Exploring the Resilience of Emergent Properties using Langton's Ants

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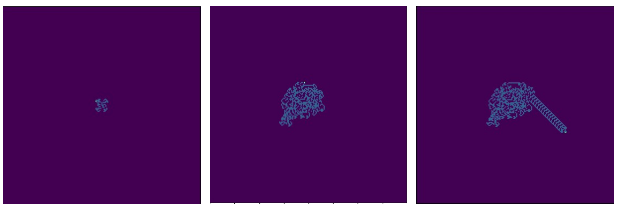

Fig. 1. symmetrical patterns – chaotic exploration – highway structure

***Abstract*—Langton's Ants are cellular automata which display complex emergent properties with very simple transitional rules. This research project seeks to test Langton's Ants and variants with larger transition rules and state counts, against random and chaotic elements. The goal is to find if simple cellular automata can maintain emergent behavior through probabilistic chaos. The measures of complexity were entropy and mutual information. The chaotic elements were the number of Ants on the board, the amount of tiles which would start in a non-uniform state, and the amount of Ants which spawned with a random transition rule-set. The tests showed that none of the Langton's Ants variants tested could maintain emergent behaviors through any level of randomness. The future of the research would likely be exploring exhaustively all Langton's Ants variants to try to discover a transition rule-set which does display resilient emergent phenomena and research why that rule-set has resistance to randomness.**

I. Introduction and Motivation

Langton's Ants are two-dimensional Turing Machines and cellular automata with very basic rule-set, which generate emergent behaviors. The two rules are, if the Ant is on a black cell, flip the color to white, turn left, and move forward one space, if the Ant is on a white cell, flip the color to black, turn right, and move forward one space. The board starts in a full black state, with a single Ant placed in the center. The Ant starts by making simple patterns which are often symmetrical before transitioning to chaotic shapes. Eventually, the Ant begins building an infinitely long "highway" in one direction (See Fig. 1). This final behavior occurs around step 11000. Furthermore, these Ants have been explored in various ways, such as by adding additional Ants and adding to the number of states and modifying or expanding the transition rules. These variants have been called Turmites (Turing machine termites).

The main research question to answer is, How resilient are the emergent behaviors of complex cellular automata to disruptions and chaos? The goal of the research is to find complex behavior which can persist through an unstable environment. Cellular automata can be used to solve problems or simulate certain environments using relatively simple transition rules. The simplicity of these algorithms and the complexity of real world problems raises an interesting parallel to explore, can cellular automata properly represent these problem spaces even through potentially unpredictable changes?

II. Related Work

Most work with Langton's Ants explores the universality of the system or seeks to implement some algorithm using them. The research into the resilience of their unique behaviors is a mostly novel idea. "Complexity of Langton's ant" shows their ability to calculate any Boolean circuit [1]. "Generalized Langton's Ant: Dynamical Behavior and Complexity" analyzes and proves the universality of the Ants on infinite bi-regular graphs of degrees 3 and 4 [2]. "Nontrivial Turmites are Turing-universal" shows how Turmites, within specific rules, can simulate Turing Machines. Furthermore, it proves the P-completeness of predicting future behavior using log-space reduction [3]. "Universality and complexity in cellular automata" explores simple one-dimensional cellular automata and places them into four classes of behavior [4]. "Complexity Measures and Cellular Automata" explores methods of measuring complexity of patterns in one dimensional cellular automata. They apply these measures to regular and context-free languages [5]. "Three Emergent Phenomena in the Multi-Turmite System and their Robustness to Asynchrony" is the closest to this research. It identifies behaviors of having multiple Turmites in the grid and analyzes the surprising resilience the behavior shows to asynchronous updates. Their approach differs from this project as it does not try to gauge complexity through metrics, and it does not explore more avenues of changing environments besides increasing the number of Turmites [6]. "Secure medical image encryption approach based on Langton's ant and jigsaw transform" applies Langton's ants to images in order to add deterministic noise and help encrypt them. [7] "Research and implementation of a two-dimensional cellular automaton" creates a software for exploring Turmites and the patterns they can produce. Many results shown use variable number of Turmites to show novel behaviors. [8] "How Fast Does Langton's Ant Move?" has an interesting premise of trying to quantify the behavior, specifically speed, of the Ants. This more applies to physics simulations with propagation rates, however the quantifying and interpretation of the behavior is similar to this research paper's. [9] "Thermodynamics of

$$-\sum_{x \epsilon X} p(x) log(p(x))$$

Fig. 2. Equation for entropy where x is each color state

emergence: Langton's ant meets Boltzmann" is a criticism of emergent behaviors in regard to artificial life. It serves to establish interesting hypotheses and explore general properties of emergent phenomena through the lens of Langton's Ants. [10].

III. Method

As stated in the Introduction, Langton's Ants are cellular automata where each state needs to encode the color of the tile, whether an Ant is on the tile, and the direction of the ant. This implementation means that the number of states and the number of colors are not equal, and it can somewhat complicate the efficient application of the transition rules on the grid. This paper uses an alternative method, which is functionally equivalent to the cellular automata implementation. In this method, the grid has a number of states that is equal to the number of colors, with a separated Ant object acting upon the grid each step of the simulation. Phrased in another way, the Ant is not part of the board, but instead a separate actor which interacts and changes the grid while keeping track of its own coordinates and direction. Furthermore, traditional Langton's Ants do not loop around the board, instead they are normally removed when they hit an edge. The implementation used here, allows them to loop to the other side. The thought process behind this is to get more consistent behavior when adding additional Ants to random non-centered tiles and so that the metrics analyzed hit a consistent observable peak, specifically with entropy.

After creating the implementation of the automata, next metrics must be decided for measuring complexity. Storing GIFs of all the experiments and going through by hand would be too costly both in compute time and human labor time, so some metrics need to be used to approximate the complexity. The metrics chosen were entropy (Fig. 2), the total number of each state over time, and mutual information (Fig. 3). Measuring complexity is a difficult problem and the chosen metrics are not perfect representations of complex behaviors, however they provide some amount of visualizable insight on the activity of automata as a whole. Additionally, because of the high number of steps required to observe the full scope of complex behaviors, these metrics are not calculated each step. Instead, they are calculated every 300 steps. Graphs in this paper, which show these complexity metrics, will have an x-axis which displays the number of these snapshots, and not the total steps. (x=1 represents step 300, x=5 represents step 1500, etc.).

Once the metrics are designed, the next step is creating our experimental variables. These variables are, transition rules, number of Ants on the board, odds of starting tiles not being black, and odds of Ants spawning with randomized transition rules.

$$\sum_{x \epsilon X} \sum_{y \epsilon Y} \frac{P(x,y)}{P(x)P(y)}$$

Fig. 3. Equation for Mutual Information where x and y are different color states

A. Alternate Transition Rules

Transition rules are internally described as a list of size 2 tuples. Where the current color state is the index of the list and the tuple represents (direction modifier, new color). So for example, the default Langton's Ant would be described as ((-1,1), (1,0)). If on a black tile (state number 0), turn left and set the tile state to white (state number 1). If on a white tile, turn right and set the tile state to black.

Besides the default Langton's Ant, 4 more variants were chosen for the experiments which are

- (1,2), (-1,0), (2, 1)
- (1,2), (-1,0), (0, 1)
- (1,1), (0,2), (-1,3), (0,4), (1,5), (0,6), (-1,7), (0,0)
- (0,1), (1,2), (-1,3), (0,4), (0,5), (1,6), (1,7), (-1,0)

B. Number of Ants

This variable refers to the number of Ants on the board. When there are multiple Ants on the board, they are initialized at random coordinates on the board.

C. Randomized Board Initialization

This refers to a probability of each tile starting as a different state than black. For example, .05 means each tile has a 5 percent chance to start as a non-black tile. If the number of states is greater than 2 and a tile is chosen to be a random color, it will choose randomly out of all non-zero tiles.

D. Random Transition Rule Ants

Finally, this variable refers to a probability that an Ant will have an entirely randomized transition rule-set. The transition rule-set is forced to iterate through every state, with the direction for each transition being random.

E. Experiment Setup

For the experiment data, every permutation of the variables was run 3 times each. The number of Ants ranged from (1, 3, 10, 20), random starting tiles from (0, 0.05, 0.1, 0.5), and random rule-set Ants from (0, 0.1, 0.2, 0.5, 1). Each experiment was run for 24000 steps with information being gathered every 300 steps. In total there were 1200 experiments run.

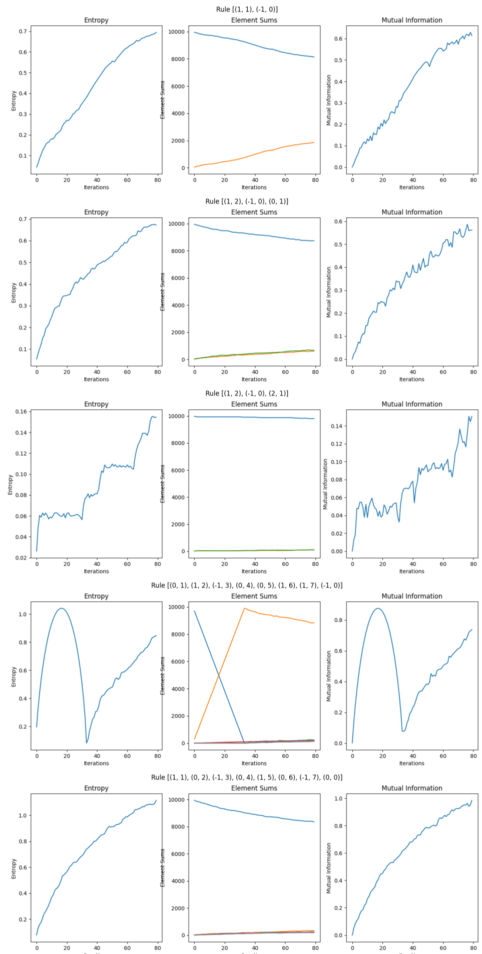

Fig. 4. Control group graphs

IV. Results

First, control groups should be established to help interpret the rest of the results. The graphs in Fig. 4 show each transition rule-sets metrics using one Ant and no random tiles or Ants. The overall trend is for entropy and mutual information to rise while the state count approaches an equilibrium in the center. 24000 steps is still relatively limiting, so it does not capture the convergence point of entropy and mutual information, where entropy cannot meaningfully increase any further. The two unique graphs, 3 and 4, both have unique entropy graphs. Rule-set 3 plateaus and climbs in cycles, while 4 has an initial parabolic curve before falling into the steady climb. These two behaviors are excellent for establishing a baseline for clearly visible behavior. As variables are introduced, it will be very obvious if this plateauing and parabolic shape persists or not.

When varying the number of Ants, there is some unique behavior that is not captured by the chosen metrics, specifically with the default rule-set. Sometimes an Ant can turn itself around and collide with a highway structure and reverse it until the entire structure is set back to default. The reason this can happen with the default transition rules, is because the turning is relative to the Ant, so an Ant that is turned backwards is turning the opposite direction compared to a forward's facing Ant. This perfectly mirrors the original rule-set and causes a reversal of the structure. While this behavior is not captured by the complexity metrics, it is still incredibly interesting, and included in the submission is a GIF of this behavior called N=5.

In fig. 5, there are unique patterns among the expected results. The expectation is for entropy to rise faster and hit a maximum quicker as more Ants are introduced. The Ants are exploring a blank space and converting those empty spaces to a different state, but eventually they explore so thoroughly that the states are evenly distributed and no more meaningful patterns or exploration can occur. Having more Ants speeds up this process in direct proportion. However, entropy graphs 3 and 4 exhibit interesting behavior. Graph 3 does have a higher entropy in proportion to the number of Ants, but the rate of entropy gain noticeably slows down after very few iterations and never properly reaches the Plateau point within the 24000 steps. Graph 4 follows the aforementioned expectations, however the parabolic curve completely disappears, indicating a loss of behavior. Mutual information follows an interesting pattern where the metric increases until it's between 3 and 10 where it begins peaking earlier. Graph 3 is again an interesting exception to this rule, where mutual information climbs almost identically to entropy. One behavior that is interesting, is that all the mutual information lines in graph 3 have occasional spikes which are mirrored between each other. Again it is seen that graph 4 loses its unique parabolic behavior under any amount of Ants.

As stated before, entropy is 0 when the board is initialized by default. The Ants as they explore spread entropy until it can no longer increase, however, if the board has some probability to have nonuniform tiles, it starts at a higher entropy. The highest probability of this happening is 50 percent, which on a 2 tile grid, means entropy should already be maxed out. This is exactly what is seen in Fig. 6 graph 1, the original rule-set. The general observed trend is that both entropy and mutual information increase at about the same rate, while simply starting at higher values. However, graph 1 is unique in that regard. It has a much steeper increase when the grid has no random tiles, which indicates some disruption or change in behavior when randomness is introduced. It seems likely that the bridging behavior is very efficient for increasing entropy and having random tiles destroys that behavior, thus decreasing the increase rate of entropy and mutual information. In graph 4, again it's observed that the parabolic shape is entirely absent from both the entropy and mutual information graphs, indicating the loss of unique behavior.

Fig. 7 shows entropy and mutual information as the probability of random transition rule-set Ants is increased. There is a wide range of behavior, unlike the previous variables. In graph 1, the trend is for entropy to increase slower the more chaotic agents there are, however 0 and 10 percent seem to be incredibly close with the entropy levels. When all Ants are chaotic, the entropy is much more disrupted and spikes more often, while reaching almost half the entropy of the other

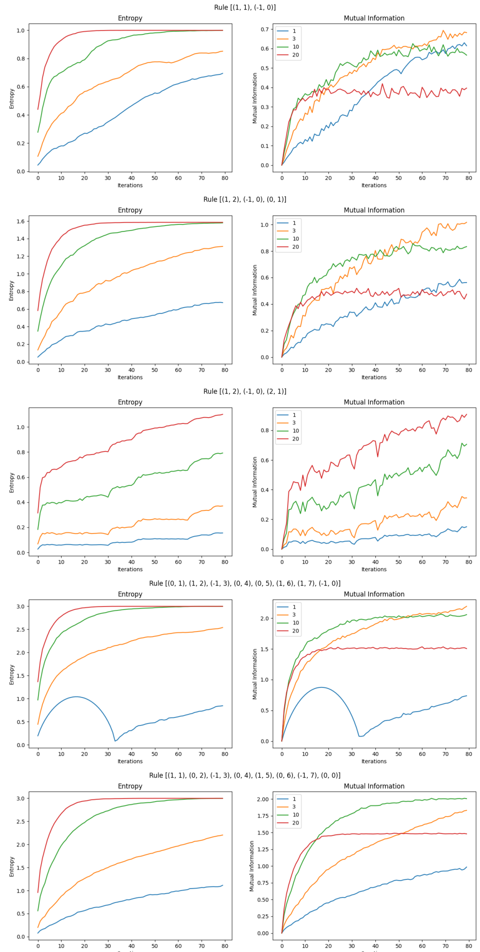

Fig. 5. Graphs showing variable number of Ants and using default parameters for the other variables

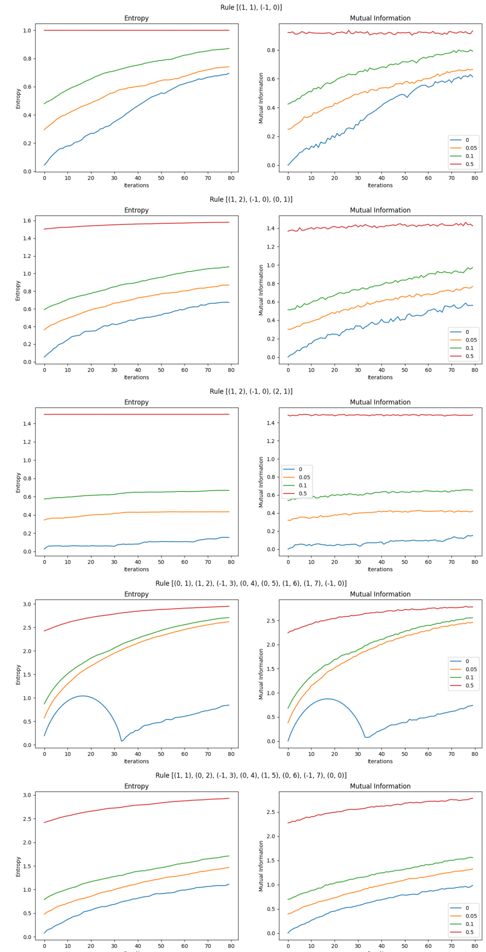

Fig. 6. Graphs showing variable probability of random tiles and using default parameters for the other variables

lines. Mutual Information is much closer together, except 100 percent chaotic Ants. However, the trend seems to be higher mutual information as chaotic agents increase, again except for the full chaos experiment. graph 2 does not show a real pattern, with 50 percent on top and 0 percent on bottom in both the entropy and mutual information graphs. graph 3 has 0, 10, and 20 percent clustered, while 50 and 100 percent fall much lower. Although interestingly, when all Ants are chaotic they form a repeating rise and fall which spans about 2400 steps, this represents new behavior. Both graph 4 and 5 share very similar graphs, with more chaotic Ants scoring lower on entropy and higher on mutual information. Note that even when there are no chaotic Ants, that graph 4 does not exhibit the parabolic behavior, this is due to the number of Ants being set to 10. The results overall do not seem to indicate any clear patterns between the rule-sets, however it could be a flaw in the experiment. The first issue is the experiment size, each permutation is only run 3 times, which is hardly significant given how probabilistic this is. The second issue is that those probabilities are not guaranteed to create chaotic agents (except 100 percent), it is quite possible for all 10 Ants in the 10 percent run to have default rules. The third and final major issue is the implementation of these random rule-sets, when viewing the graphs of their behavior, it is observed that many of these Ants move in insignificant and local ways. Some may move in a small 2×2 square, another may travel vertically forever, while others actually exhibit unique behaviors. Given the small sample size, the experiments seem insignificant.

V. Conclusion

Overall, the observed behavior is that the complex emergent phenomena entirely breaks down when any amount of randomness is inserted. Even with the flaws of the chosen complexity metrics and limited sample size, it seems very clear that these behaviors are incredibly delicate. This does not mean that all Langton's Ants, Turmites, or cellular automata are as fragile, simply that the chosen rule-sets are. However, given the great difficulty of measuring complexity, it seems very difficult to properly search for these cellular automata. Furthermore, even if one is found, it is unclear whether there would be any meaningful information which could be extracted from it's structure.

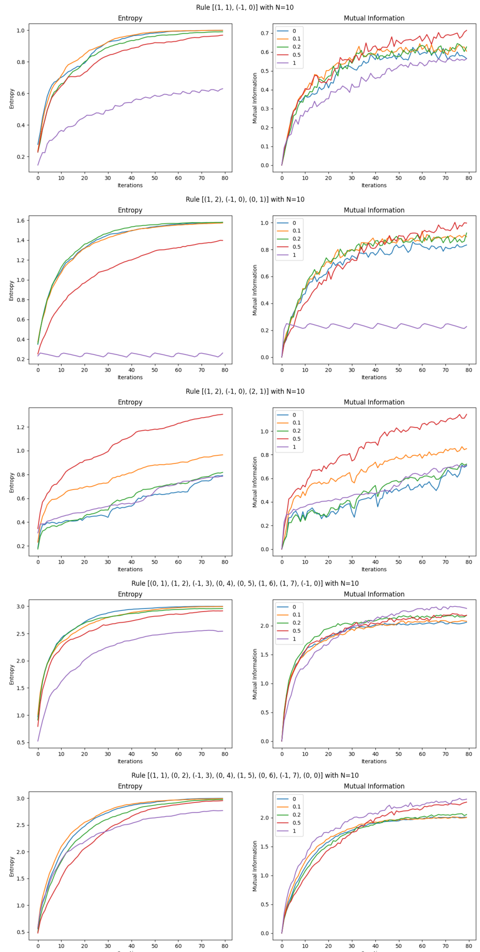

Fig. 7. Graphs showing differing probabilities of random rule-set Ants using 10 Ants per run

A. Future Work

Running more samples is likely to be unfruitful. The behavior seems to pretty obviously breakdown with any level of randomness. If this project were to be continued or expanded, the direction would be in experimenting with more rule-sets or different cellular automata entirely. If a cellular automata displays complex behaviors which can persist in some meaningful way through disruption, it could provide interesting insights, however these rule-sets fail to do so. Similarly to the rarity of complex behavior across the space of all cellular automata, maybe resilience is a similarly rare behavior which together are massively unlikely.

References

[1] A. Gajardo, A. Moreira, E. Goles, Complexity of Langton's ant, Discrete Applied Mathematics, Volume 117, Issues 1–3, 2002, Pages 41-50, ISSN 0166-218X, https://doi.org/10.1016/S0166-218X(00)00334-6. (https://www.sciencedirect.com/science/article/pii/S0166218X00003346)

[2] Gajardo, A., Goles, E., Moreira, A. (2001). Generalized Langton's Ant: Dynamical Behavior and Complexity. In: Ferreira, A., Reichel, H. (eds) STACS 2001. STACS 2001. Lecture Notes in Computer Science, vol 2010. Springer, Berlin, Heidelberg. https://doi.org/10.1007/3-540-44693-1_23

[3] @miscmaldonado2017nontrivial, title=Nontrivial Turmites are Turing-universal, author=Diego Maldonado and Anahí Gajardo and Benjamin Hellouin de Menibus and Andrés Moreira, year=2017, eprint=1702.05547, archivePrefix=arXiv, primaryClass=cs.CC

[4] Stephen Wolfram, Universality and complexity in cellular automata, Physica D: Nonlinear Phenomena, Volume 10, Issues 1–2, 1984, Pages 1-35, ISSN 0167-2789, https://doi.org/10.1016/0167-2789(84)90245-8. (https://www.sciencedirect.com/science/article/pii/0167278984902458)

[5] K. Lindgren and M. G. Nordahl, "Complexity Measures and Cellular Automata," 1988.

[6] Selma Belgacem, Nazim Fates. "Three Emergent Phenomena in the Multi-Turmite System and their Robustness to Asynchrony", March 9, 2010. https://inria.hal.science/inria-00462438v1/document

[7] Ernesto Moya-Albor, Andrés Romero-Arellano, Jorge Brieva, Ivan Cruz-Aceves, Juan Gabriel Avina-Cervantes, Martha Alicia Hernandez-Gonzalez M.D., and Luis Miguel Lopez-Montero M.D. "Secure medical image encryption approach based on Langton's ant and jigsaw transform", Proc. SPIE 12088, 17th International Symposium on Medical Information Processing and Analysis, 1208815 (10 December 2021); https://doi.org/10.1117/12.2606294

[8] G. C. Stănică and P. Anghelescu, "Research and implementation of a two-dimensional cellular automaton," 2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Ploiesti, Romania, 2022, pp. 1-4, doi: 10.1109/ECAI54874.2022.9847412.

[9] Boon, J.P. How Fast Does Langton's Ant Move?. Journal of Statistical Physics 102, 355–360 (2001). https://doi.org/10.1023/A:1026581213671

[10] H. Hamann, T. Schmickl and K. Crailsheim, "Thermodynamics of emergence: Langton's ant meets Boltzmann," 2011 IEEE Symposium on Artificial Life (ALIFE), Paris, France, 2011, pp. 62-69, doi: 10.1109/ALIFE.2011.5954660.