Genotypic Diversity (low to high as gap between RWSP and GHC increases)

RQ2: Genotypic Diversity Quantification? (3)

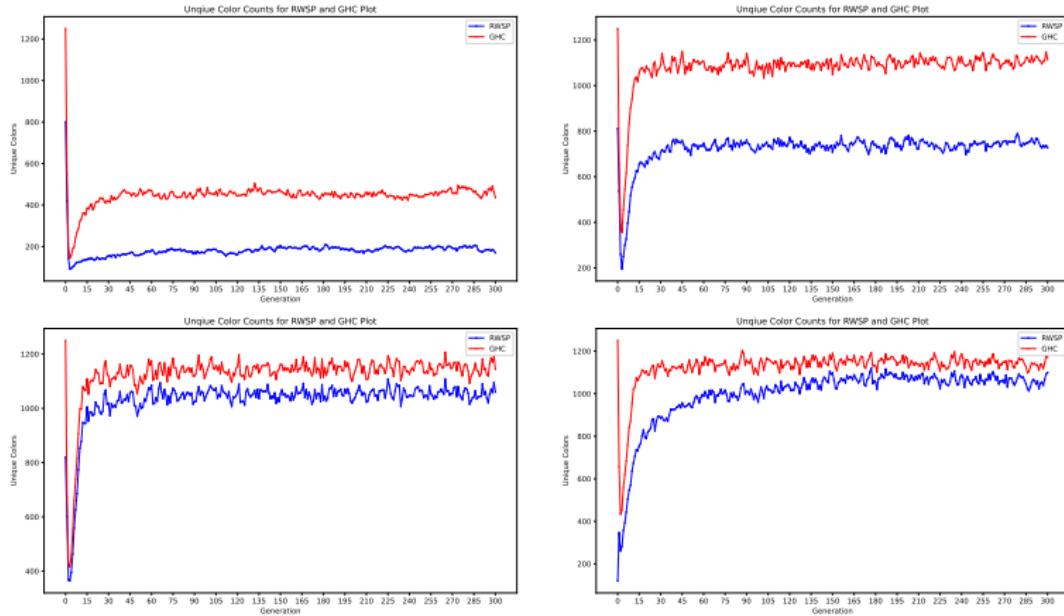


Figure: Unique Color Count Plots of RWSP and GHC for effect of PPP on Genotypic Diversity (low to high)

RQ2: Genotypic Diversity Quantification? (4)

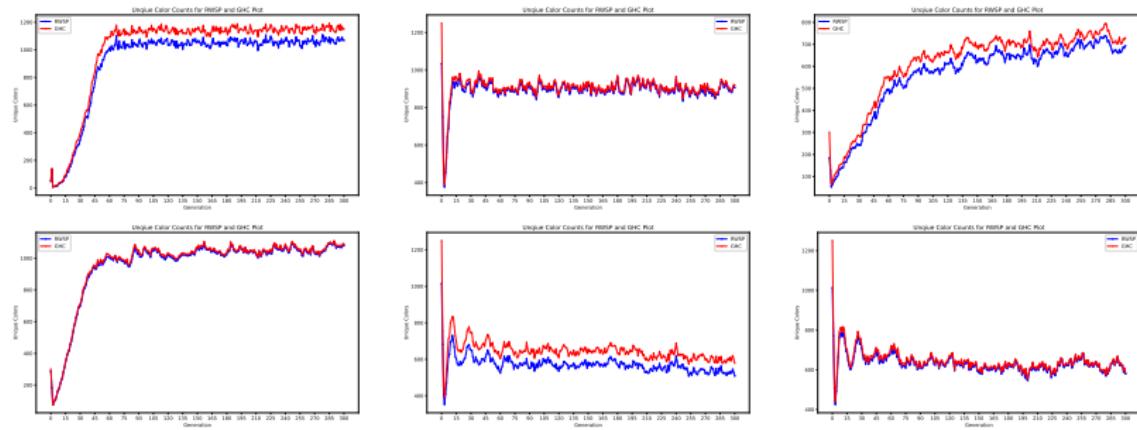


Figure: Unique Color Count Plots of RWSP and GHC for effect of High PPP, Initial Probability, High Budget and High Inheritance on Genotypic Diversity

RQ3: Impact of rules on genetic makeup (1)

- Learn to maintain the diversity over generations;
- Budget counter, ensures robustness of NCA. NCA reaches criticality, the agents were never able to capture complete space of the NCA but they self-replicate, produce new genes and becomes adaptable to evolve and reproduce to grow.

RQ3: Impact of rules on genetic makeup (2)

- Genetic material are propagated in further generations which make them continue to produce diversity over time even if they are dying, its not like all alleles have died, even if there are some chances that material is perturbed, it can still be preserved in a system with higher budget as higher chance of inheritance taking place. Thus system behaves as if it has learned to preserve diversity by creating self;
- NCA evolves mechanisms ensuring ongoing functionality and capacity to respond to environmental changes.

RQ4: What contributes to diversity?

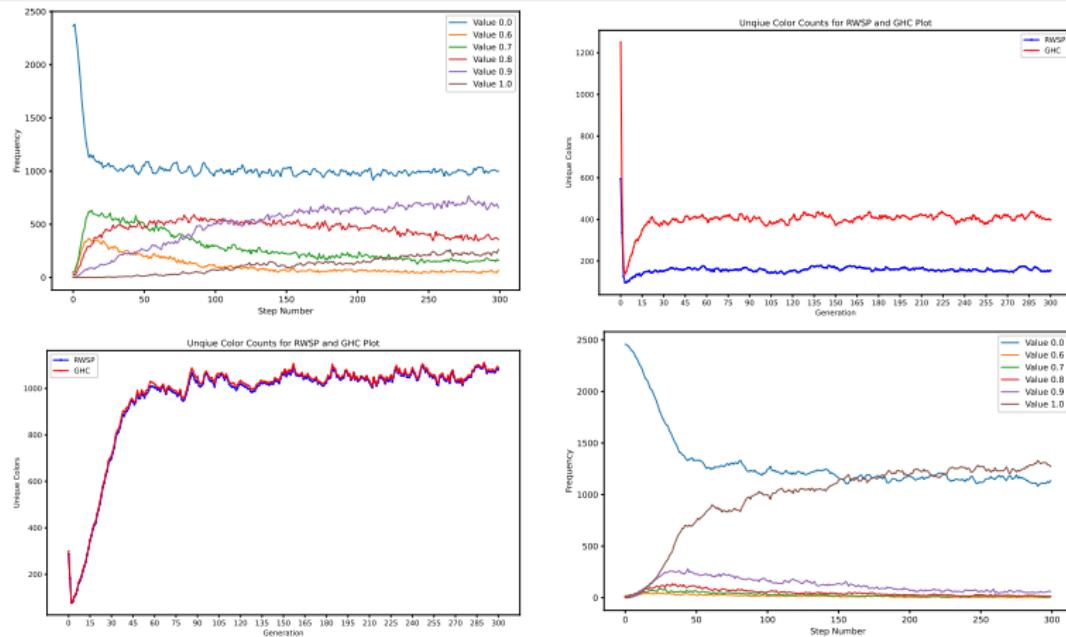


Figure: Tradeoff Visualised. First row shows CTFP plot preserving the PD while RWSP-GHC count plot shows decreased GD. Second row shows RWSP-GHC count plot preserving GD while CTFP plot shows decreased diversity as one species overrides other species

RQ5: Sensitivity to initial conditions

Categorisation of experiments are as follows:

- Coexistence of Species;
- PD-GD tradeoff;
- Species Consumes All Space of NCA to Coexist;
- One Species Dominate (Loss of Diversity case);
- High mutations leading some species to co-dominate;
- Low mutations helping different species to coexist with balanced GD;
- Mediocre mutations show glider like behavior;
- Very high mutations makes agents forced to adapt the environment at cost of losing genetic information very fast.

Conclusion & Scope of Improvement

- NCA as biome where cellular agents, when allowed to perform local interactions by self-replication and inheritance, continue to grow and show interesting long term dynamics;
- Using CTFP, GEP, GCVP, and CLOGV for PD and RWSP and GHC for GD, enabling analyse various NCA biomes quantitatively and qualitatively respectively;
- NCA is not only robust to these conditions but also able to interesting dynamics and self-discover new ways to self-maintain;
- These conditions, though enforced *in-silico* for NCA, could also be suitable for *in-vitro* (petridish) experiments where NCA can be assumed as isolated closed-system experiment like test-tube experiments (wetware).
- In short, NCA can be seen as biome that evolves over generations and PD-GD tools work as coarse grainining lens to analyse the behavioural changes of the NCA.

Clustering approach can be corrected with properly tracking the centroids. This is introduced as Clustering Neural Weights Approach (CNWA). If this gets to work properly, it should show following illustrations. These illustrations are generated for very small data and hence just are glimpse of bigger runs in future.

CNWA (1)

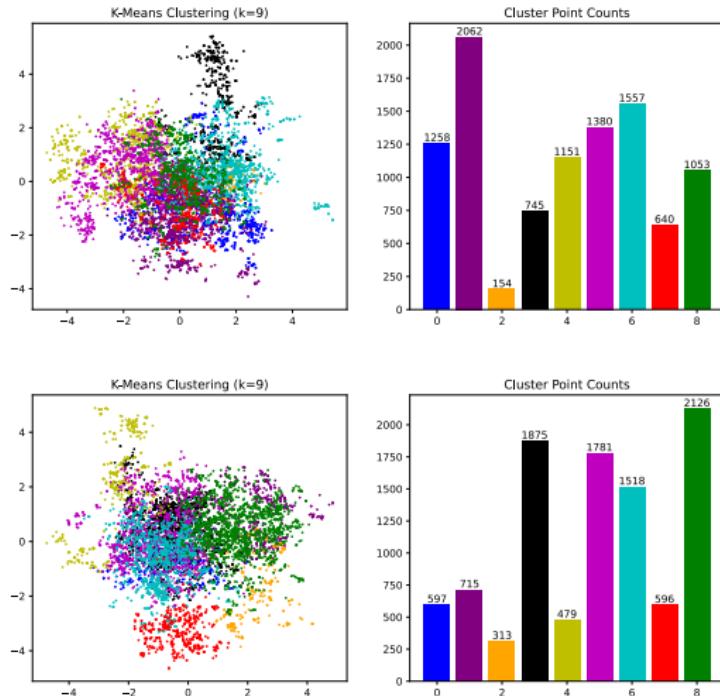


Figure: CNWA results for two different runs at a specific generation

CNWA (2)

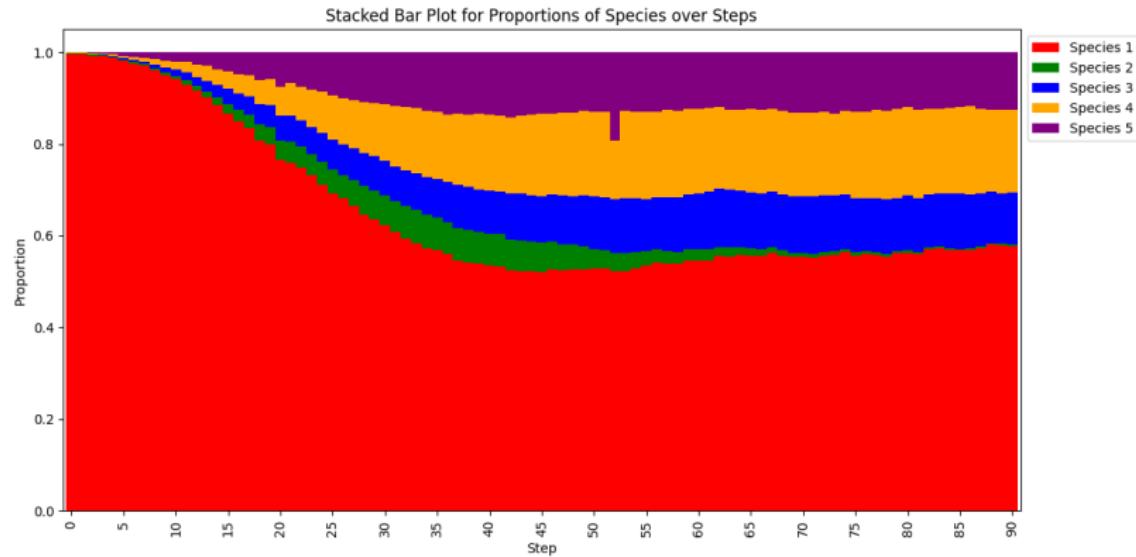


Figure: Speciation plots example, derived from CNWA tool

The next step to progress this work includes:

- Plugging in a task specific to solve some AI problem (Running evolution), like self-classification of MNIST [Randazzo et al., 2020].
- Removing dependency on lattice-like substrate and using network-like substrate [Gershenson, 2004].

Thank You

Thank You! Scan the QR below for direct access to the code on GitHub.

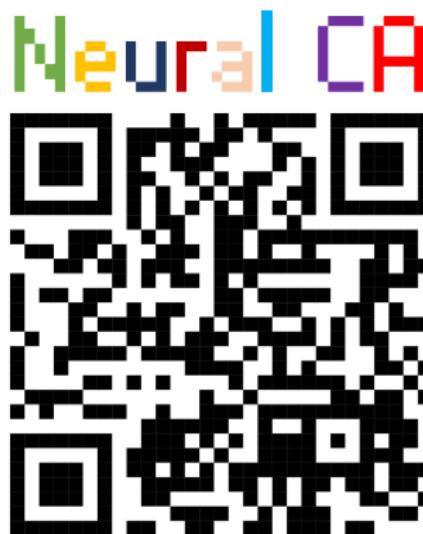


Figure: Scan for GitHub Repository

Major References

-  Ball, P. (2023).
Synthetic morphology lets scientists create new life-forms.
Scientific American.
 -  Gershenson, C. (2004).
Introduction to random boolean networks.
arXiv preprint nlin/0408006.
 -  Gregor, K. and Besse, F. (2021).
Self-organizing intelligent matter: A blueprint for an ai generating algorithm.
arXiv preprint arXiv:2101.07627.
 -  Greydanus, S. (2022).
Studying growth with neural cellular automata.
<https://greydanus.github.io/2022/05/24/studying-growth/>.
 -  McCaskill, J. S. and Packard, N. H. (2019).
Analysing emergent dynamics of evolving computation in 2d cellular automata.
In *Theory and Practice of Natural Computing: 8th International Conference, TPNC 2019, Kingston, ON, Canada, December 9–11, 2019, Proceedings 8*, pages 3–40. Springer.
 -  Medernach, D., Kowaliw, T., Ryan, C., and Doursat, R. (2013).
Long-term evolutionary dynamics in heterogeneous cellular automata.
In *Proceedings of the 15th annual conference on Genetic and evolutionary computation*, pages 231–238.
 -  Mordvintsev, A., Randazzo, E., Niklasson, E., and Levin, M. (2020).
Growing neural cellular automata.
Distill, 5(2):e23.
 -  Randazzo, E., Mordvintsev, A., Niklasson, E., Levin, M., and Greydanus, S. (2020).
Self-classifying mnist digits.
Distill, 5(8):e00027–002.
 -  Slackerman, W. (2021).
Understanding multiple neighborhood cellular automata.
Slackerman.
 -  Stanley, K. O., Lehman, J., and Soros, L. (2017).
Open-endedness: The last grand challenge you've never heard of.
While open-endedness could be a force for discovering intelligence, it could also be a component of AI itself.
- 
- Høgskolen i Østfold