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Necessary Conditions for Open-Ended Evolution

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NECESSARY CONDITIONS FOR OPEN-ENDED EVOLUTION

by

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ABSTRACT

Evolution on Earth is widely considered to be an effectively endless process. Though this phenomenon of *open-ended evolution* (OEE) has been a topic of interest in the artificial life community since its beginnings, the field still lacks an empirically validated theory of what exactly is necessary to reproduce the phenomenon in general (including in domains quite unlike Earth). This dissertation (1) enumerates a set of conditions hypothesized to be necessary for OEE in addition to (2) introducing an artificial life world called Chromaria that incorporates each of the hypothesized necessary conditions. It then (3) describes a set of experiments with Chromaria designed to empirically validate the hypothesized necessary conditions. Thus, this dissertation describes the first scientific endeavor to systematically test an OEE framework in an alife world and thereby make progress towards solving an open question not just for evolutionary computation and artificial life, but for science in general.

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TABLE OF CONTENTS

LIST OF FIGURES	viii
CHAPTER 1: INTRODUCTION	1
CHAPTER 2: LITERATURE REVIEW	5
Evolutionary computation	5
Quality diversity	6
Open-ended evolution	8
CHAPTER 3: HYPOTHESIS	16
Hypothesized necessary conditions	17
Differences from previous approaches	20
CHAPTER 4: METHODOLOGY	23
Chromaria	23
Phenotypes and Genotypes	24
Evolutionary mechanisms	27
Novelty search	27

Open-ended evolution	28
Preliminary Work	31
Experiment	31
Results	32
Main Experiment Setup	34
Experimental controls	35
Metrics	36
CHAPTER 5: STANDARD RUN RESULTS	41
CHAPTER 6: CONTROL 1 (NO MINIMAL CRITERION) RESULTS	48
CHAPTER 7: CONTROL 2 (NO INTERACTIONS) RESULTS	56
CHAPTER 8: CONTROL 3 (NO NEURAL NETWORKS) RESULTS	65
CHAPTER 9: SYNTHESIS: ASSESSING OPEN-ENDEDNESS IN CHROMARIA . . .	75
Beyond validation	80
CHAPTER 10: DISCUSSION AND FUTURE WORK	84
Implications for artificial life	85

Implications for complex systems	87
Implications for computer science	89
CHAPTER 11: CONCLUSION	95
LIST OF REFERENCES	96

LIST OF FIGURES

Figure 4.1: Chromaria. The first Chromarian is born at the center of the world and then must find an appropriate place to plant. Each successive Chromarian is then born wherever its parent planted. The color-rich borders initially provide the only viable options, but more emerge as Chromarians continue to thrive in the environment (right).	24
Figure 4.2: Morphology-encoding CPPN and sample morphology. The CPPN encodes both the outline and fill of the Chromarian’s morphology. Input b is a bias set to the constant value 1.0.	25
Figure 4.3: Behavioral controller. The maximum number of connections in this network is 30,448. Arrows between planes in this schematic denote <i>sets</i> of connections between one plane and another. Each plane represents a layer of neurons (also called <i>nodes</i>), with the bottom layer corresponding to the RGB and compass sensors. The two types of sensor information remain uncombined until the output layer is reached. The four output nodes control behavior.	26

Figure 4.4: **RGB ratio calculation.** Each pixel of both the morphology and sensor field is placed into one of eight bins: black, white, red, green, blue, yellow, cyan, or magenta. Here, a simple morphology is shown to the left of its binned equivalent. The bins are defined by halving the ranges [0,255] that the R, G, and B component values can take. For instance, any pixel with $R \in [0, \frac{255}{2}]$ (more non-red than red), $G \in [0, \frac{255}{2}]$ (more non-green than green), and $B \in [0, \frac{255}{2}]$ (more non-blue than blue) falls into the black bin because black has values $R,G,B = 0,0,0$. Once every pixel is binned in this way, color ratios are calculated for each bin by dividing the bin size by the total number of pixels. Ratios are recorded for both the morphology and sensor field. The differences between these ratios for each color are summed to get a *matching value*. If this value is less than 1 (out of 8), the planting function is satisfied. . 29

Figure 4.5: **Representative standard world snapshots.** The standard version of Chromaria was run through 50,000 reproductions using two different initial seeds (one magenta and one blue). Here, representative standard worlds are shown at various reproduction numbers. While each run followed a different trajectory, *every* standard run exhibited principled growth beyond the initial world state. 32

Figure 4.6: **Typical standard run end states.** At 50,000 reproductions, standard runs in the magenta world typically exhibit circular patterns of growth. However, while such patterns are discernible, differences in the individual snapshots indicate unique trends in individual runs. 33

Figure 5.1: **Standard run visual snapshots.** Snapshots are taken at 125,000, 250,000, 375,000, and 500,000 reproductions. Each row contains snapshots from a single run. 43

Figure 5.2: Further standard run visual snapshots (one run per row) continued from Figure 5.1 44

Figure 5.3: Visual snapshots from a single standard run at 125,000, 250,000, and 375,000 reproductions. These snapshots illustrate the variety and complexity of individual Chromarians. 45

Figure 5.4: Visual snapshots from the single standard run shown in Figure 5.3 at reproductions 416,500, 458,250, and 500,000. The formation of niches is observed in these later stages of this particular run and a variety of morphology types can be seen in the bottommost snapshot. 46

Figure 6.4: **Median last new species, Control 1.** The last new species emerges at reproduction 44,000 out of 500,000. In contrast, the last new species in the standard world emerges at reproduction 330,750. This result indicates that evolution stops generating anything novel significantly earlier (compared to the standard world; $p=6.29 \times 10^{-8}$) in the runs. Without a minimal criterion, evolution in Chromaria fails to overcome the change and novelty barriers. . . . 53

Figure 6.5: **Median total species, Control 1.** In this world, individuals that attempt to plant are guaranteed to succeed regardless of how closely their morphologies match the world they inhabit. Removing the minimal criterion results in a significantly higher total number of species (22) than in the standard runs (16; $p=5.52 \times 10^{-8}$) because individuals that would normally fail to satisfy the morphological matching function in the standard are completely viable in this control world. As a result, evolutionary search is able to traverse more of the morphology space. 54

Figure 6.6: **Median successful planting attempts, Control 1.** While initially the lack of minimal criterion allows normally nonviable individuals to succeed, and as a result allows many new species to emerge, the rate of planting attempt successes strictly decreases over time. While this result may initially seem counterintuitive given that every planting attempt in this control is guaranteed to succeed, it is explained by the conclusion that planting attempts themselves are actually declining and eventually becoming nonexistent. 55

Figure 7.5: **Median total species count, Control 2.** The inability for evolution to access most areas of morphology space is again evidenced by the significantly lower number of total species found (7) compared to the standard world (16; $p=5.77 \times 10^{-8}$). This low total species count combined with the relatively early emergence of the last new species indicates that evolution exhausts all available opportunities for innovation early on and then fails to discover or take advantage of new ones. 63

Figure 7.6: **Median successful planting attempts, Control 2.** Planting attempt success rates are lower when individuals cannot interact with each other compared to in the standard world. Interestingly, the planting success rate at the end of the run in the control world is approximately the success rate at the beginning of the standard runs. Given that morphology-encoding genomes tended to increase in size in this world, it is possible that morphological complexity is potentially at least a partial contributor to this result because the colored background that provides the only opportunity for planting does not itself become more complex. 64

Figure 8.1: **Control 3 visual snapshots.** Behavior in this world is decided semi-randomly instead of being controlled by an evolved neural network. Snapshots are taken at 125,000, 250,000, 375,000, and 500,000 reproductions. Each row contains snapshots from a single run. 68

Figure 8.2: Control 3 visual snapshots (each row is a single run) continued from Figure 8.1 69

Figure 8.7: **Median successful planting attempts, Control 3.** These rates are atypically high because every individual is forced to attempt to plant once its location has been (semi-randomly) determined. However, a planting attempt can still fail if the individual is either placed in a location that is not adjacent to colors matching the individual's morphology or if the individual's heading is incorrect. Note that planting attempt success rates increase slightly as the runs progress and the world becomes visibly more homogeneous. 74

Figure 9.1: Snapshots from a single run of the standard world demonstrating ecosystem diversity. Small flashes of green on a few individuals at reproduction 150,000 lead to the emergence of primarily green Chromarians by reproduction 187,500. (Continued in Figure 9.2.) 82

Figure 9.2: Snapshots from a single run of the standard world continued from Figure 9.1 . 83

CHAPTER 1: INTRODUCTION

Evolution is a powerful creative force. It is the process that allowed humans to eventually emerge from what was once an amalgamation of much simpler chemicals. Though such leaps in the long term may seem daunting from our relatively limited human perspectives, they are not so unreasonable when considered over the course of our planet's four and a half billion years. Of course, humans are not the only interesting byproduct of evolution. From jungles and forests to grasslands and plains, life in the natural world offers a dizzying array of possibilities. This diversity of life forms, unimaginable from its humble beginnings, lends Earth its splendor.

Artificial life (alife) is the study of life not just as it exists on Earth, but also *life as it could be* (Langton, 1988). In artificial life worlds, which are discussed in this dissertation, life forms run the gamut from binary strings of ones and zeroes to three-dimensional polygon creatures. The hope is that by constructing and manipulating these worlds in ways that we cannot manipulate Earth, we can gain unique insight into the principles behind not only long-term evolutionary processes but also intelligent processes in general.

One goal of this work is understanding the processes that caused increasingly more complex life to evolve on Earth. Though scientists and philosophers have hypothesized about the origins of complexity, controlled experiments wherein a virtual world can be manipulated and tested were impossible before the advent of modern computing. Of course, even today it would be impossible to construct an exact replica of Earth in its entirety, but even if it were possible to reconstruct a virtual Earth, studying it would not tell us much about the process of life in general; we would only be able to learn about the process of life as it occurs within this one, potentially idiosyncratic system. If we aim to talk about the origins of evolutionary complexity in a scientifically rigorous way, then alife is the viable option.

This dissertation is about constructing artificial evolutionary processes that make new discoveries indefinitely as evolution appears to do in nature. This perpetual discovery-making is known in the alife community as *open-ended evolution* (OEE). Though the phenomenon has been a longstanding topic of interest, the field generally lacks consensus on its exact definition (Bedau et al., 1998; Channon, 2003, 2006; Juric, 1994; Maley, 1999). For example, OEE has been described as the continual production of either novel (Bedau et al., 1997; Lehman and Stanley, 2011a; Nellis, 2012; Standish, 2003) or adaptive (Bedau et al., 1998) forms. Nonetheless, the OEE community aims to replicate some dynamics of biological evolution (which is frequently interpreted as an effectively open-ended process) in the hope of creating *more* such open-ended processes.

A major goal remains to observe open-ended evolution in an alife world (Bedau et al., 2000). Many such worlds have been constructed since the advent of the field, and some have passed tests designed to detect particular signatures of open-endedness (Bedau et al., 1998; Channon, 2003, 2006). However, the phenomenon is still considered unachieved because no system today definitely reproduces the full generativity of nature (Dolson et al., 2015; Nellis, 2012). The fact that open-ended evolution has not been achieved in any domain aside from Earth indicates that something is missing from our understanding of the process. This dissertation aims to fill this knowledge gap by first posing a set of four necessary conditions that are hypothesized to be prerequisites for an open-ended evolutionary process, then showing how these conditions can be tested using a novel alife world called *Chromaria* that implements all four conditions, and finally empirically validating these conditions with experiments in Chromaria. The following distinctions clarify the scope of this work:

This dissertation is not about biological plausibility. The goal of the work described herein is not to create a model or simulation of evolution on Earth; biological evolution inspires and informs evolution in virtual worlds, but it does not constrain it (Lehman and Stanley, 2015). Instead, evolution is treated as an abstract process that could be implemented in any number of domains,

real or artificial. As an example, consider the following analogy: dalmatians and poodles are both instances of dogs even though one has spots and the other does not. If you had only seen dalmatians, you might conclude that spots are an inherent feature of dogs. Similarly, biological evolution and artificial evolution are both instances of abstract evolutionary processes even though their exact features may differ. Determining which features *matter* in general is precisely the aim of this dissertation.

This dissertation is not about self-replication or self-organization. In recent years, some alife researchers have claimed that “true” open-endedness can only be achieved in domains where reproduction is an emergent feature instead of being controlled by an evolutionary algorithm (Nellis, 2012; Taylor, 2014). However, if open-endedness exists on a continuum, the binary definition becomes less compelling (Dolson et al., 2015). Nonetheless, it is still clear that the majority of systems, both with and without emergent or endogenous reproduction, eventually stop being interesting after an observable amount of time. The aim in this dissertation is to identify domain features that inhibit such open-endedness in general and thereby to provide guidelines for constructing more productive domains.

This dissertation is not about optimization. Evolution is frequently treated in evolutionary computation (EC) as an active selective force that weeds out underperformers and thus ensures continual progress via the survival of the fittest (De Jong, 2006). Furthermore, evolutionary search has historically been considered successful if it converges to optimal solutions. Though evolutionary algorithms *can* solve optimization problems in some domains, such approaches are not the focus of the proposed thesis because the goal of OEE algorithm design, in contrast, is to create an intentionally *divergent* search that intelligently explores as long as the search space has not been exhausted (Taylor et al., 2016).

The major contributions of this dissertation are as follows:

1. A set of conditions hypothesized necessary for open-ended evolution,
2. an experimental platform for artificial evolution experiments that can test the hypothesized conditions,
3. a set of empirical results validating the hypothesized conditions.

The dissertation continues in Chapter 2 with a brief overview of evolutionary computation and open-ended evolutionary algorithms, followed by a review of major artificial life worlds and previous attempts to enumerate the characteristic features of open-ended evolution. Chapter 3 presents the first contribution of this dissertation, which is a novel set of necessary conditions for open-ended evolution. Chapter 4 then details the second contribution, which is an artificial life world called *Chromaria* that implements the four hypothesized necessary conditions. This chapter also presents preliminary work demonstrating how Chromaria can be used to systematically study open-ended evolutionary dynamics and then describes the expanded experimental setup and metrics used for the more comprehensive study described in this dissertation. Chapters 5 through 8 detail the results of this study, with each experiment detailed in a separate chapter. Chapter 9 synthesizes the results of these experiments and discusses the level of open-endedness in Chromaria. Chapter 10 then presents the implications of the validated conditions for the fields of artificial life, complex systems, and computer science.

CHAPTER 2: LITERATURE REVIEW

EC and alife serve as the foundation for open-ended evolution (OEE). This chapter first provides a brief introduction to EC and then focuses on open-ended evolution. Prior attempts to reproduce open-ended phenomenon in alife simulations are reviewed, followed by a discussion of the few prior attempts to identify necessary conditions for OEE.

Evolutionary computation

Not coincidentally, the foundations of evolutionary computation came from some of the greatest thinkers in the history of computer science. Claude Shannon (1940), often referred to as the father of information theory, wrote his doctoral dissertation on *An Algebra for Theoretical Genetics* sixteen years before he helped found the field of artificial intelligence at the Dartmouth Conference. John von Neumann (1963) was also interested in evolution at the time, focusing on self-reproducing machines and cellular automata more than higher-level evolutionary processes. Modern evolutionary computation is the synthesis of a few related yet separate research areas: evolutionary programming (Fogel et al., 1966), genetic algorithms (Holland, 1975), evolutionary strategies (Rechenberg, 1971; Schwefel, 1975), and genetic programming (Koza, 1992). Though there are algorithmic differences between these four areas, they share a common goal of automated problem solving that incorporates mechanisms from Darwinian evolution. Today, **evolutionary computation** is an umbrella term for these and similar disciplines (De Jong, 2006).

In general, evolutionary computation implements nature-inspired algorithms to search a space for solutions to some problem. Typical problem domains range from finding values for variables in mathematical equations to generating control schemes for intelligent robotic systems. Each po-

tential solution is represented by a sequence of symbols called a **genotype**, which can be decoded into a functional **phenotype**. The phenotype can then be evaluated according to a domain-specific performance metric known as a **fitness function** and iteratively varied via algorithm-mediated reproduction. Early applications primarily implemented a method akin to selective breeding or artificial selection, wherein candidate solutions with the highest fitness are chosen to reproduce at the expense of lower-fitness individuals. The principle behind such an approach is that incremental movement towards a targeted global optimum should eventually result in *reaching* that optimum.

In practice, however, this objective-based approach fails to reach the global optimum in what are called *deceptive* domains (Lehman and Stanley, 2011a; Stanley and Lehman, 2015). In these domains, finding the stepping stones to high fitness or high complexity paradoxically requires exploring seemingly low-fitness areas of the search space that would have normally been avoided. Novelty search (Lehman and Stanley, 2011a) was one of the first evolutionary search algorithms to abandon the objective-based paradigm. The algorithm replaces the traditional objective fitness function with a *novelty metric* that measures the distance in the search space between an individual and its predecessors. This approach has proven beneficial to navigating deceptive domains (and for this reason is used to find a nontrivial starting point for evolution in the experiments described in this dissertation).

Quality diversity

Novelty search and other similarly motivated divergent search algorithms belong to a new subfield of evolutionary computation called *quality diversity*, or QD (Pugh et al., 2016, 2015). The philosophy behind this approach is that there is not always exactly one desired or optimal solution, but that a number of interesting solutions could exist for many problems. Evolution, then, becomes less of an optimizer and more of what Nguyen et al. (2015) call an *innovation engine*. Yet, these

QD algorithms are distinct from OEE because they are not intended to run indefinitely; exhausting the space being searched would be ideal. Furthermore, there still exists a goal, as in traditional evolutionary computation, of maximizing fitness. The main difference with QD is that a diverse set of high-performing individuals must be found to maximize the fitness function.

The first true quality diversity algorithm (combining both fitness and behavioral diversity) was novelty search with local competition (NSLC; Lehman and Stanley (2011b)). In the first experiments, this algorithm was used to evolve virtual creature morphologies and gaits. Subsequent applications included ambulating stick creatures (Szerlip and Stanley, 2013), walking behaviors for hexapod robots (Cully and Mouret, 2013), and feature detectors for neural networks aimed at classification tasks (Szerlip et al., 2015). MAP-Elites (Mouret and Clune, 2015) emerged as an alternative to NSLC, with applications in adaptive walking strategies for physical robots (Cully et al., 2015) and image generation for testing deep neural networks. MAP-Elites discretizes the search space into qualitatively distinct bins. The object, then is to fill as many bins as possible with individuals of high quality, where quality is measured according to some domain-specific metric. In maze navigation domains, for instance, quality might be quantified as progress on a path toward the maze goal (Pugh et al., 2016).

The Voxelbuild experimental platform (Pugh et al., 2017; Soros et al., 2017) was created to highlight explicitly the creative potential of QD algorithms. Voxelbuild is inspired by Minecraft¹, which is an open-ended sandbox game wherein players occupy a procedurally generated block world and, generally, build settlements or other more artistically motivated structures. However, these constructions are entirely motivated by the player’s whims, as there is no point system and no way to win or complete the game. Unlike traditional evolutionary robotics domains such as quadruped locomotion (where the goal is to walk the farthest) or maze navigation (where the goal is to reach

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the end of the maze), Voxelbuild has no inherent objective (though an evolutionary algorithm can impose an objective by e.g. rewarding agents for building tall block structures). Instead, Voxelbuild agents are placed on an initially empty flat plane and are able to place blocks, destroy blocks, or move around the world. Once ground-level blocks are placed, agents can walk on top of them to build arbitrarily tall and complex structures.

Though Voxelbuild was designed to evaluate the creative potential of evolutionary algorithms, it was not designed to accommodate evolutionary algorithms that run forever. The environment is reset to its initial empty state between individual trials and as a result the environment cannot become more complex over time. This outcome is at odds with the goals of OEE, which will be detailed in the next section. Still, like OEE the aims of the Voxelbuild domain and quality diversity algorithms are qualitatively distinct from optimization-oriented evolutionary computation. This distinction reinforces the utility of conceptualizing open-endedness as existing on a spectrum with optimization on its opposite end and QD somewhere in between.

Open-ended evolution

The term *open-ended evolution* was coined by the alife community to describe processes in the spirit of natural evolution. Though the idea has been actively explored since its conception, its precise definition is still a contentious topic without a universally satisfying resolution. For example, OEE has been variously described as:

- “a process in which there is the possibility for an indefinite increase in complexity” (Ruiz-Mirazo et al., 2008),
- “a system in which components continue to evolve new forms continuously, rather than grinding to a halt when some sort of optimal or stable position is reached” (Taylor, 1999),

- in which the “number of possible types by far exceeds the number of individuals (copies, sequences,etc.) in a plausible (realistic) population” (Maynard-Smith and Szathmary, 1995), or
- the “on-going and indefinitely creative production of significantly new kinds of adaptive responses to significantly new kinds of adaptive challenges and opportunities” (Bedau, 1998).

This list illustrates the extent to which there is disagreement about the salient features of evolution. The characterization of evolution as continuously producing novel forms is one of the more popular definitions (Lehman and Stanley, 2011a; Standish, 2003; ?). It should be noted that these definitions are not necessarily mutually exclusive. For this reason, the approach taken in the experiments described in this dissertation (detailed in Chapter 4) is to evaluate open-endedness with a variety of metrics that capture many different aspects of the phenomenon.

Alife simulations implement some limited set of features of the natural world that are hypothesized to be essential to life in general, not just life on Earth. Note that the word *simulation* in this context does not necessarily imply that the goal is to replicate biological dynamics; many alife worlds intentionally deviate from the structure and function of Earth. While not an exhaustive review, the rest of this section describes many of the major systems that have informed the study of open-ended evolution. The intent is not to detail each system completely, but simply to illustrate the different forms artificial life can take. It will then later become clear that the alife system described as a major contribution of this dissertation is different from every other world implemented thus far. Generally speaking, the simulations described in this section progress from computationally-focused worlds (sometimes called *digital evolution*) to more embodied virtual worlds.

Tierra (Ray, 1992) is one of the first alife simulations that explicitly aimed to recapitulate an Earth-like level of diversity. The Tierran environment consists of a virtual machine that executes machine code. Tierran creatures are programs (i.e. sets of machine code instructions) that are

stored in RAM along with a “soup” of random instructions. A central time-sharing system lets the programs take turns executing on the CPU, so the creatures indirectly compete for CPU cycles (which are considered the central resource in Tierra). Evolution in Tierra begins from a single *ancestor*, a creature that has been handcrafted to successfully reproduce. Experiments with Tierra (Ray, 1992) have shown that at least a dozen distinct creature classes (defined by creature size) can evolve from the single ancestor.

A number of interesting code-based worlds have been inspired by Tierra, including the **Avida** (Ofria and Wilke, 2004) platform. As in Tierra, the environment in Avida is a virtual machine. Digital organisms consist of machine code that can be executed on a central CPU. However, unlike in Tierra, CPU time in Avida is not allocated to each organism uniformly, but proportionately to a fitness measure called *merit* that is based on a creature’s ability to perform various computations. Individuals compete for CPU cycles via indirect interaction; they are typically not allowed to modify each other’s code. However, organisms can be allowed to inject their code into other organisms and thereby consume their CPU cycles, allowing parasitism distinct from that in Tierra. Individuals also compete for space, as they reside in a fixed-capacity grid that determines which individuals can interact with each other. When organisms reproduce, their offspring are randomly placed by the system on a cell adjacent to the parent, destroying that cell’s previous occupant. As in Tierra, evolution begins with a simple ancestor that can self-reproduce (but that cannot perform any merit-giving computations). Experiments with Avida (Lenski et al., 2003) have shown that the evolution of complex behaviors (i.e. the ability to perform nontrivial computations) can stem from the evolution of simpler ones.

Other alife worlds have explored evolution in less abstract domains. **PolyWorld** (Yaeger, 1994), for example, is a graphical environment that contains trapezoidal organisms situated on a flat plane. These organisms must use vision to forage for food and thereby maintain a nonzero energy level. Though naturally-occurring food is scattered throughout the world, organisms can also cannibalize

other organisms that have been killed via combat. Evolution begins from an initial *seed population*. This population is evolved using an ad hoc fitness function until it develops sufficient reproductive behaviors to keep its numbers stable, at which point there is no fitness function except survival. At each time step, an individual uses its evolved neural network to select from a set of predefined primitive behaviors that includes fighting, moving, and mating (which occurs whenever two overlapping organisms try to reproduce). Though physical characteristics such as size and strength are genetically determined, general morphological structure is fixed and evolution thus focuses on finding interesting behavioral strategies. In the original PolyWorld experiments (Yaeger, 1994), certain complex behaviors (i.e. combinations of the primitive behaviors) repeatedly emerged even when the structure of the environment varied between runs. While these results reiterate how evolution can lead to increased complexity, they also show how the environment can constrain innovation.

Geb (Channon and Damper, 2000) is a similar (yet independently conceived) world to Polyworld consisting of a toroidal, two-dimensional grid. The triangular organisms that live on this grid are controlled by neural networks and choose to move, kill, or reproduce based on the outputs of their neighbors' neural networks. An individual that attempts to mate with another individual will always succeed; there are no constraints on which individuals can reproduce as long as they can locate and move to a partner. Attempts to kill another individual are likewise always successful and unconstrained. Experiments with Geb have reinforced the idea that evolutionary dynamics can emerge even in the absence of traditional fitness-based artificial selection seen in most evolutionary algorithms (Channon and Damper, 2000).

Additionally, Geb is the first and only alife system thus far to qualify as *unbounded* according to the activity statistics classification system (Bedau et al., 1998; Channon, 2001, 2003). This system measures the persistence of advantageous genotypes over the course of evolution, following from the assumption that a gene that is not naturally selected against is necessarily a beneficial adaptation. However, there is debate as to whether or not this assumption is valid (Kimura, 1983;

Miconi, 2008b). Furthermore, it is not clear that achieving *unbounded adaptation* is equivalent to achieving a *complexity explosion*.

Though the alife worlds reviewed thus far have focused exclusively on evolving interesting behaviors for fixed bodies, others have evolved creature morphologies in addition to behavioral strategies. Much of this work derives from Sims (1994), in which pairs of coevolving creatures compete for control of a single cube located at the center of a three-dimensional arena. The creatures themselves are compositions of rectangular blocks that are controlled by systems of sensors and artificial neurons. These neurons differ from those traditionally included in ANNs by implementing an extended function set (beyond sum and threshold functions) and can have at most three inputs. Both the morphologies and behavioral controllers are genetically encoded as directed graphs. Unlike more natural alife systems, evolution proceeds generationally from a random initial population. Fitness is defined by the final distance of the competitors from the target cube. A fixed proportion of elite individuals at each generation reproduce and generate offspring proportionally to their fitness. Experiments with two opponent species show that a variety of strategies and counter-strategies emerge, but that the rate of evolution varies widely from run to run. Additionally, most creatures effectively ignore their opponents (though some do evolve adaptive behaviors).

Sims's work has inspired others to simulate block creatures in entire ecologies instead of only in an isolated arena. The **Division Blocks** (Spector et al., 2007) environment, for example, consists of square islands on a square ocean, with a sun that circles the world and provides energy. This energy is metabolized by the creatures, who must maintain a nonzero energy level to stay alive. Individuals impact each other's energy levels via collisions, which cause energy loss, or via altruistic energy donations. Each creature is controlled by a fixed-topology recurrent neural network, which is evolved along with the morphology and the parameters for a developmental process. Evolution begins with a population of random individuals at random locations on the world. Nonviable individuals are removed and replaced until there are 250 individuals that are viable parents. In

contrast with Sims (1994), reproduction occurs endogenously instead of being managed by the EA; whenever a block becomes sufficiently large, it simply splits into two offspring. Correspondingly, there is no explicit fitness function. Interestingly, the reported preliminary results (though sparse) indicated a high incidence of altruistic behavior.

Independently of Division Blocks, Miconi and Channon (2005) embedded modified versions of Sims's block creatures in a spherical "micro-planet" called the **Evosphere**. Evosphere creatures stay alive by maintaining a nonzero energy level and can deplete each other's energy reserves by engaging in direct physical combat. However, creatures also consume a small amount of energy by simply being alive and thus can die of natural causes. A creature that is killed in combat is replaced by an offspring of its killer, but a creature that simply becomes too old is replaced by the offspring of random parents. Regardless of the parent type, new offspring are placed at random locations on the Evosphere. While Sims (1994) created special neurons for the behavioral controllers, Miconi and Channon (2005), like Spector et al. (2007), used networks of simple McCulloch-Pitts neurons. Additionally, like both Sims (1994) and Spector et al. (2007), Miconi and Channon (2005) emphasized competitive coevolution and dynamic fitness landscapes as the keys to generating arbitrary levels of complexity. However, experimental results (Miconi, 2008a) show that such mechanisms encourage adaptation without necessarily generating complex behaviors.

Worlds such as those reviewed here show how alife experiments can inform our understanding of evolutionary dynamics in general. However, open-ended evolution in alife so far qualitatively does not appear to match the products of natural evolution. This result begs the question, then, of what is truly necessary for open-ended evolution. If such a set of requirements could be validated, then it would illuminate the reasons why alife worlds so far seem limited.

The geneticist C. H. Waddington (1969) gives a characterization of individuals, environments, and the interactions between the two in a "typical" evolutionary system. This work is the first known

effort to specify a minimal set of conditions for OEE. The requirements are quoted here verbatim (*ibid.* p. 120):

- A genetic system whose items (Q_s) are not mere information, but are algorithms or programs which produce phenotypes (Q_s).
- There must be a mechanism for producing an indefinite variety of new Q^L s, some of which must act in a radical way which can be described as rewriting the program.
- There must also be an indefinite number of environments, and this is assured by the fact that the evolving phenotypes are components of environments for their own or other species.
- Further, some at least of the species in the evolving biosystem must have means of dispersal, passive or active, which will bring them into contact with the new environments (under these circumstances, other species may have the new environments brought to them). These environments will not only exert selective pressure on the phenotypes, but will also act as items in programs, modifying the epigenetic processes with which the Q_s become worked out into Q^L s.

Tim Taylor (2004) implemented an experimental model called Cosmos that was designed to meet the requirements of Waddington's paradigm, however Taylor notes that "there were no coherent theoretical reasons for deciding which features should be modelled [*sic*], and which should be left out. This weakness is not specific to Cosmos, but is shared by all of the Tierra-like systems I have come across." Beyond his work on Waddington's paradigm, Taylor (2012, 2015) identifies his own set of minimal conditions for OEE. The conditions include:

- Robustly reproductive individuals,
- A medium allowing the possible existence of a practically unlimited diversity of individuals and interactions, at various levels of complexity,
- Individuals capable of producing more complex offspring,
- An evolutionary search space which typically offers mutational pathways from one viable individual to other viable (and potentially fitter) individuals, and
- Drive for continued evolution.

The main drawback of both Waddington's and Taylor's paradigms is that they have never been empirically validated. It is therefore difficult to make grounded claims about them beyond speculation. That being said, it should be noted that there are similarities between the works of Waddington and Taylor and the novel set of hypothesized conditions for OEE presented in the next chapter. The existence of such similarities is not surprising given that scientists have been studying evolution for centuries with moderate success; clearly *something* has been learned about open-ended evolution. However, as the next chapter will show, though some aspects of Waddington's and Taylor's conditions are similar to the conditions presented in this proposal, there are indeed substantial differences that differentiate this work from its predecessors. Furthermore, the paradigm described in the next chapter will be validated (in contrast to prior proposed sets of conditions) according to an experimental methodology, which is described in Chapter 4.

CHAPTER 3: HYPOTHESIS

This chapter presents the main theoretical contribution of this dissertation: an empirically testable set of necessary conditions for open-ended evolutionary domains.

It is important to first clarify what exactly is meant when a condition is deemed to be necessary. In general, a *necessary* condition is a prerequisite for some outcome; the outcome cannot occur if even one necessary condition is not satisfied. However, satisfying a necessary condition does not guarantee that the outcome will occur. If satisfying some condition does in fact guarantee an outcome, then that condition is said to be *sufficient*, not necessary, for that outcome. Note that claiming sufficiency of any condition, or joint sufficiency of a set of conditions, would preclude the future identification of additional conditions that are also necessary for the outcome (which in this case is open-endedness). While the hypothesis in this dissertation is that the four conditions described in this chapter are all necessary for open-ended evolution, whether they are sufficient is left open. However, the hope is that the set of necessary and sufficient conditions can be kept as small as possible.

At the same time, what is intentionally left out can be just as illuminating as what is included (Lehman and Stanley, 2015). For example, one prominent omission from the four hypothesized conditions is any reference to traditional *fitness*. While the fitness function is ubiquitous in much of evolutionary computation (De Jong, 2006), any explicit conception of fitness, wherein some individuals are destined to fail not as a function of the environment but due to selection only of top performers, risks unnecessarily blocking potentially promising paths through the search space that could otherwise support open-endedness.

Hypothesized necessary conditions

It is important to note up front that a domain can only support *open-ended* evolution if it is suitable to evolution in general. That is, any artificial or natural evolutionary system must satisfy certain minimal prerequisites to have *any* success at all (open-ended or not). These prerequisites include a good genetic representation (tightly coupled with the phenotype space) (De Jong, 2006), a sufficiently large world for every individual to be evaluated, and some initial *seed* (like the first cell on earth) or starting point (such as a random initial population) from which evolution begins. Assuming that these general prerequisites are met, the main hypothesis is that the minimal necessary conditions for open-ended evolution are as follows:

Condition 1: A rule should be enforced that individuals *must* meet some nontrivial minimal criterion (MC) before they can reproduce.

Interestingly, in evolutionary computation, with a few exceptions (Lehman and Stanley, 2010), most EAs implement no such MC: usually all individuals have at least some small probability of reproduction (De Jong, 2006). The role of the MC in this case is to ensure that a minimal level of complexity must always be maintained by every viable organism, thereby ensuring that the population can never degenerate into trivial behaviors. On Earth, for example, individuals become eligible to reproduce only by developing and maintaining functional reproductive apparatuses. No lineage can persist that does not maintain this nontrivial capability, which is the MC on Earth. In worlds that are unlike Earth, however, fundamentally different MC are conceivable; for example, the criterion need not concern the *mechanics* of reproduction at all. That is, offspring could be created by the system, as is common in evolutionary algorithms (EAs), without any reproductive apparatus in the individuals themselves. There simply must be some meaningful limit on which individuals can reproduce, thereby ensuring that the system will not degenerate into triviality. For

example, every individual could be required to perform a particular task. To be *nontrivial*, the criterion should involve interacting with the world in some way. An example of a *trivial* MC on Earth might be requiring that individuals have green eyes to reproduce. In this case, the MC is completely decoupled from behavior. If the MC is too arbitrary, the results of evolution will be uninteresting. On the other hand, if it is too specific then the search will be too restricted.

This condition implies a necessary **corollary**: The initial seed (from which evolution begins) must itself meet the MC and thereby be nontrivial enough to satisfy Condition 1. Otherwise, if evolution began without any individuals who satisfy the MC, then no one would be allowed to reproduce and the experiment would end. This corollary further diverges from traditional EAs (and even many alife worlds), which often begin with a random population. If no individual in the initial population of such an experiment meets a nontrivial MC then the algorithm could not satisfy Condition 1. In fact, obtaining the starting seed (such as the first cell on Earth, which already began with a reproductive apparatus) is a challenge in its own right that must be confronted for open-ended evolution even to initiate.

Condition 2: The evolution of new individuals should create novel opportunities for satisfying the MC.

If evolution is to sustain itself, then it must continually find paths from simpler phenotypes to more complex ones. However, such novel paths will be explored only as long as each link in the chain continues to satisfy the MC. Thus it is critical that *new opportunities* to satisfy the MC through previously unsupportable strategies continually open up so that evolution can explore paths that lead arbitrarily beyond the relatively simple initial seed. Furthermore, *evolution itself* is the only viable generator of such novel opportunities because a human designer could not realistically conceive a ladder of tasks sufficiently rich to continue without limit. The trajectory of biological

evolution exhibits many such transitions where new life forms paved the way for further genetic innovation in other lineages. Giraffes, for instance, could not have evolved on Earth before there were trees. In this way, the evolution of trees created an opportunity for evolution later to explore a previously unsupportable path (namely, the path to giraffes) by generating a novel opportunity to satisfy the MC. If the nature of individual interactions is too restrictive (such as predators simply bumping into prey in alife worlds), then this condition may not be possible to satisfy.

Condition 3: Decisions about how and where individuals interact with the world should be made by the individuals themselves.

Such decisions determine whether an individual will successfully seek out and exploit novel opportunities for satisfying the MC. Though the MC primarily serves to maintain some degree of complexity, it also creates a coupling between successful phenotypes and the environment. (This coupling follows from the requirement that a nontrivial MC must involve interacting with the world in some way, such as gathering food for sustenance of the reproductive apparatus in natural evolution.) While this condition may initially sound unnecessary or unintuitive, recall that the rules for behavior in artificial life worlds are practically unrestricted and often diverge from what we are used to seeing on Earth. Thus there can (and do) exist systems where individuals are not completely autonomous and have some behaviors mediated by an external algorithmic mechanism. However, if an individual cannot choose both its actions and their targets (geographical or otherwise), then the environmental coupling is disrupted and phenotypic evaluation becomes arbitrary. That is, if the individual does not play at least some role in deciding where it interacts, then some kind of *oracle* would need to determine for the individual its best opportunity to satisfy the MC. However, this oracle would require intimate knowledge of the search space to anticipate all possible future opportunities, most of which could not even exist when the search began. In this sense, any decision made by such an oracle would be effectively arbitrary. Thus no human designer can

realistically construct such an oracle. For these reasons, behavioral decisions must be made by the individuals themselves, who thereby decide for themselves which opportunities to exploit (like giraffes heading for the trees).

Condition 4: The potential size and complexity of the individuals' phenotypes should be (in principle) unbounded.

In practice, the growth of the phenotype must have some limit (e.g., the size of the universe in the natural world); achieving infinite growth would of course require infinite time and infinite space. However, at a practical level, the salient point is that the complexity of the phenotype should not be limited by its representation, as there needs to be room for complexity to increase for the kind of complexity explosion desired in open-ended evolution to be realized.

Note that there exist many definitions of “complexity” (Mitchell, 2009), just as there exist multiple definitions of “open-ended evolution.” However, while different definitions of complexity might change the way the proposed conditions in this dissertation are applied, *given* a particular definition or notion of complexity, the conditions serve as guidelines to institute open-endedness in the service of that notion.

Differences from previous approaches

The hypothesized necessary conditions bear some similarity to the works of Waddington (1969) and Taylor (2015), mentioned in Chapter 2. However, the idea that reproduction is achieved only by satisfying some minimal criterion, and that all individuals meeting the MC are treated equally, is a concept unseen in other OEE frameworks. The MC selects *against* badness, not *for* fitness. This difference is subtle, yet contrasts with the explicitly competitive mindset that is ingrained in

many artificial life worlds. It can be tempting to look for the *why* behind change, and to subscribe to the philosophy that everything that persists serves some evolutionary purpose, but there is not necessarily a causal mechanism beyond random mutations linking a parent to its offspring. Some changes end up being for the better, some for the worse, and many end up being neutral. As long as the bad is not bad enough to preclude reproduction (whether endogenous or externally managed), the offspring was good enough. By introducing a mechanism that evaluates individuals without judging them against each other, evolution can maintain nontriviality without compromising on diversity. The benefits of search not driven by explicit objectives has been explored previously in e.g. Lehman and Stanley (2011a). Of course, fitness is indeed an important concept in natural evolution (Orr, 2009), but it can be viewed in the context of the hypothesized conditions as an emergent byproduct of the MC in nature (i.e. to construct a copy of oneself) that changes over time rather than an explicit *a priori* constraint imposed from outside. By thereby reducing the conditions to rely solely upon the constraint of the MC instead of fitness, the simplest possible hypothesis on the origin of open-ended dynamics can be explored, and fewer assumptions must be satisfied to construct open-ended domains.

The work described in this dissertation is furthermore distinguished from its predecessors by presenting clear, implementable requirements whose utility can also be empirically tested. To our knowledge the tenets of Waddington’s paradigm have never been broken down and systematically tested. In fact, Taylor (2004) notes that “little work has been devoted to exploring [Waddington’s] proposal, presumably because of the difficulties in capturing it fully with an analytic model.” Taylor’s own set of minimal criteria for OEE has similarly never been empirically tested. Again, the idea is that, once validated, the conditions can be applied to other domains to determine their susceptibility to unwanted convergence.

The next chapter describes a new artificial life world called Chromaria that implements the four necessary conditions described in this chapter. This world will serve as the foundation for the

empirical studies described in later chapters.

CHAPTER 4: METHODOLOGY

This chapter first describes the artificial life world of Chromaria that is designed to test the conditions introduced in the previous chapter, and then explains the experimental methodology for performing those tests. Chromaria helps to illuminate the issues in open-endedness by providing a highly visual interpretation of its dynamics. Furthermore, because open-endedness is challenging both to achieve and to analyze formally, a number of novel approaches are introduced to facilitate such analysis, including several new metrics inspired by recent discussion on the barriers to open endedness by Dolson et al. (2015). The main contributions of this chapter then are a new artificial life platform and a companion approach to analyzing its results.

Chromaria

As highlighted in the previous chapter, this dissertation describes the first scientific endeavor to systematically test an OEE framework in an alife world. The world detailed in the rest of this chapter, called **Chromaria**, was introduced in the ALIFE '14 publication *Identifying Minimal Conditions for Open-Ended Evolution through the Artificial Life World of Chromaria* (Soros and Stanley, 2014) expressly for the purpose of testing the four proposed necessary conditions. First, the nontraditional minimal criterion (MC) for reproduction in Chromaria is detailed, followed by a description of individuals' genotypes and phenotypes. The ways in which Chromaria satisfies the hypothesized necessary conditions will be explicitly pointed out along the way.

The colorful creatures (called *Chromarians*) evolved in Chromaria use artificial neural networks to actively explore and search for a place to *plant* and thereby reproduce (figure 4.1). Each Chromarian is allowed only one planting attempt. If the Chromarian's RGB sensor field contents satisfy

a specific *planting function* involving matching its color (detailed later), then the planting attempt succeeds and the successful creature is eventually allowed to reproduce. Thus the MC in Chromaria, which is quite unlike Earth’s MC, is to navigate to a position in the world with colors matching the Chromarian’s own coloring. If this MC is not met within a fixed amount of time, then the Chromarian is removed without planting and does not reproduce. Thus Chromaria clearly satisfies hypothesized Condition 1.

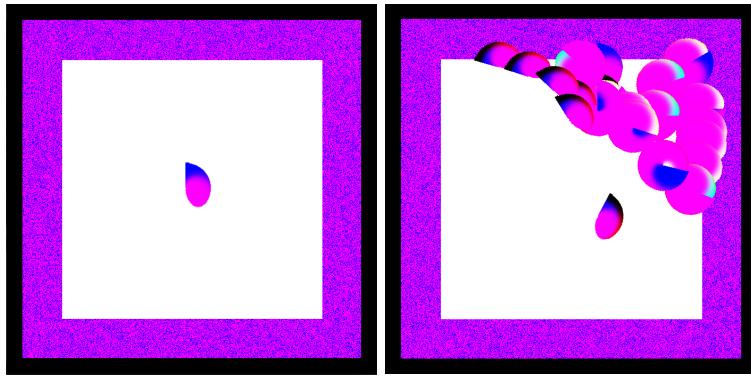


Figure 4.1: **Chromaria.** The first Chromarian is born at the center of the world and then must find an appropriate place to plant. Each successive Chromarian is then born wherever its parent planted. The color-rich borders initially provide the only viable options, but more emerge as Chromarians continue to thrive in the environment (right).

Phenotypes and Genotypes

Each Chromarian’s morphology (equivalently its body, its phenotype) consists of a 2D image composed of RGB pixels. The genotype that encodes this morphology is a *compositional pattern producing network* (CPPN; Stanley 2007), a neural-network-like structure that generates patterns with regularities seen in nature such as symmetry, repetition, and repetition with variation. Each Chromarian’s genome actually contains *two* CPPNs: one that encodes its behavioral controller, and another that encodes its morphology. A generic morphology-encoding CPPN and a sample

decoded phenotype are shown in figure 4.2:

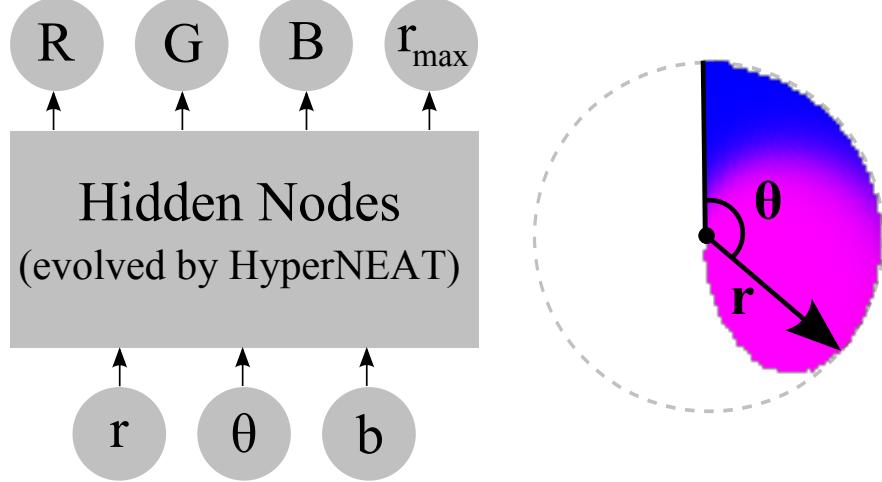


Figure 4.2: **Morphology-encoding CPPN and sample morphology.** The CPPN encodes both the outline and fill of the Chromarian’s morphology. Input b is a bias set to the constant value 1.0.

The morphology-encoding CPPN is decoded by passing a series of different input signals to it and using the resulting outputs to draw the morphology pixel by pixel. The network is iteratively activated with pairs of polar coordinates r and θ as input.¹ Upon activation, the CPPN returns an r_{max} for each value of θ , which determines how far the perimeter of the Chromarian’s body extends at that angle. The other outputs are temporarily ignored. Then, the CPPN is activated again for every r on the interior of this border to get the corresponding RGB values. In this way the CPPN determines both the shape (via the r_{max} output) and internal color (via the RGB outputs) of the Chromarian. These characteristics ultimately determine where the Chromarian can successfully plant. Note that by evolving new morphological patterns and then becoming part of the world in which *other* individuals plant, successful planters create novel opportunities for new kinds of Chromarians to succeed and thereby satisfy the hypothesized Condition 2.

¹ r is scaled from [0,49] to [0,1], and θ from $[-\Pi,\Pi]$ to [-1,1].

Each Chromarian is equipped with a rectangular visual field composed of 100 RGB sensors and centered at the forefront of the Chromarian’s body. Half of the sensors fall underneath the body and the rest extend in front of the creature. The exact resolution of the field depends on the creature’s morphology; as its length and width increase, the distance between neighboring sensors grows. Additionally, each Chromarian is equipped with a heading-sensitive *compass* consisting of 8 pie slice sensors. All sensor values are scaled and then input to a multimodal neural controller (figure 4.3), the connection weights of which are encoded by the second CPPN.

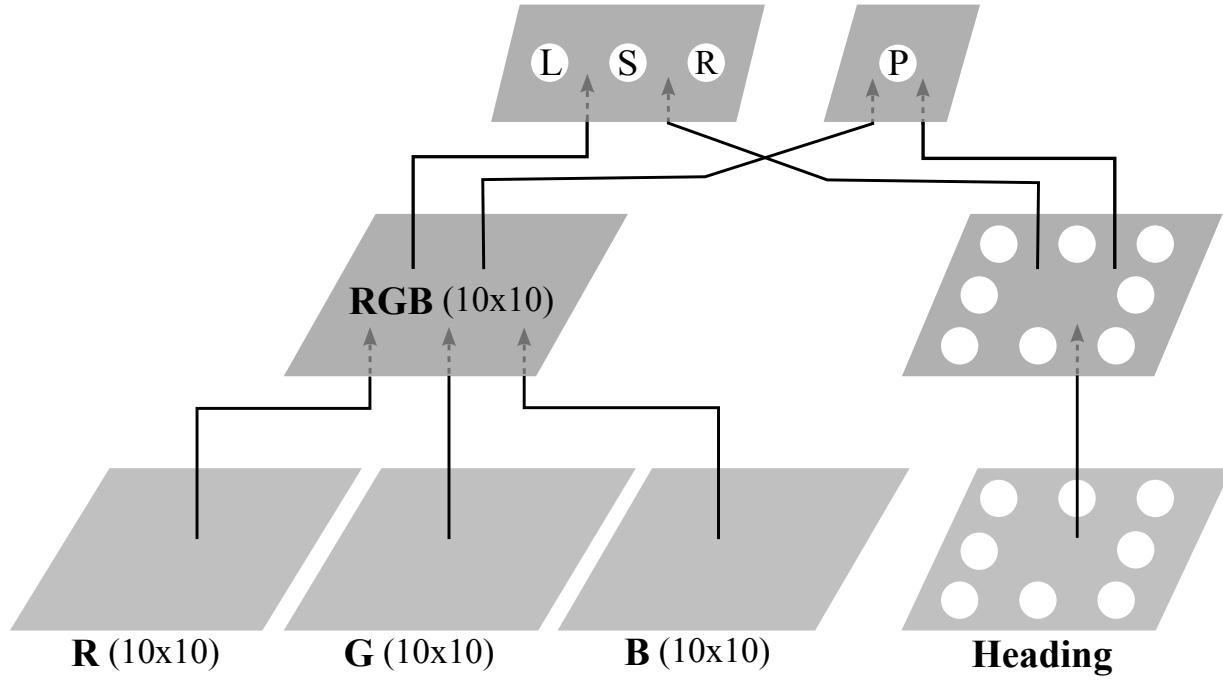


Figure 4.3: **Behavioral controller.** The maximum number of connections in this network is 30,448. Arrows between planes in this schematic denote *sets* of connections between one plane and another. Each plane represents a layer of neurons (also called *nodes*), with the bottom layer corresponding to the RGB and compass sensors. The two types of sensor information remain uncombined until the output layer is reached. The four output nodes control behavior.

The output layer, which receives connections from the hidden layers, has four effector nodes corresponding to the Chromarian's rotation (L and R), speed (S), and inclination to plant itself (P). If the planting node value exceeds a certain threshold, the Chromarian is immobilized and it never moves again. Otherwise, the rotation and speed nodes determine the Chromarian's next movement. Note that it is through this ability of the Chromarian to decide for itself when and where to plant (based on its senses) that Chromaria satisfies Condition 3.

Evolutionary mechanisms

Evolution in Chromaria proceeds in two stages. First there is a preliminary search for an initial seed that satisfies the MC (i.e. an individual that successfully plants itself), followed by the open-ended phase (which proceeds without a particular desired behavior or morphology).

Novelty search

Satisfying the corollary to Condition 1 (that evolution must start with an initial seed that satisfies the MC) presents a puzzle: how can the initial seed be obtained? The proposed solution in Chromaria is to begin with a preliminary search for it. This search for an initial seed is important because it decides the starting point for subsequent open-ended evolution (and thereby influences which potential paths to complexity evolution will explore). In the proposed experiment, novelty search (Lehman and Stanley, 2011a) is the approach chosen to find a successful controller for the initial morphology (which was generated through a separate process called *interactive evolution*). As mentioned in Chapter 2, novelty search replaces the fitness function found in traditional evolutionary algorithms with a *novelty metric*, which measures how different an individual is from those that have previously been found. This approach has been shown sometimes to avoid deception (Lehman and Stanley, 2011a) and to produce a better representation (Woolley and Stanley,

2011) than traditional objective-based fitness. Novelty calculations in this preliminary search are based on the individual's (x,y) position and planting attempts (indicated by a binary value) measured at every fifth tick of the trial. Novelty search, and hence the preliminary search, succeeds when it finds an individual that successfully plants itself. Planters discovered by novelty search for particular morphologies can then be used as seeds in the open-ended main evolutionary phase.

Open-ended evolution

Once an initial seed has been selected, evolution is governed by an entirely new algorithm. In the unconventional main loop in Chromaria, the Chromarians that have successfully planted most recently are kept in a *parent queue* capped at 100 individuals. When the simulation begins, the parent queue only contains one Chromarian (i.e. the initial seed found in the preliminary search). That initial seed individual then attempts to plant. Each tick of the simulation (capped at 200 ticks per Chromarian) proceeds as follows:

1. The Chromarian's sensors are updated and its controller is activated.
2. If the planting effector node is negative, the Chromarian moves according to its other effector nodes. Otherwise, the Chromarian attempts to plant at its current location. This attempt succeeds if the the RGB ratios in the Chromarian's morphology are collectively no greater than 12.5% different from the RGB ratios in its sensor array contents (figure 4.4). Furthermore, to ensure that Chromarians must learn to move (to keep the MC nontrivial), they are eliminated if they attempt to plant within a small radius of their starting position (wherever their parent planted).
3. If the planting attempt succeeds, the Chromarian generates an offspring. Note that reproductive dynamics in Chromaria are unlike those in many other alife worlds. The next Chromarian to reproduce is always next in the parent queue, indicated by a *current parent* pointer. If

the current parent is at the end of the queue, the pointer simply wraps back to the start of the queue. In this way, *all* Chromarians who successfully plant eventually get to reproduce. That is, explicit competition, which is usually central to alife worlds, is intentionally absent from Chromaria (because it still satisfies the four conditions anyway). As soon as an offspring is created from the current parent, it attempts to plant, starting near its parent’s location. If it succeeds, then it is inserted into the parent queue directly *preceding* its own parent. Then the next Chromarian in the queue reproduces, and so on. This mechanism of always inserting offspring preceding their parent forces the system to allow every preexisting member of the population to reproduce before a newcomer.

- Whenever a new Chromarian succeeds at planting, the oldest preexisting member is removed from the population list if the list contains at least 100 members. However, *all* bodies of previously successful planters remain in the world for the duration of evolution.

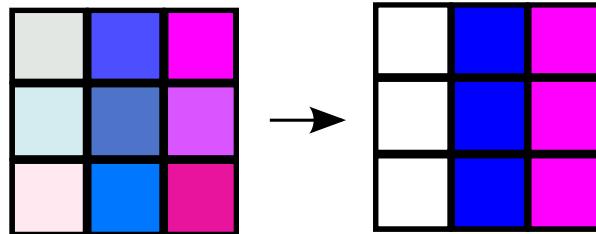


Figure 4.4: RGB ratio calculation. Each pixel of both the morphology and sensor field is placed into one of eight bins: black, white, red, green, blue, yellow, cyan, or magenta. Here, a simple morphology is shown to the left of its binned equivalent. The bins are defined by halving the ranges $[0,255]$ that the R, G, and B component values can take. For instance, any pixel with $R \in [0, \frac{255}{2}]$ (more non-red than red), $G \in [0, \frac{255}{2}]$ (more non-green than green), and $B \in [0, \frac{255}{2}]$ (more non-blue than blue) falls into the black bin because black has values $R,G,B = 0,0,0$. Once every pixel is binned in this way, color ratios are calculated for each bin by dividing the bin size by the total number of pixels. Ratios are recorded for both the morphology and sensor field. The differences between these ratios for each color are summed to get a *matching value*. If this value is less than 1 (out of 8), the planting function is satisfied.

CPPNs are evolved using HyperNEAT (Stanley et al., 2009), a neuroevolution method that gradually complexifies its underlying genetic representation over time. HyperNEAT’s ability to evolve multimodal neural networks with tens of thousands of connections is what enables creating an artificial life world like Chromaria, where autonomous control decisions are made based on rich sensory input. Through the indirect CPPN encoding, HyperNEAT can efficiently evolve complex connectivity patterns that reflect the geometry of their inputs. The large HyperNEAT substrate neural networks (up to 30,448 connections) in this experiment provide sufficient space for complexity to increase significantly over the course of a run, thereby satisfying Condition 4. The current version of Chromaria uses a modified version of the HyperSharpNEAT 2.1 implementation of HyperNEAT, which is based on Colin Green’s SharpNEAT (Green, 2006). Parameter settings are included with the released code, available at <http://eplex.cs.ucf.edu/chromaria/home>.

As demonstrated in this chapter, Chromaria satisfies the four hypothesized necessary conditions for open-ended evolution: (1) individuals must satisfy a nontrivial MC (finding a valid location in which to plant) before they can reproduce; (2) individuals can create novel opportunities for satisfying the MC by planting and becoming part of the world; (3) individuals decide for themselves where and when to plant based on information from their sensors; and (4) the CPPN encodings for the creatures’ morphologies and controllers have no complexity ceiling; thus complexity has room to increase significantly.

The next section details preliminary experiments with Chromaria. These experiments demonstrate the utility of Chromaria for empirical testing.

Preliminary Work

In the introductory publication (Soros and Stanley, 2014), one of the four hypothesized necessary conditions was tested through a controlled experiment to show how the artificial life world can serve as a testbed for further investigations. This previously-published experiment is described in this chapter both to give some intuition about what happens in Chromaria after a significant amount of time has passed and to preview the methodology for the experiments described in this dissertation. Note that the methodology is expanded for the dissertation experiments and will be described in more detail at the end of this chapter.

Experiment

In this initial experiment, the second condition (that the evolution of new individuals should create novel opportunities for satisfying the minimal criterion) is controlled by preventing Chromarians from sensing each other. That way, individuals' decisions about where to try and plant would only be based on the initial environment and thus new opportunities to plant could never arise beyond those provided by the initial colored border region and white background. Note that in these experiments, unlike in the dissertation experiments described in Chapters 5 through 8, each Chromarian is born at the center of the world regardless of where its parent planted. Five runs each of the **control** and **standard** (i.e. satisfying all four conditions) versions of Chromaria were performed, starting from the same initial seed (discovered by novelty search to plant in a magenta and blue border region) and ending after 50,000 reproductions. Additionally, a second set of five control and five standard runs was initiated from a different initial seed. The goal of this preliminary experiment was to observe the continual production of novel and successful planters in the unaltered version of Chromaria, and to show that such continued innovation (hinting at open-ended evolution) is precluded when Condition 2 goes unmet.

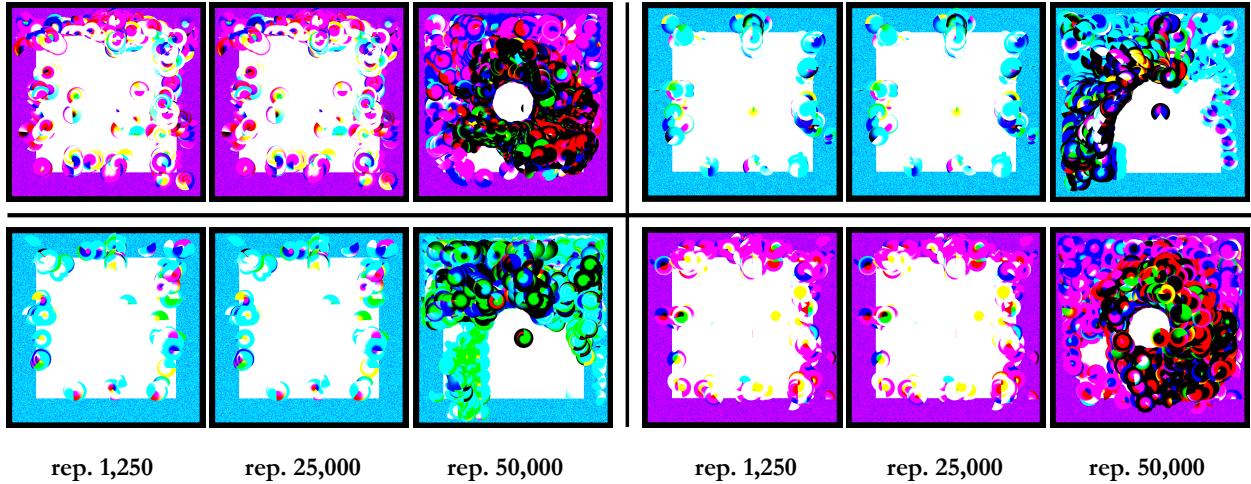


Figure 4.5: Representative standard world snapshots. The standard version of Chromaria was run through 50,000 reproductions using two different initial seeds (one magenta and one blue). Here, representative standard worlds are shown at various reproduction numbers. While each run followed a different trajectory, *every* standard run exhibited principled growth beyond the initial world state.

Results

A key benefit of the visual design of Chromaria is that observing the implications of different variants is easy even before descriptive statistics are calculated.

The world states shown in figure 4.5 illustrate a clear expansion and diversification (both in terms of planting locations and colors) of the population, which was observed in *every* standard run but absent from the control runs. Furthermore, distinct color-behavioral groups can be seen gradually emerging and unfolding over the 50,000 reproduction attempts of each world. Importantly, appreciating the full breadth of Chromaria requires observing Chromarians in action (i.e. exploring and attempting to plant) because much of the complexity of evolved Chromarians is in their dynamic *behavior*, which is based on their rich sensory inputs. For that purpose highlight videos are available at <http://eplex.cs.ucf.edu/chromaria/home>.

Another intriguing result was that even though the world is stochastic, the end states among the standard runs exhibit some consistent dynamics (an outcome that could not necessarily be predicted from the start). As shown in figure 4.6, the magenta worlds results consistently in ringlike configurations.

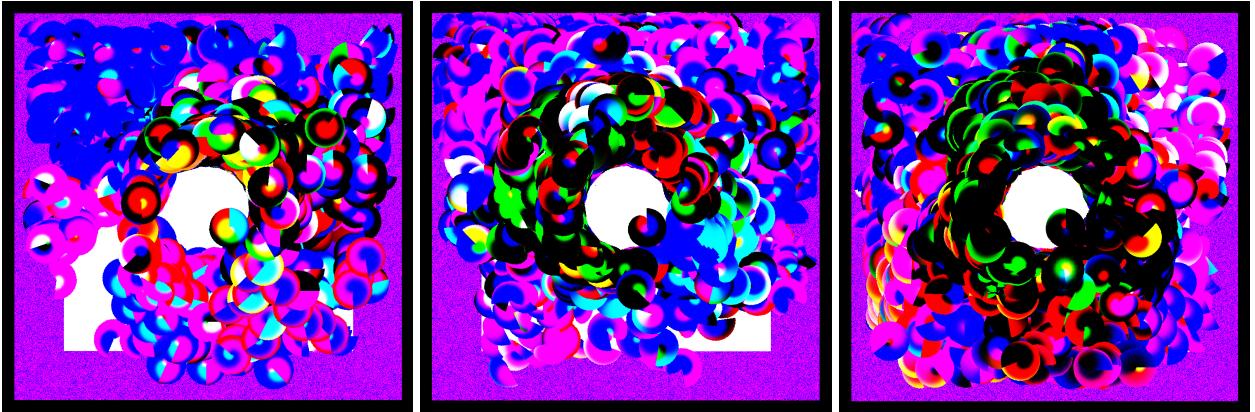


Figure 4.6: Typical standard run end states. At 50,000 reproductions, standard runs in the magenta world typically exhibit circular patterns of growth. However, while such patterns are discernible, differences in the individual snapshots indicate unique trends in individual runs.

To quantify the dramatic difference Condition 2 makes, the diversity of behaviors generated in different variants was measured. For the purpose of sampling the variance of behaviors, position is sampled ten times (at every 20 simulation ticks), giving a vector of length 20 for each individual. The path of an individual Chromarian is represented as a vector of (x, y) coordinates with range $[(0, 0), (1000, 1000)]$. The breadth of behavioral trajectories in a run can then be characterized by calculating the average variance in position (\overline{var}) at each sampled tick. It is important to note that these behaviors (represented by the vector of all sampled positions) capture both a period of intelligent seeking and then planting once a suitable color destination is identified. Given that successful planting is a nontrivial behavior, this metric captures not just the amount of diversity produced by evolution, but the amount of *interesting* or *nontrivial* diversity. In the blue world, the

average \overline{var} is 379.8 (with its own *across-runs* standard deviation $ar-\sigma = 96.4$) for control runs and 1,272.9 ($ar-\sigma = 465.4$) for standard. In the magenta world, the average \overline{var} is 625.31 ($ar-\sigma = 114.8$) for control runs and 1579.40 ($ar-\sigma = 123.8$) for standard. In both worlds, the p-value from a Student's t-test is under 0.05, indicating statistical significance. Thus the quantitative results match the intuition that a significantly wider breadth of intelligent planting behaviors results when Condition 2 is met.

The next section describes how the preliminary experiments will be expanded for the main experiments.

Main Experiment Setup

The experiment detailed in the previous chapter demonstrates an initial methodology for testing one of the hypothesized necessary conditions. The approach in this dissertation is to control and evaluate all four conditions using more comprehensive metrics.

It should be noted that a new mechanism for determining a new Chromarian's birth location was implemented for the dissertation experiments to avoid the circular growth patterns shown in Figure 4.6. In this new version of the world, each new Chromarian is born within a fixed radius of its parent. This mechanism is both more consistent with nature and less likely to unintentionally produce phenomena such as the inescapable black ring observed in many of the preliminary experiments.

The next sections describe the controls for the four hypothesized necessary conditions and then detail metrics (expanded from the preliminary experiments) for quantifying the relevant aspects of open-endedness.

Experimental controls

Each control is described in this section after its corresponding condition is reviewed.

Condition 1: A rule should be enforced that individuals *must* meet some minimal criterion (MC) before they can reproduce, and that criterion must be nontrivial. **Control:** All individuals are allowed to reproduce regardless of what they do in the world.

Condition 2: The evolution of new individuals should create novel opportunities for satisfying the MC. **Control:** Individuals cannot see each other, which means that the evolution of new individuals has no impact on other individuals in the world. Note that this control was already demonstrated in short preliminary experiments by Soros and Stanley (2014), as described earlier in this chapter. Longer experiments with more comprehensive metrics are described in Chapter 7 of this dissertation.

Condition 3: Decisions about how and where individuals interact with the world should be made by the individuals themselves. **Control:** Randomness is introduced into Chromarian interaction and reproduction via a two-step process. First, each new Chromarian is born in a random location within a fixed radius of its parent (instead of at the center of the world). The new Chromarian is then given a random heading. This way, the individual's planting location is determined entirely by a combination of chance and parent location. Interestingly, this offspring placement scheme is reminiscent of the default rules in the Avida system (Ofria and Wilke, 2004). To completely remove the neural network from Chromarian behavior, each new Chromarian is forced to attempt to plant once its location and heading are determined (instead of having the neural network determine whether or not a Chromarian should plant during its lifetime). Reproduction is still dependent on satisfying the standard color matching function described earlier in this chapter.

Condition 4: The potential size and complexity of the individuals' phenotypes should be (in principle) unbounded. **Control:** This condition is controlled by setting an upper limit on the number of nodes and connections allowed in each individual's genome network (i.e. its CPPN), which in effect limits phenotypic complexity.

Metrics

As discussed in Chapter 2, the question of how to define and quantify open-endedness is contentious. There is a reasonable position that the phenomenon is related to the continual production of novelty (Bedau et al., 1997; Lehman and Stanley, 2011a; Nellis, 2012; Standish, 2003), but measuring novelty with respect to *what* is still a question without a universally satisfying answer. In an attempt to work around this issue, Dolson et al. (2015) propose that instead of trying to quantitatively define what an open-ended system *is*, perhaps it would be more productive to start with what an open-ended system is *not* (much in the spirit of the experiments described in this dissertation). To this end, Dolson et al. suggest five **barriers to open-endedness** that describe negative outcomes for evolutionary processes. These barriers are illustrated through five accounts of unproductive evolution (quoted verbatim from Dolson et al. (2015)):

Change barrier: The population stops changing at all after a certain point: As is often the case in genetic algorithms, the population may converge to a local optimum and never leave.

Novelty barrier: Novel organisms stop appearing in the population: Perhaps the population doesn't completely converge, but instead oscillates among a set of survival strategies.

Complexity barrier: Organismal complexity stops increasing: The organisms hit a limit on the amount of environmental information that they can incorporate into their genomes, preventing them from producing more sophisticated behaviors.

Ecological barrier: Ecosystem diversity stagnates: The population as a whole hits a limit on the sum total of information about the environment that it is able to incorporate across genomes. Note that other organisms are part of the environment that any given organism experiences, so this effectively amounts to organisms creating new niches and trophic levels via their interactions with other organisms.

Transition barrier: Shifts in individuality are impossible. In nature, major transitions in evolution often change what it means to be an individual – the most profound example being the transition to multicellularity. Systems that pre-define what it means to be an individual fundamentally limit the types of evolution possible; theoretically an open-ended system should be able to undergo any number of such shifts.

The position advocated in this dissertation, and supported by the framework of Dolson et al. (2015), is that there is likely not just one key dimension of novelty or open-endedness; many factors contribute to a system's evolutionary dynamics. Thus the approach in this dissertation is to paint a broad picture of evolution by collecting a variety of quantitative and qualitative data points that speak to the barriers described by Dolson et al. (2015). Each metric is described as it is implemented in Chromaria. Additionally, metrics are described in the order they will be presented in the successive results chapters.

Visual snapshots

This metric illuminates environmental change and the ability of the system to overcome the **ecological barrier**. Recall that successful planters leave their bodies on the topmost layer of the world,

rendering the previous planters underneath invisible. Then, by taking visual snapshots of the world and observing the amount of change between successive snapshots, we can infer fairly easily how much the environment (which determines what species can interact) is changing.

Metric 1: Genome network size

The aim of this metric is to indicate the system's tendency to avoid the **complexity barrier**. At the genome level, complexity can be approximated by measuring the number of nodes and connections in each individual's CPPNs. Once the CPPNs are decoded, the resulting phenotypes (each a morphology coupled with a behavioral controller) must be assessed independently. Genomic complexity is a good proxy for organismal complexity because the size of the genome represents a theoretical cap on the complexity of the organism, and CPPNs gradually increase in size through NEAT (the neuroevolution algorithm in Chromaria).

Metric 2: Median reproduction number of last new species' emergence

The frequency at which new individuals appear directly measures the system's tendency to avoid the **change barrier** and **novelty barrier** by showing that the population has not converged to a single fixed point. Such nonconvergence is guaranteed if new species continue to emerge in the system. The species of an individual is determined by comparing its morphology color ratios with the color ratios of representatives of all previous species. If two individuals' ratios satisfy the planting function described in Figure 4.4, these individuals are considered to be members of the same species. If an offspring is determined to belong to a novel species (i.e. the planting function is not satisfied when comparing its morphology to the morphology of any previously found species representative), then it becomes the representative for a new species. This metric tracks the last occurrence of new species' emergence.

Metric 3: Median total species count

The total number of unique species that emerge during a run quantify how much of the morphological search space is explored during a run. While this metric does not necessarily map to a specific barrier to OEE, it quantifies the degree of generativity of a system.

Metric 4: Planting attempt success rate

This metric, considered in tandem with the time of last species emergence and total species count, helps create a holistic quantification of the system's evolutionary dynamics. Specifically, it can potentially quantify how difficult it is to satisfy the MC throughout a run. If the planting attempt success rates drops to an unusually low level, it can also indicate a pathology in the system.

The **transition barrier** is not analyzed here because this work is not designed to illuminate evolutionary shifts in individuality. A domain can arguably still be open-ended even without them because exhausting the space that contains just *one* type of individual could still consume infinite time.

One final issue that has not yet been addressed is how long to perform the proposed experimental runs. The concept of open-endedness poses a challenge because it suggests that an evolutionary process that runs for only a finite amount of time is not genuinely open-ended. However, to study the phenomenon scientifically, we must be able to run repeatable experiments. To repeat an experiment, it must definitively end. The question then is, given that forever is infeasible, how long is long enough?

To address this question, 500,000 reproductions is the chosen run length for the proposed experiments. This number follows the methodology of the experiments on long-term evolution by Pugh et al. (2015). Though the evolutionary mechanisms are not exactly the same, the domain in those

experiments is intentionally designed to allow a variety of ways to succeed and as such is philosophically similar to the domain of the experiments described in this proposal. The experiments conducted by Pugh et al. (2015) were run until the population seemed to converge, which occurred by 250,000 reproductions in most cases.

CHAPTER 5: STANDARD RUN RESULTS

The primary purpose of running experiments in a world that satisfies all of the conditions hypothesized to be necessary for OEE (i.e. the standard runs) is to establish a baseline for comparison with the control worlds (wherein one of the conditions is not satisfied in the world). Visual snapshots are presented first in Figures 5.1 and 5.2 to provide an intuition for the evolutionary trajectories of each of these runs. Note that each row in each of these figures contains evenly spaced snapshots of a single run. Additionally, visual snapshots from a single sample run are presented in Figures 5.3 and 5.4 to give a more fine-grained sense of the evolutionary trajectories that are observed in this world. Quantitative results will be presented following the visual snapshots, followed by a general discussion of these qualitative and quantitative results. A more comprehensive discussion of open-endedness in Chromaria is deferred to the synthesis chapter so that a full comparison to the control experiment results is possible.

One unexpected outcome is that genome size actually *decreases* over time (Figure 5.5). However, this result does not necessarily indicate a lack of open-endedness in Chromaria, or even that individuals are not themselves becoming more complex over time. In fact, complex behavioral patterns can be observed at the ends of runs and in fact navigating the world (which becomes more complex over time as a greater variety of Chromarians embed themselves in it) arguably requires more complex behavior than simply moving forward and planting when pink patches are found (which is the behavior displayed by the initial seed Chromarian evolved through novelty search). The conclusion is that the fact that controller genome size generally decreases suggests that the genetic encoding in Chromaria (e.g. CPPNs) is sufficiently expressive that capping genome size would not have an impact on the complexity of observed behaviors.

That is, given a sufficiently high-dimensional representation, an evolving population can in principle

ple increase in complexity until the full capacity of that representation is exhausted. Because we do not know how long it may take to reach that capacity, any finite-length experiment may exhibit increasing complexity (according to any measure) throughout a run even with a fixed-capacity representation. While it is true that theoretically the size of the representation would still need to expand, we cannot know with certainty when (i.e. at what iteration) the need for such expansion would arise. The result that the standard runs do not exhibit measurable increases in complexity therefore does not indicate on its own a deficit in open-ended dynamics. Rather, it points to the fact that even though in theory representation should be unbounded for the purpose of open-ended experiments, in practice it may prove unnecessary in cases where the amount of time it would take to reach a complexity cap is far longer than the time and computation available to complete the experiment. In this way, this result may inform future thinking about experiments in open-endedness, by hinting that fixed-length representation are least eligible for consideration for finite-length experiments if their capacity is sufficiently high.

Our intuition that a reasonably open-ended world should not be completely predictable appears satisfied; there is an observable diversity in terms of end states among the various runs depicted in Figures 5.1 and 5.2. (As will be discussed shortly, the control runs will not display such a wide diversity of outcomes.) It is not obvious at the beginning, or even the middle, of these runs what the world will look like at 500,000 reproductions (when the experiments are stopped). Even then, looking at any individual run it is hard to predict with any confidence what the world would look like at 1,000,000 reproductions. Would it stay the same, or would it look completely different?

Whether or not Chromaria is indeed open-ended (which is a question that will be addressed after discussing the results of the control experiments), this world at least informs our analysis by giving us a sense of what is “normal” in this unique world.

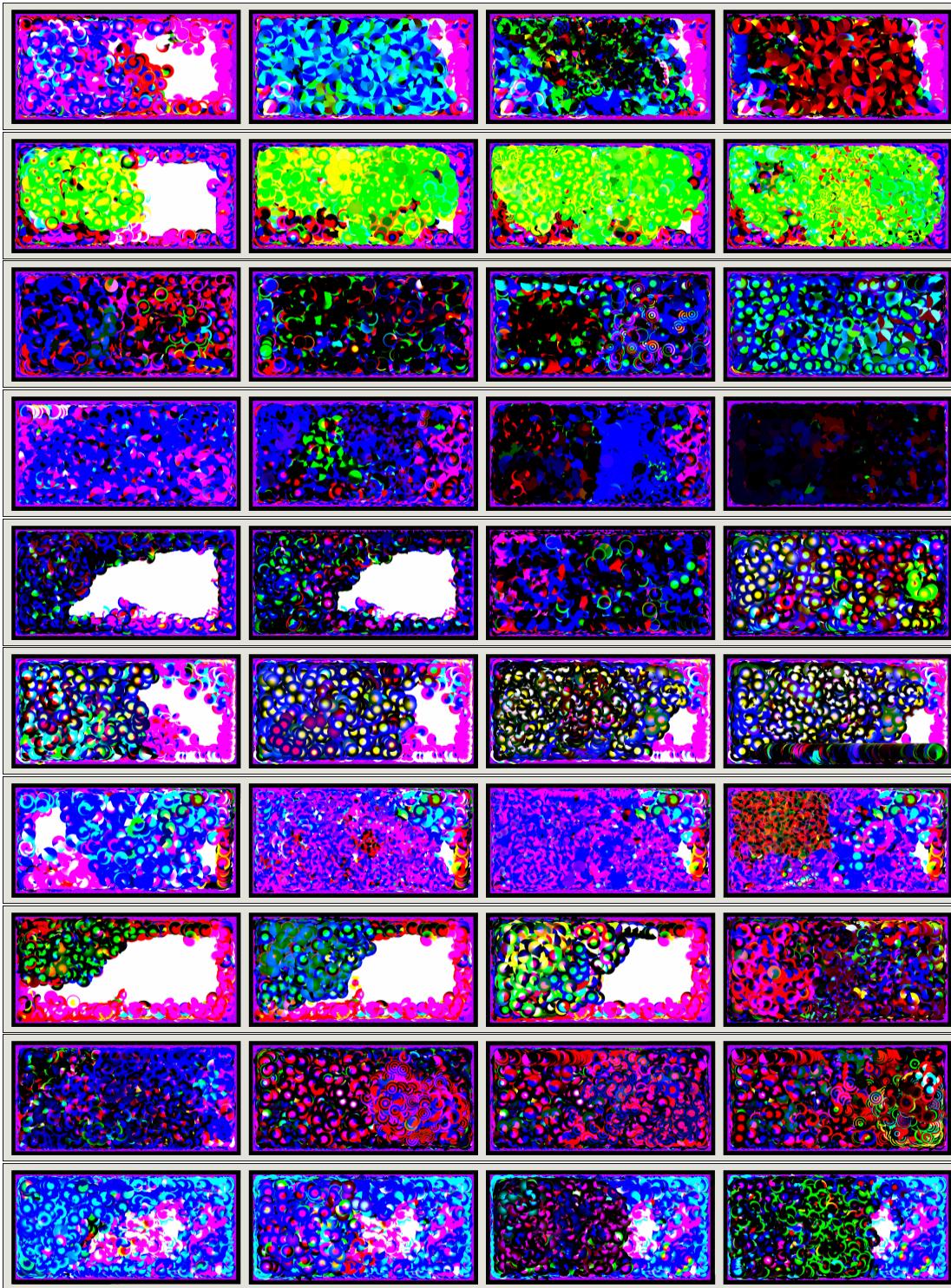


Figure 5.1: **Standard run visual snapshots.** Snapshots are taken at 125,000, 250,000, 375,000, and 500,000 reproductions. Each row contains snapshots from a single run.

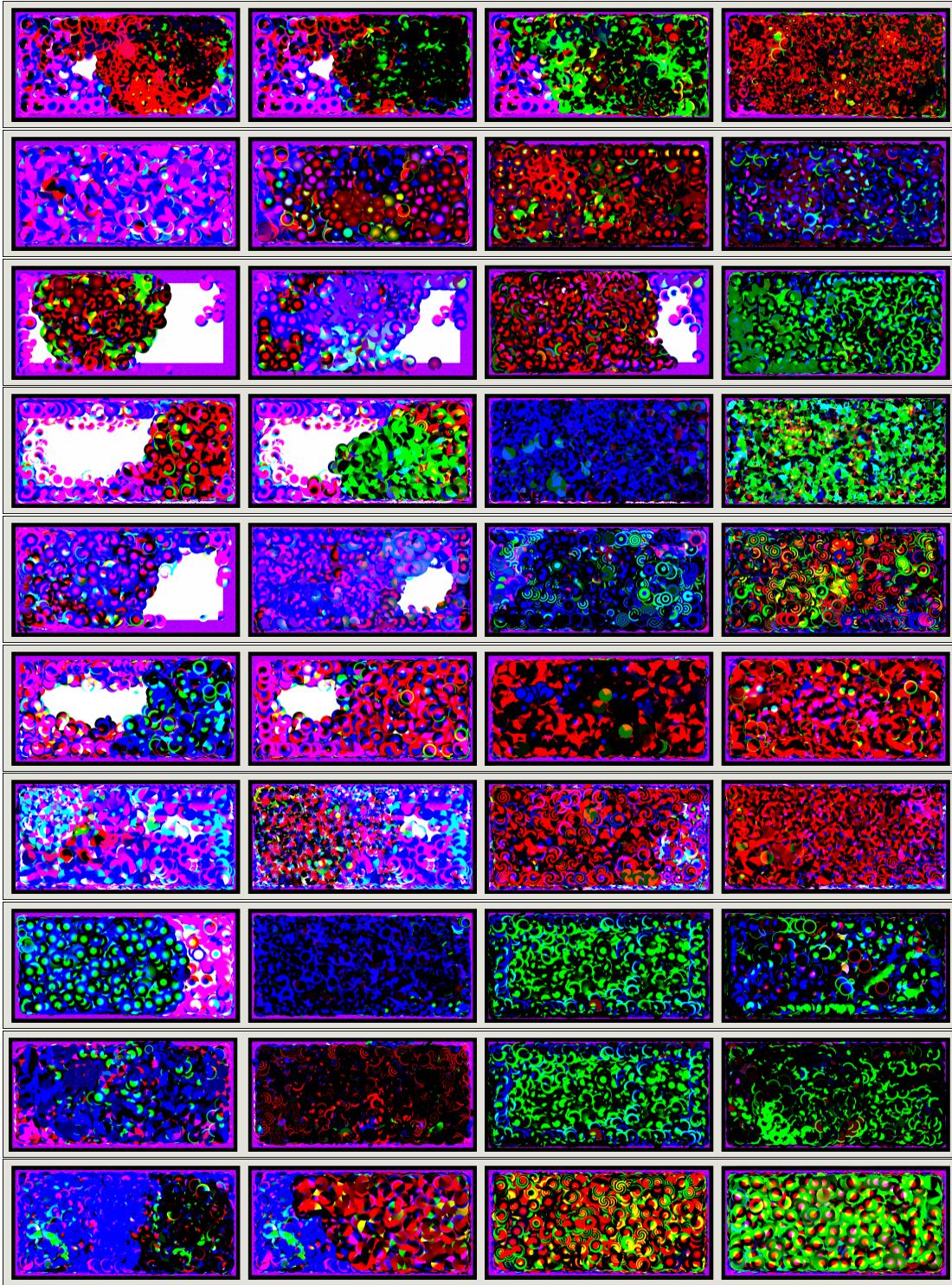


Figure 5.2: Further standard run visual snapshots (one run per row) continued from Figure 5.1

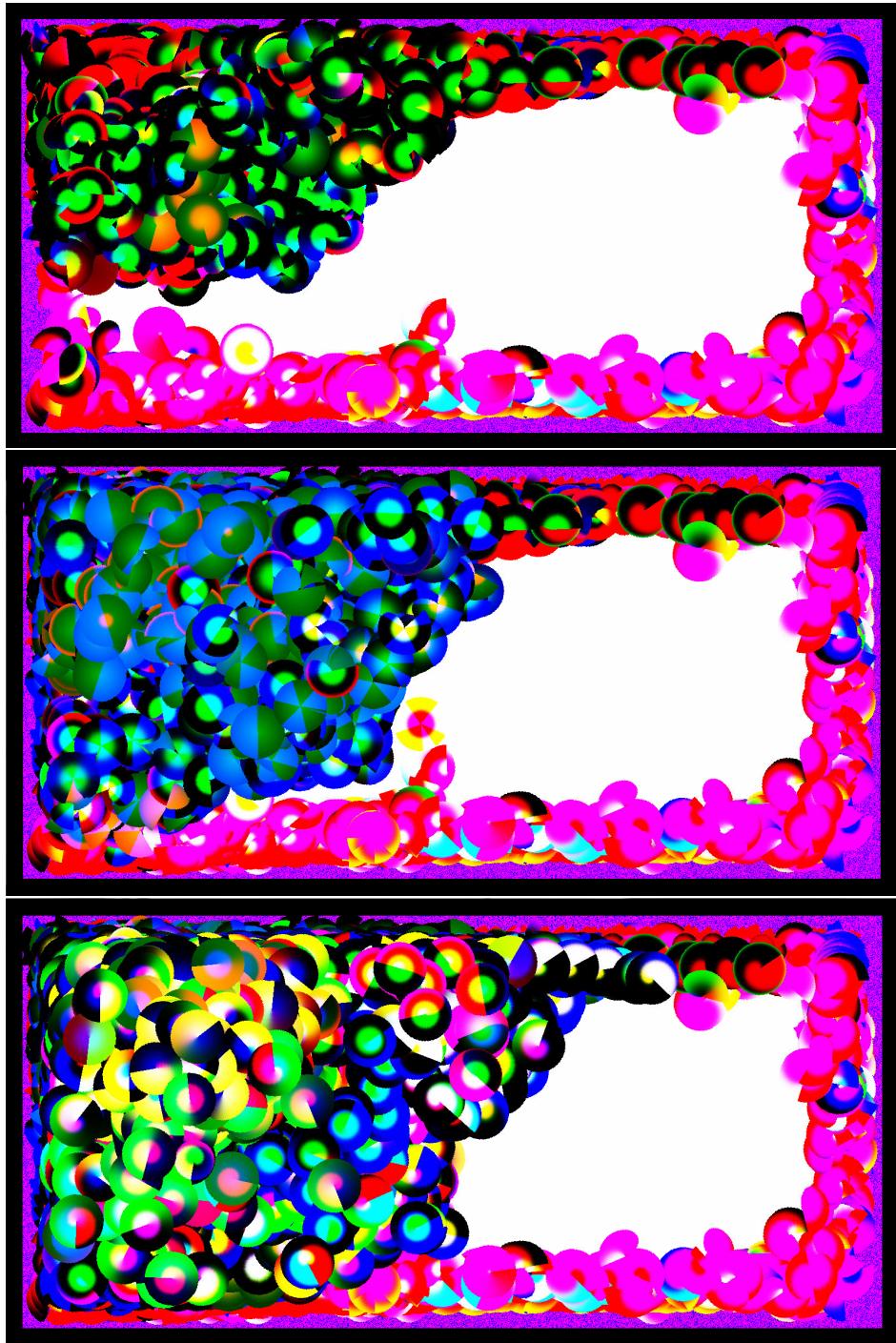


Figure 5.3: Visual snapshots from a single standard run at 125,000, 250,000, and 375,000 reproductions. These snapshots illustrate the variety and complexity of individual Chromarians.

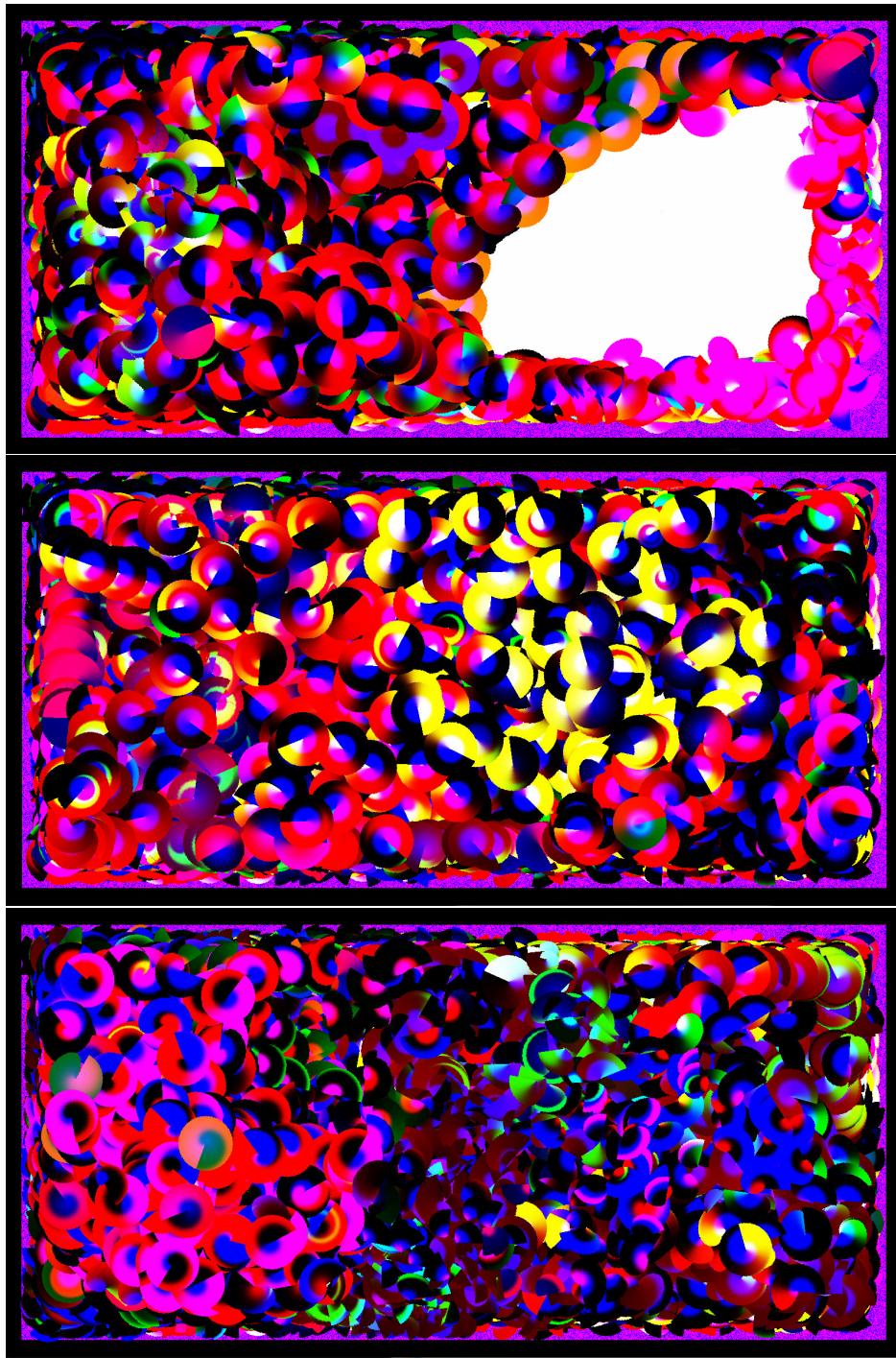


Figure 5.4: Visual snapshots from the single standard run shown in Figure 5.3 at reproductions 416,500, 458,250, and 500,000. The formation of niches is observed in these later stages of this particular run and a variety of morphology types can be seen in the bottommost snapshot.

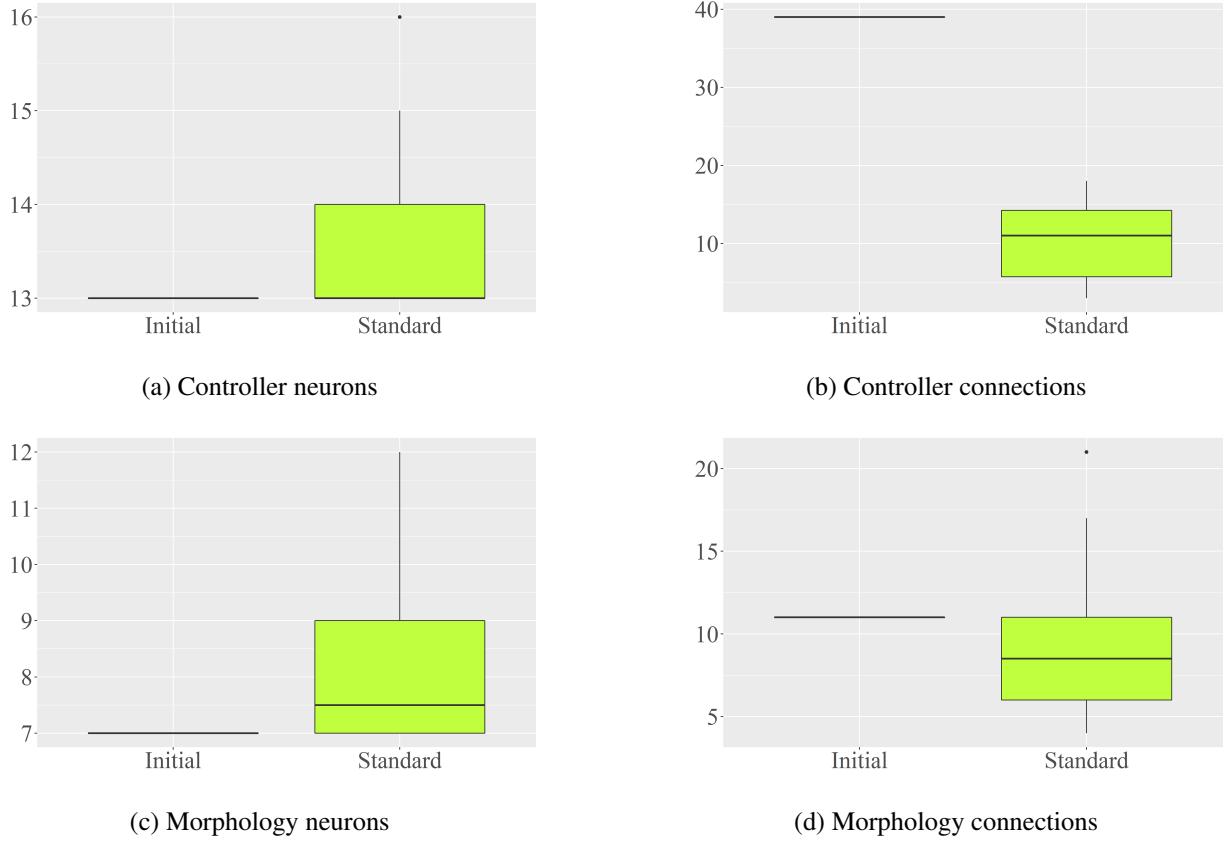


Figure 5.5: Genome network size in standard runs. The second and third quartiles of each dataset are represented by a colored box with a line in the middle indicating the median, while the first and fourth quartiles are denoted by lines above and below the colored box. Dots above or below these lines indicate outliers. Note that the genomes themselves are CPPNs with distinct neuron and connection counts. The average averages reported correspond to the average counts over the last 250 individuals in a run averaged over 20 runs. Interestingly, the number of connections in controller genomes *decreases* over time. This result initially seems counterintuitive; genomes generally become larger, not smaller, over the course of evolution. However, this result does not necessarily indicate that genome complexity itself is decreasing because genome size (particularly with an indirect encoding) does not strictly map to genome complexity. Instead, this result suggests that the genetic encoding in Chromaria is sufficiently expressive to encode neural networks capable of generating complex behaviors even at small genome sizes.

CHAPTER 6: CONTROL 1 (NO MINIMAL CRITERION) RESULTS

Novelty search (Lehman and Stanley, 2011a) and other related algorithms such as its minimal criterion variant (Lehman and Stanley, 2010) showed that there are viable alternatives to the traditional paradigm of objective-based optimization or “survival of the fittest”. Still, novelty search is not like evolution on Earth, and few would claim that evolution on Earth explicitly rewards individuals simply for being different. (In fact, many creatures on Earth would not be able to reproduce without there existing other individuals of the same species, which is not true for robots evolving to solve the Hard Maze of novelty search.) Then, there is still a need to arrive at a minimal conception of evolution that escapes the objective-based paradigm. One of the goals of this experiment is to see how much of evolution’s ability to innovate can be explained by simple evolutionary drift (i.e. mutation-driven diffusion throughout the search space). Condition 1 tests the importance of the minimal criterion to controlling such drift:

Condition 1: A rule should be enforced that individuals *must* meet some minimal criterion (MC) before they can reproduce, and that criterion must be nontrivial. **Control:** All individuals are allowed to reproduce regardless of what they do in the world.

If evolution continues to innovate in a meaningful way (i.e. still produces new kinds of things that aren’t completely degenerate or random) even without enforcing a minimal criterion, then we might conclude that drift is sufficient to enable open-ended evolution. On the other hand, if evolution did fail to produce new kinds of novelty and complexity, we would conclude that some nontrivial minimal criterion is indeed necessary to sustain open-ended evolution.

Figure 6.6 reveals a dramatic phenomenon that *planting rates drop off completely* before the runs are even halfway complete. In fact, the time at which the last species emerges, on average, is near the beginning of the run (at least compared to the standard runs; Figure 6.4). Most significantly,

the fact that visual snapshots of the world (Figures 6.1 and 6.2) look identical to each other indicate that no Chromarian even attempts to plant, as any planting attempt whatsoever would succeed and thereby cause a new morphology to become embedded in the world. The cause of this outcome can be understood by observing the behaviors of individuals in the world as planting rates begin to decline. Whereas behaviors demonstrate some semblance of intelligence (such as edge following and generally reacting to environmental stimuli) in the earlier stages of the runs, late stage Chromarians have reverted to simply running into walls repeatedly. Others do not move at all. These results suggest that without an MC enforcing some minimal level of complexity, there is no pressure causing individuals to attempt to plant. Evolutionary innovations seem susceptible to a “use it or lose it” mechanism.

It is also interesting to note that a significantly higher (than standard) median number of species emerge in this world (Figure 6.5; $p=5.52 \times 10^{-8}$)¹, and that the last species to emerge does so significantly earlier on in these runs (Figure 6.4; $p=6.29 \times 10^{-8}$). These results together suggest a rapid initial proliferation of disparate forms followed by a steep descent into chaos. Additionally, this world contains little of the organic-seeming clusters and cohesion present in the standard version of the world (Figures 6.1 and 6.2).

Generally, this experiment supports two conclusions: (1) that a minimal criterion is indeed necessary for open-endedness, and (2) that the minimal criterion offers a viable alternative to a traditional fitness-based gradient.

It is also instructive to consider the results of this experiment with respect to Dolson’s barriers to OEE. The inability of any new individuals to reproduce indicates that the system eventually runs into the change barrier (when the population stops changing at all), which is conceived as the most elementary obstacle to open-endedness.

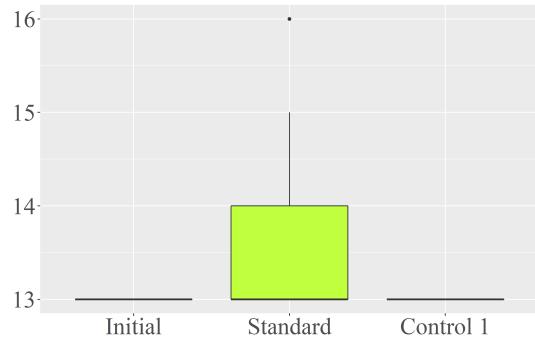
¹Controls in this and future chapters are compared to the Standard world using the Wilcoxon rank-sum test.



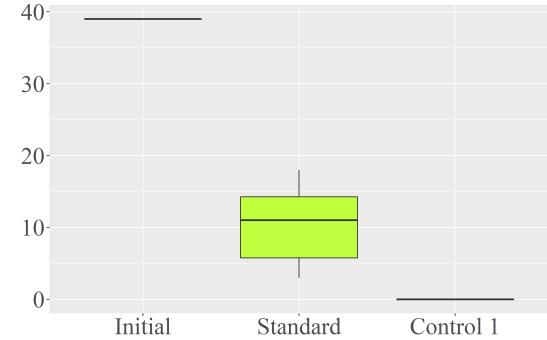
Figure 6.1: **Control 1 visual snapshots.** Individuals do not have to satisfy any minimal criterion to reproduce. Snapshots are taken at 25,000, 62,500, 125,000, and 162,500 reproductions. Each row depicts a single run.



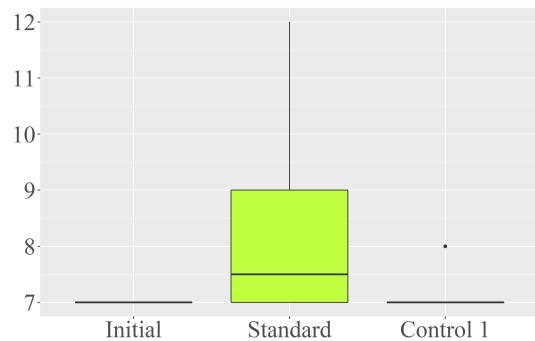
Figure 6.2: Additional Control 1 visual snapshots (one run on each row) continued from Figure 6.1



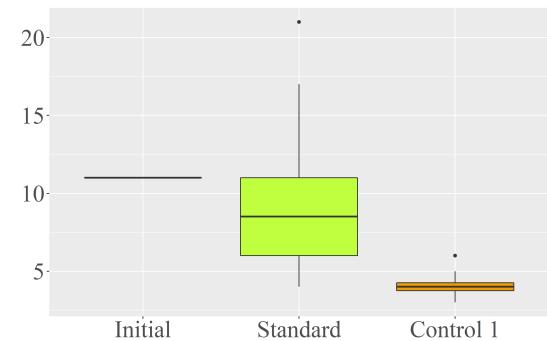
(a) Controller neurons



(b) Controller connections



(c) Morphology neurons



(d) Morphology connections

Figure 6.3: **Genome network size, Control 1.** The average averages reported correspond to the average counts over the last 250 individuals in a run averaged over 20 runs.

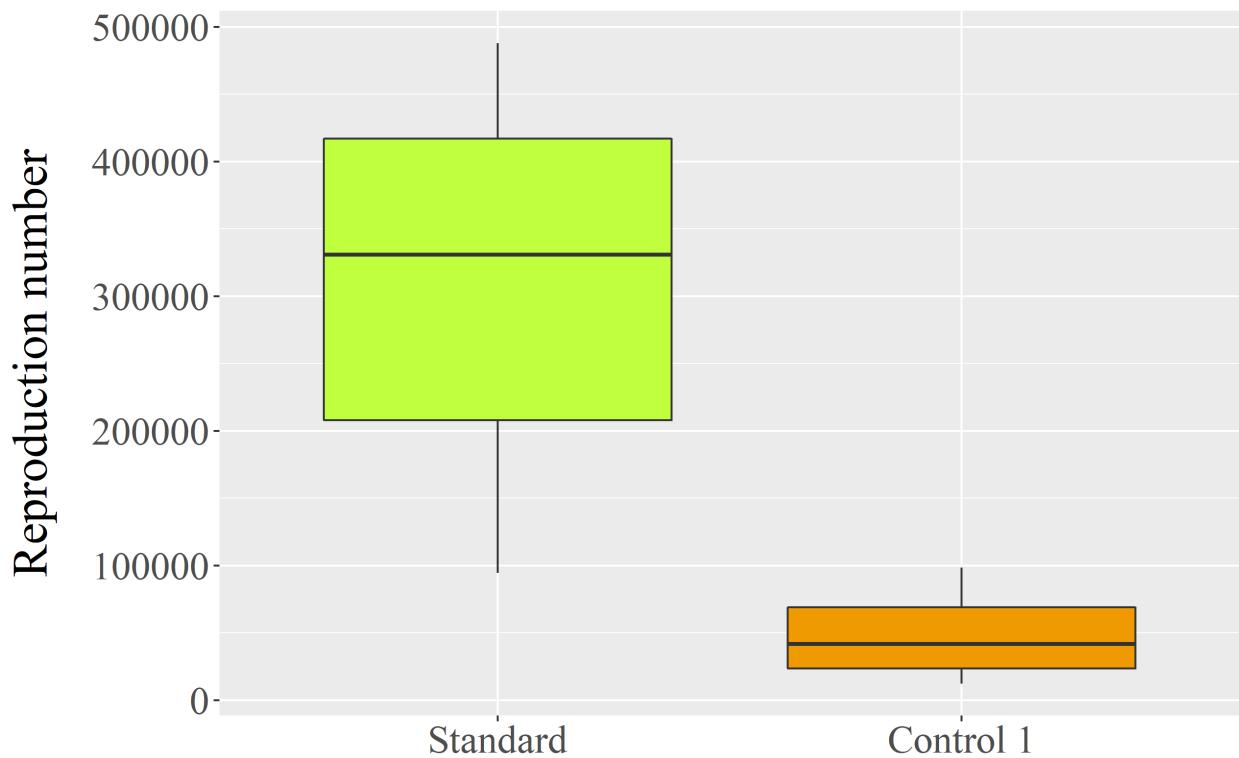


Figure 6.4: **Median last new species, Control 1.** The last new species emerges at reproduction 44,000 out of 500,000. In contrast, the last new species in the standard world emerges at reproduction 330,750. This result indicates that evolution stops generating anything novel significantly earlier (compared to the standard world; $p=6.29 \times 10^{-8}$) in the runs. Without a minimal criterion, evolution in Chromaria fails to overcome the change and novelty barriers.

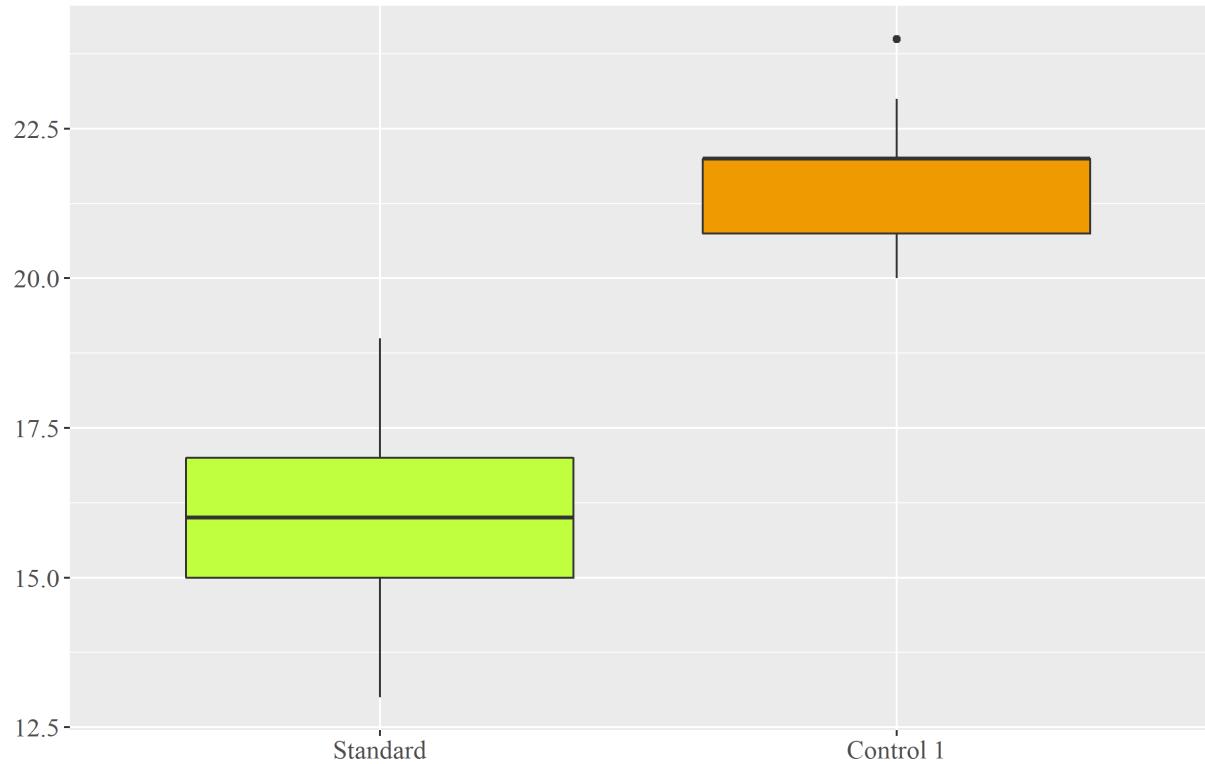


Figure 6.5: **Median total species, Control 1.** In this world, individuals that attempt to plant are guaranteed to succeed regardless of how closely their morphologies match the world they inhabit. Removing the minimal criterion results in a significantly higher total number of species (22) than in the standard runs (16; $p=5.52 \times 10^{-8}$) because individuals that would normally fail to satisfy the morphological matching function in the standard are completely viable in this control world. As a result, evolutionary search is able to traverse more of the morphology space.

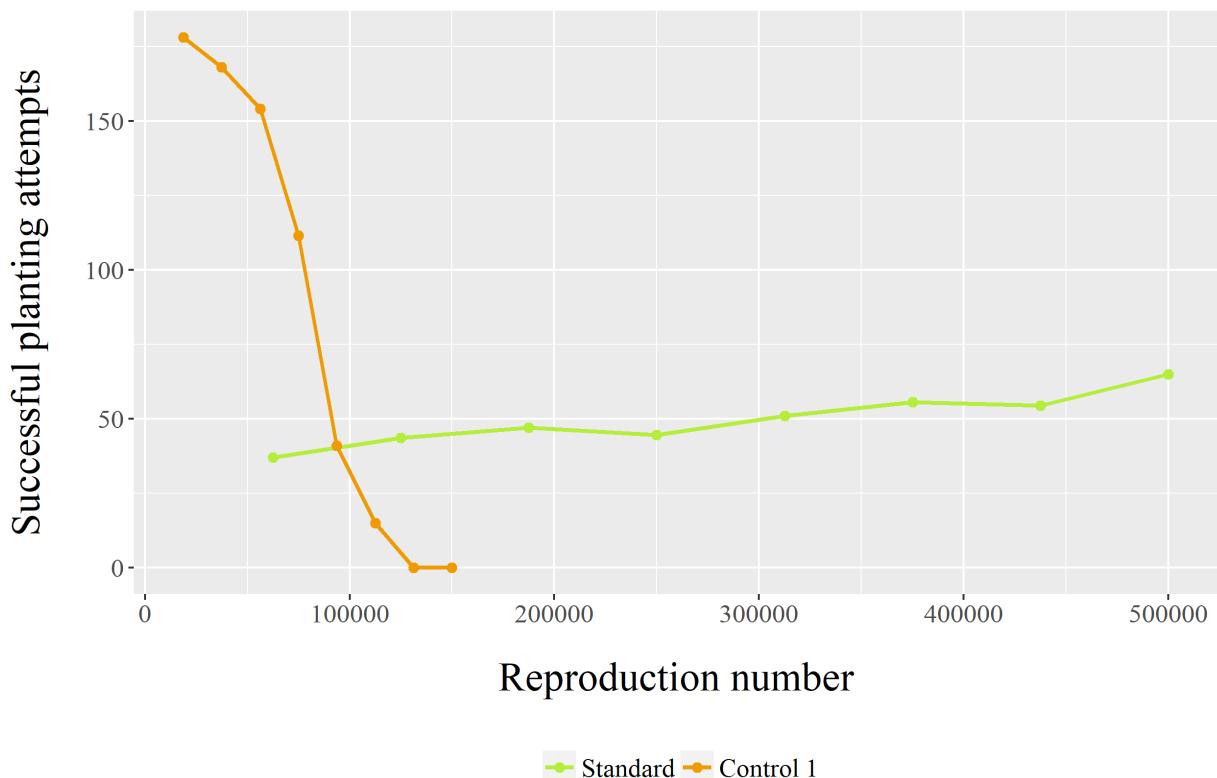


Figure 6.6: **Median successful planting attempts, Control 1.** While initially the lack of minimal criterion allows normally nonviable individuals to succeed, and as a result allows many new species to emerge, the rate of planting attempt successes strictly decreases over time. While this result may initially seem counterintuitive given that every planting attempt in this control is guaranteed to succeed, it is explained by the conclusion that planting attempts themselves are actually declining and eventually becoming nonexistent.

CHAPTER 7: CONTROL 2 (NO INTERACTIONS) RESULTS

The existence of an individual can permanently change the environment that other creatures (of the same type and of different types) inhabit. The changes to the world that one individual makes can make possible further changes to the world by another individual in the future. As an example, consider the fact that many humans today, at least in the West, rely either directly or indirectly on fossil fuels to enable our day-to-day lives. The existence of prehistoric creatures (along with many other evolutionary events) thus created an opportunity for modern humans to live the way we do. The set of experiments in this chapter explores the impacts of interactions between individuals on evolutionary dynamics.

Condition 2: The evolution of new individuals should create novel opportunities for satisfying the MC. **Control:** Individuals cannot see each other (and therefore cannot interact), which means that the evolution of new individuals has no impact on other individuals in the world.

Individuals that satisfy the MC (of reproduction) in the same way are said to belong to the same species. That way, a world where novel opportunities for satisfying the MC are either few in number or hard to take advantage of would almost certainly see the emergence of fewer species. In a world where individuals cannot see each other, we would expect that new innovations could not be exploited.

It is clear that *something* about Earth and about the standard version of Chromaria yield novel opportunities for satisfying the MC and that individuals are able to take advantage of them, resulting in the emergence of new species over time. If evolution continues to innovate in this modified version of Chromaria despite the fact that individuals are not affected by the innovations of other individuals, then something else would have to be creating novel opportunities for satisfying the MC.

A preliminary suite of experiments described in Chapter 4 provided some initial insights into the ramifications of this control. These results, from a slightly different version of Chromaria wherein all new Chromarians are born in the center of the world, suggested that indeed new species fail to emerge when evolutionary innovations cannot build on each other. The comprehensive experiments in this chapter are performed on a longer timescale than the previous experiments. An important question, then, is about what phenomena would be expected in this world given more time.

Morphologies that are primarily white might evolve as a result of random mutation and manage to plant in the white center of the world. More evolutionary time (which results in more reproductions and, accordingly, more mutations) could increase the chances of such an innovation occurring. However, due to the constraints imposed on this special (control) version of the world, it is impossible for creatures to ever plant based on pixels that are not present in the world at reproduction 0. Additional colors do not become available to future Chromarians no matter how much time passes. The chance of at some point evolving (by mutation) an individual capable of planting based on those initial colors may potentially increase with time. However, there is no reason to believe that more time will otherwise lead to increased evolutionary innovation in this version of the world because no new opportunities are emerging.

The world depicted in visual snapshots is akin to a world of ghosts; the bodies of dead Chromarians are not visible to the living Chromarians. However, the parent queue is very much alive, and a creature that succeeds at planting in this world (which has not changed since the beginning of time) will generate an offspring as usual.

Looking at these worlds visually reveals stark homogeneity (Figures 7.1 and 7.2). This observed homogeneity is also reflected quantitatively in the significantly decreased number of total species that emerge over the course of runs in this world compared to the standard world (Figure 7.5; $p=5.77 \times 10^{-8}$). Additionally, species emergence in general tapers off twice as fast as it does in

the standard world (Figure 7.4; $p=6.29 \times 10^{-8}$). Though planting rates are high (Figure 7.6), this effectively guaranteed success comes at the expense of diversity and innovation.

The impact that one individual, or one evolutionary innovation, can have on the system as a whole is limited. It is only through the combined and often complex interactions among *many* evolutionary innovations (such as new types of individuals) that higher levels of novelty and complexity become accessible to evolutionary search. Without the ability to build off of prior innovations, such a search is restricted to a narrow radius of its starting point. The results from this experiment support the conclusion that interaction between individuals indeed is necessary for open-ended evolution.

Regarding Dolson’s barriers to OEE (Dolson et al., 2015), it is impossible to overcome the change and novelty barriers (which both require the emergence of new kind of individuals) when new kinds of individuals are not able to thrive. A small number of runs seem more able, by chance, to better overcome these barriers by evolving (via mutation) primarily white individuals with a splash of color. However, the space of viable individuals in this world is fundamentally limited to those primarily composed of pink, purple, and white pixels because these colors are readily available in the “ground” world that is always accessible. As a result, the world would not be expected ever to display a significant amount of novelty in the long run.



Figure 7.1: **Control 2 visual snapshots.** Individuals in this world cannot see each other and thus cannot take advantage of evolutionary innovations. Snapshots are taken at 125,000, 250,000, 375,000, and 500,000 reproductions. Each row contains snapshots from a single run.

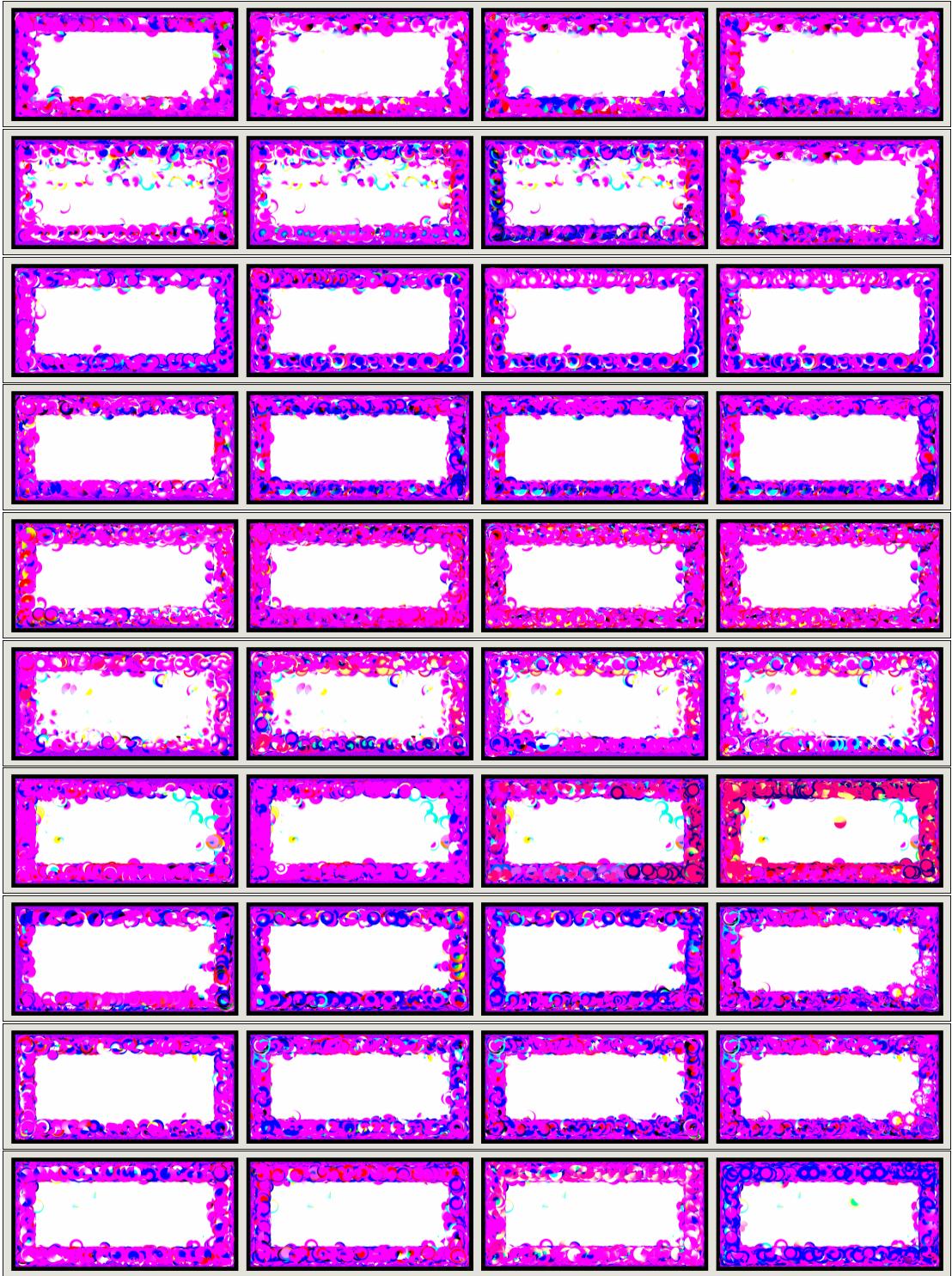
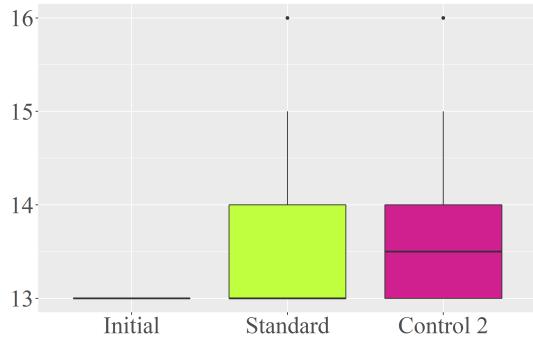
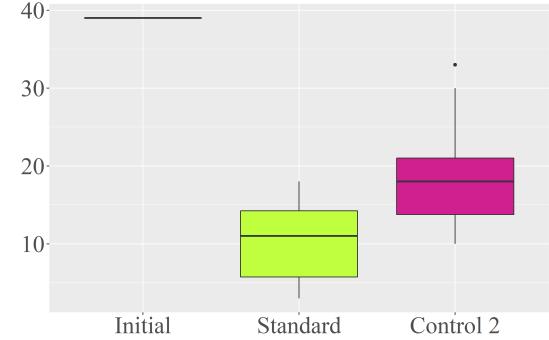


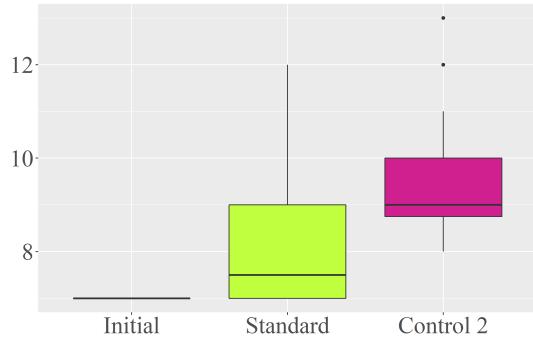
Figure 7.2: Control 2 visual snapshots (one run in each row) continued from Figure 7.1



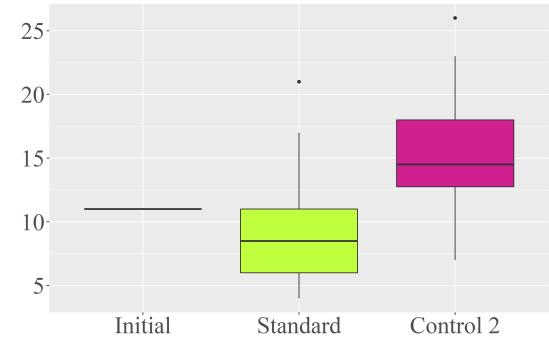
(a) Controller neurons



(b) Controller connections



(c) Morphology neurons



(d) Morphology connections

Figure 7.3: **Genome network size, Control 2.** The average averages reported correspond to the average counts over the last 250 individuals in a run averaged over 20 runs. Neuron counts in controller-encoding genome networks stay approximately the same over the course of each run, while the connection count decreases. These results obey the same general patterns as the standard runs, but the decrease in connection count is not as dramatic in this control. However, both neuron and connection counts increase for morphology-encoding genomes in these control runs.

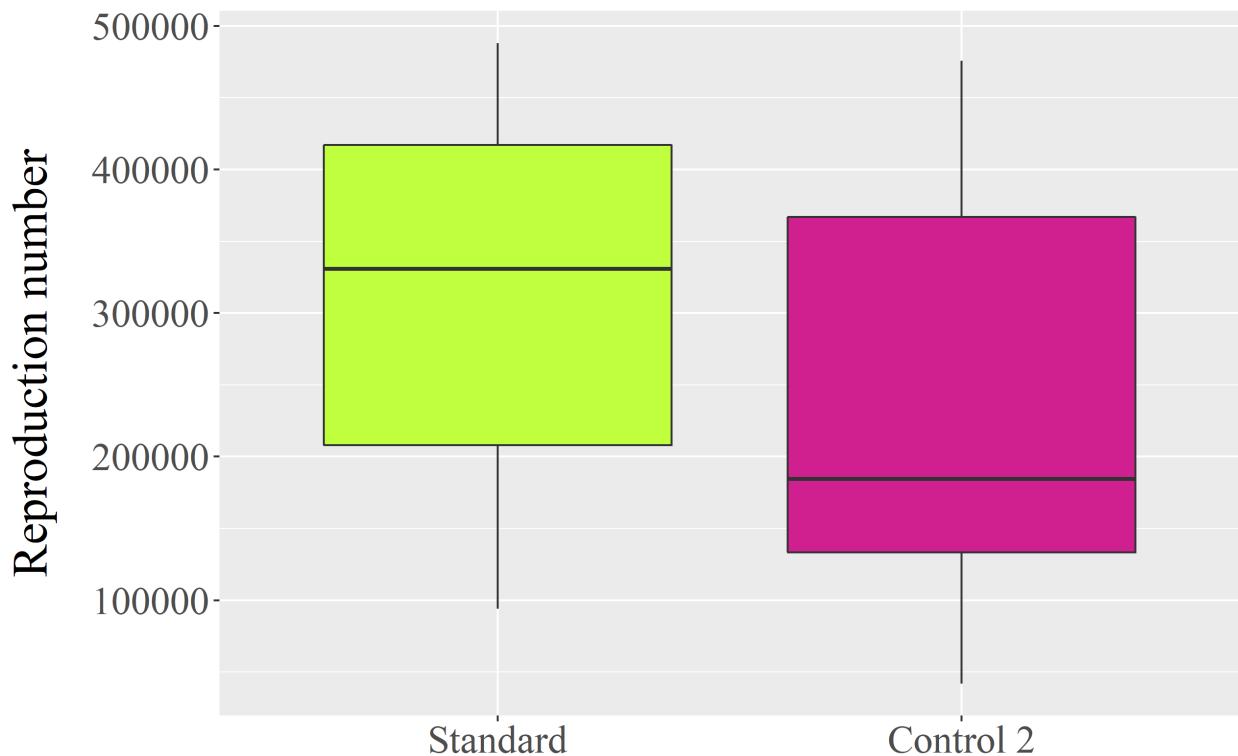


Figure 7.4: Median last new species reproduction number, Control 2. The last species in this world emerges significantly earlier, at median reproduction 171,000, when individuals can't see or interact with each other, compared to reproduction 330,750 in the standard world ($p=6.29 \times 10^{-8}$). It is clear from observing the visual snapshots that it is difficult, if not impossible, for evolution to traverse morphology space beyond the colors present in the initial state of the world. Thus, this result provides evidence that Chromaria fails to overcome the novelty and change barriers in this case.

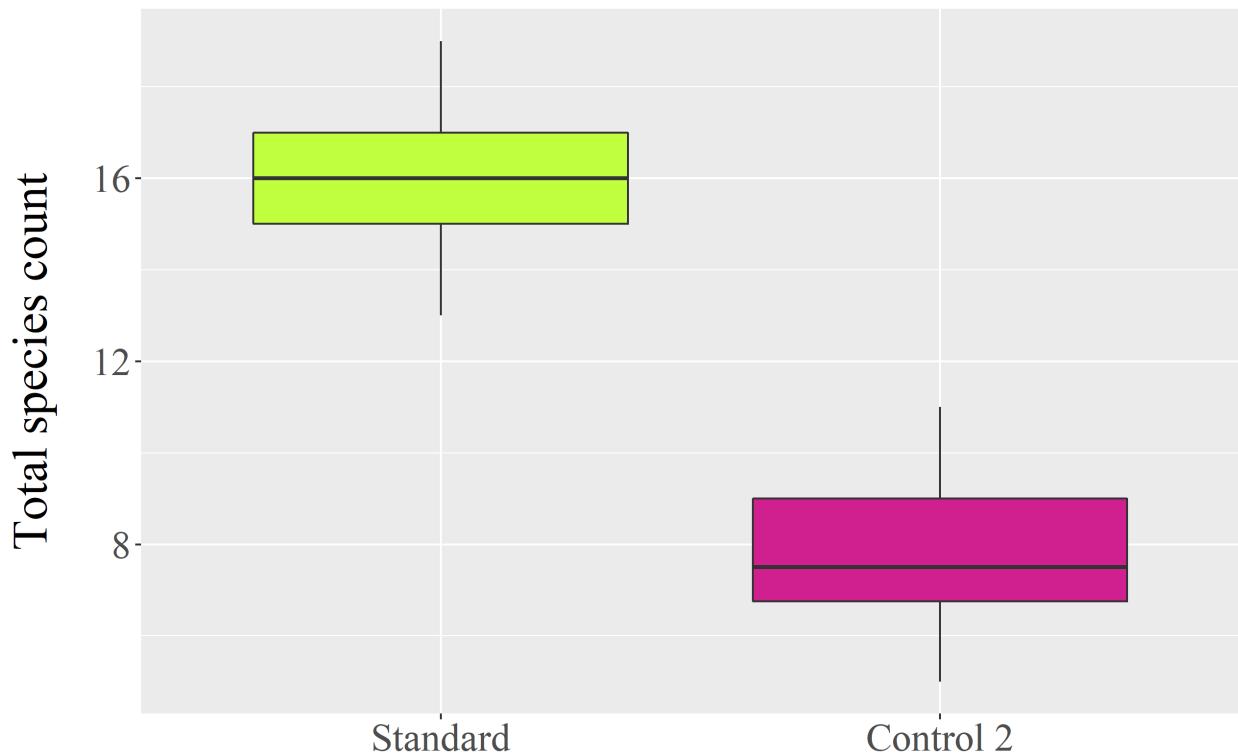


Figure 7.5: Median total species count, Control 2. The inability for evolution to access most areas of morphology space is again evidenced by the significantly lower number of total species found (7) compared to the standard world (16; $p=5.77 \times 10^{-8}$). This low total species count combined with the relatively early emergence of the last new species indicates that evolution exhausts all available opportunities for innovation early on and then fails to discover or take advantage of new ones.

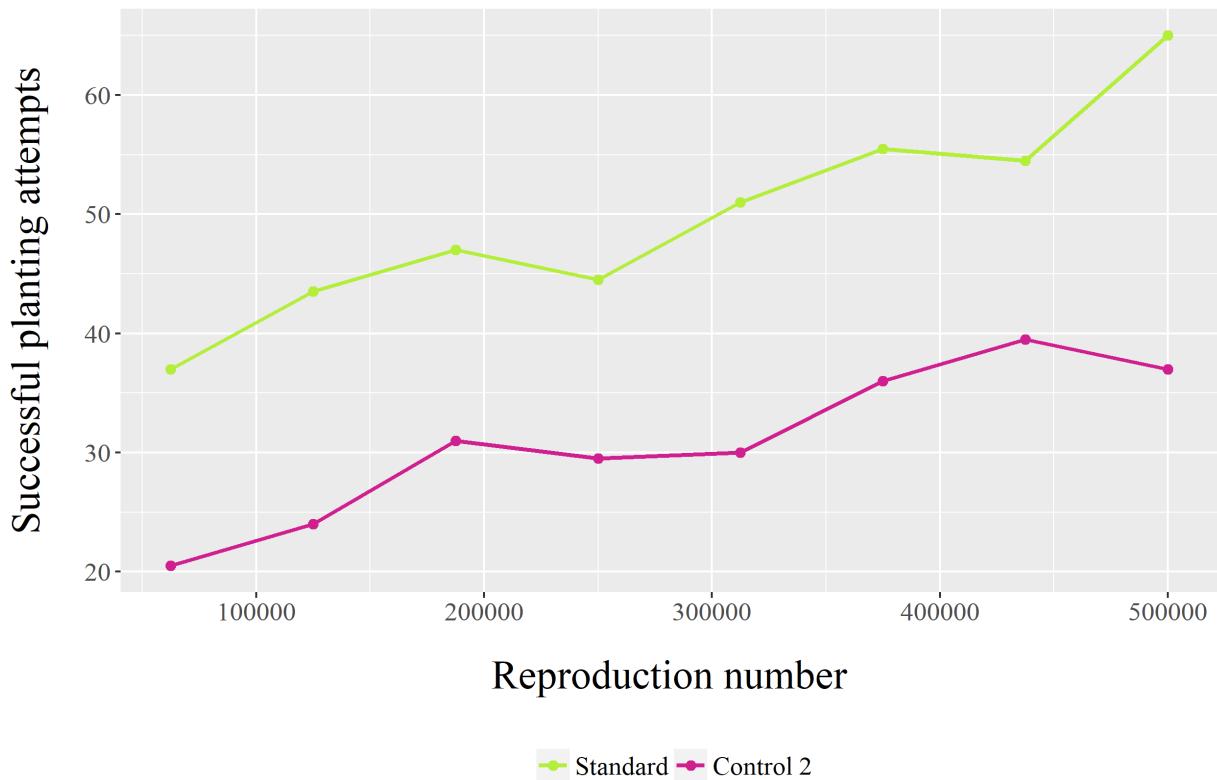


Figure 7.6: Median successful planting attempts, Control 2. Planting attempt success rates are lower when individuals cannot interact with each other compared to in the standard world. Interestingly, the planting success rate at the end of the run in the control world is approximately the success rate at the beginning of the standard runs. Given that morphology-encoding genomes tended to increase in size in this world, it is possible that morphological complexity is potentially at least a partial contributor to this result because the colored background that provides the only opportunity for planting does not itself become more complex.

CHAPTER 8: CONTROL 3 (NO NEURAL NETWORKS) RESULTS

Artificial life worlds take many forms, from cellular automata to worlds with fully embodied agents. The purpose of this particular experiment more broadly is to understand the role that agency and individuality play in evolution. The planting scheme in this world is inspired by the approach to reproduction in the popular alife platform Avida (Ofria and Wilke, 2004). (As a reminder, digital organisms in Avida exist on a two-dimensional grid and when an offspring is born it is placed randomly in one of the cells adjacent to its parent.)

Condition 3: Decisions about how and where individuals interact with the world should be made by the individuals themselves. **Control:** Randomness is introduced into Chromarian interaction and reproduction via a two step process. First, each new Chromarian is born in a random location within a fixed radius of its parent. The new Chromarian is then given a random heading. This way, the individual's planting location is determined entirely by a combination of chance and parent location. To completely remove the neural network from Chromarian behavior, each new Chromarian is forced to attempt to plant once its location and heading are chosen by the system (instead of having the neural network determine whether or not a Chromarian should plant during its lifetime). Reproduction is still dependent on satisfying the standard color matching function described in Chapter 4.

If it turns out that evolution is not as productive as in the standard word, then there would be evidence supporting the position that the self-chosen actions of individuals play an important role in open-ended evolution. There would also be reason to believe that certain classes of alife systems can be predicted to be fundamentally limited in their potential for open-endedness.

These worlds appear to be more homogeneous than standard Chromaria in terms of color composition (Figures 8.1, 8.2, 8.3); in this world, having a morphology with 50% black pixels seems

to become a requirement for success when the neural networks are removed. It is possible that black pixels, which occupy a special place at the extreme of the RGB color space (which is important to reproductive success in Chromaria), are a mechanism for coping with the high amounts of randomness in this world.

The total number of species that emerge during these runs are significantly higher (but with a lower degree of significance than comparisons with other controls) than the number of species that emerge in the standard runs (Figure 8.6; $p=0.01017$). However, the last species emerges significantly earlier in the runs without neural networks (Figure 8.5; $p=6.29 \times 10^{-8}$). One way to interpret this result is that the world has converged or is beginning to converge to a stable (though visually chaotic) state. If novelty and surprise are correlated in some way with open-endedness, then this world is less open-ended than the standard world. It is easier to predict at least the general features of an end state in this world.

Planting success rates are unusually high in this world (Figure 8.7) because of the intentional decision to force every individual to make a planting attempt when it is placed randomly into the world. (This approach was taken to avoid unfairly making the minimal criterion of reproduction too difficult.) However, planting attempts do become increasingly more successful after the point where the last species tends to emerge. This result further substantiates the theory that the world has indeed converged.

Without the possibility of intentional motion, it is nearly impossible to take advantage of opportunities that arise in the world. In this case, “opportunities” is meant broadly – opportunities for reproduction count, but also opportunities to simply respond to a new kind of stimulus in the world. The best strategy for survival in a world where individuals have to make do with whatever environment the world places them in is simply to be somewhat generic. If all areas of the world present the same kinds of opportunities, and if new kind of opportunities do not arise in the world, then

there is a higher chance of survival.

What would have happened on Earth if nervous systems had never evolved? What if there were plants, but not animals? Life in such a world would certainly be evolutionary, and the world itself might even be beautiful, but we know that much more is possible. The results from this experiment suggest that individual initiative is important for avoiding premature convergence. Thus, we conclude that decisions about how and where individuals interact with the world should indeed be made by the individuals themselves.

In terms of Dolson's barriers to OEE, the visible and seemingly inevitable darkness combined with the premature dropoff in species emergence together indicate that these runs eventually fail to overcome the novelty barrier. That is, the world may still demonstrate change, but the types of individuals in the world may cycle and old types of individuals may reemerge but no innovations are occurring.

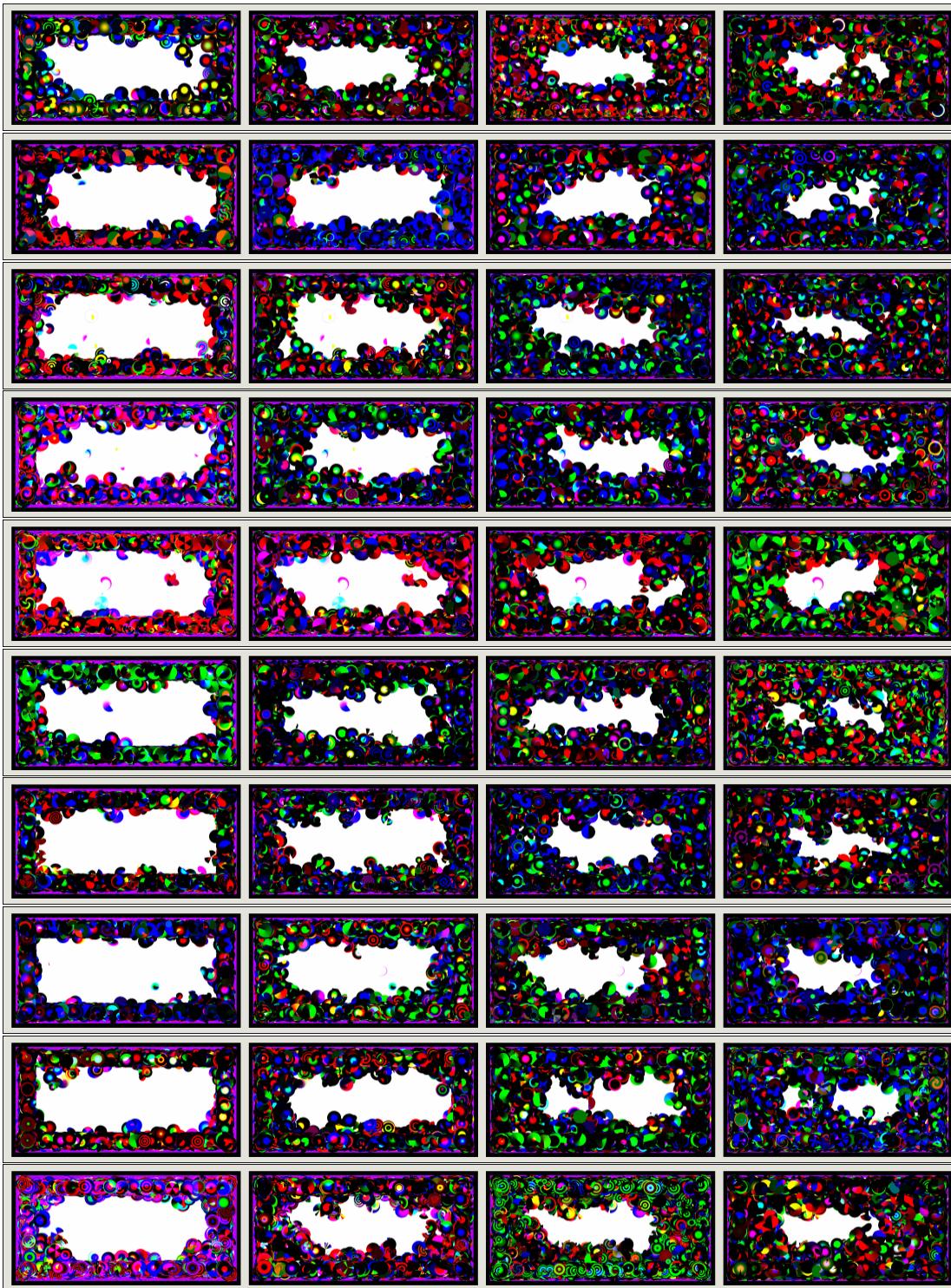


Figure 8.1: **Control 3 visual snapshots.** Behavior in this world is decided semi-randomly instead of being controlled by an evolved neural network. Snapshots are taken at 125,000, 250,000, 375,000, and 500,000 reproductions. Each row contains snapshots from a single run.



Figure 8.2: Control 3 visual snapshots (each row is a single run) continued from Figure 8.1

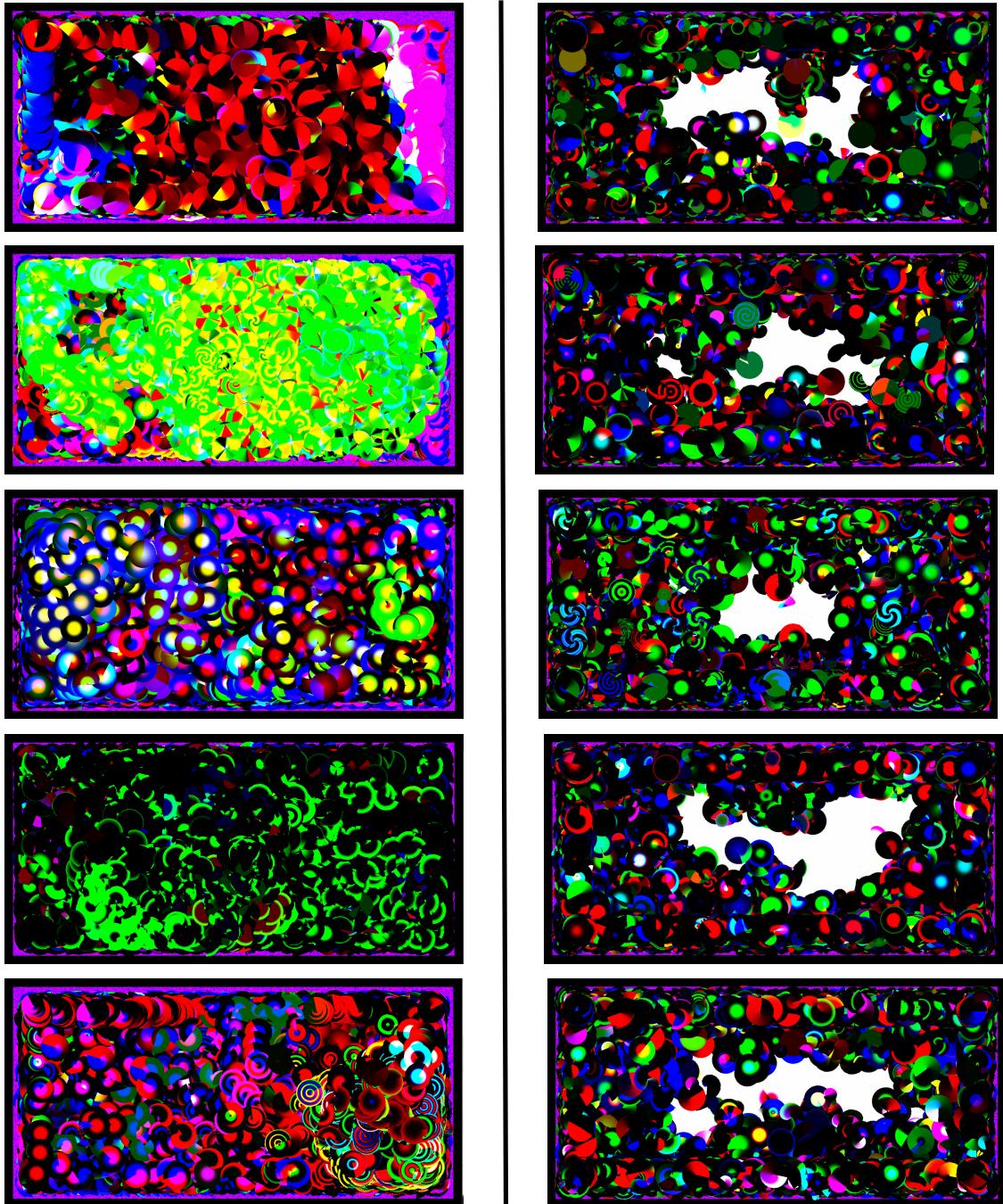
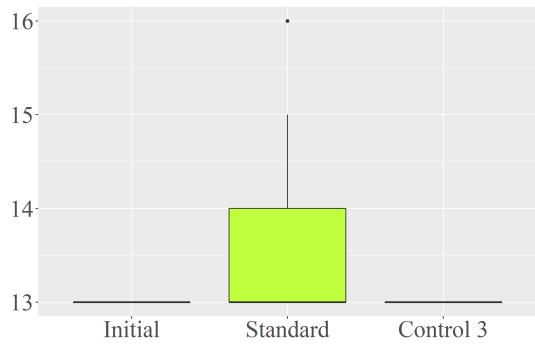
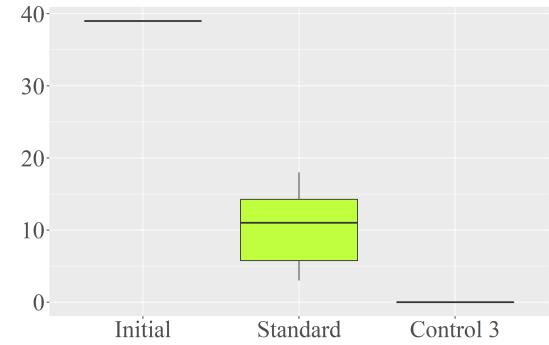


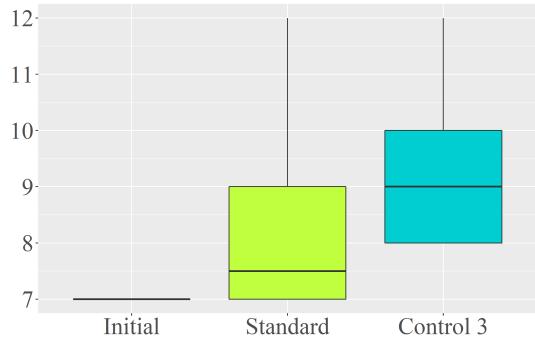
Figure 8.3: Representative end states, Standard and Control 3. End states of sample standard runs (left) are presented side by side with end states of sample control 3 runs (right). The visual disparity between these two sets of end states underscores the relative homogeneity that is generated when individuals cannot make decisions about their own actions.



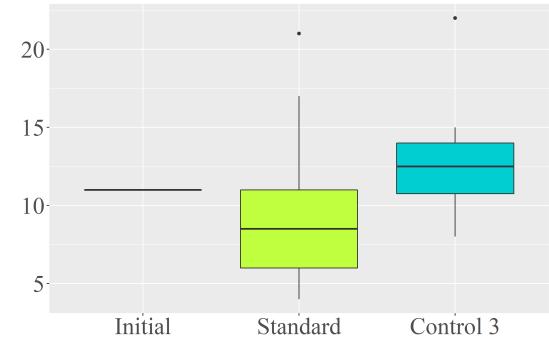
(a) Controller neurons



(b) Controller connections



(c) Morphology neurons



(d) Morphology connections

Figure 8.4: Genome network size, Control 3. The average averages reported correspond to the average counts over the last 250 individuals in a run averaged over 20 runs. Controller-encoding networks become completely disconnected when controllers no longer serve the purpose of deciding behaviors.

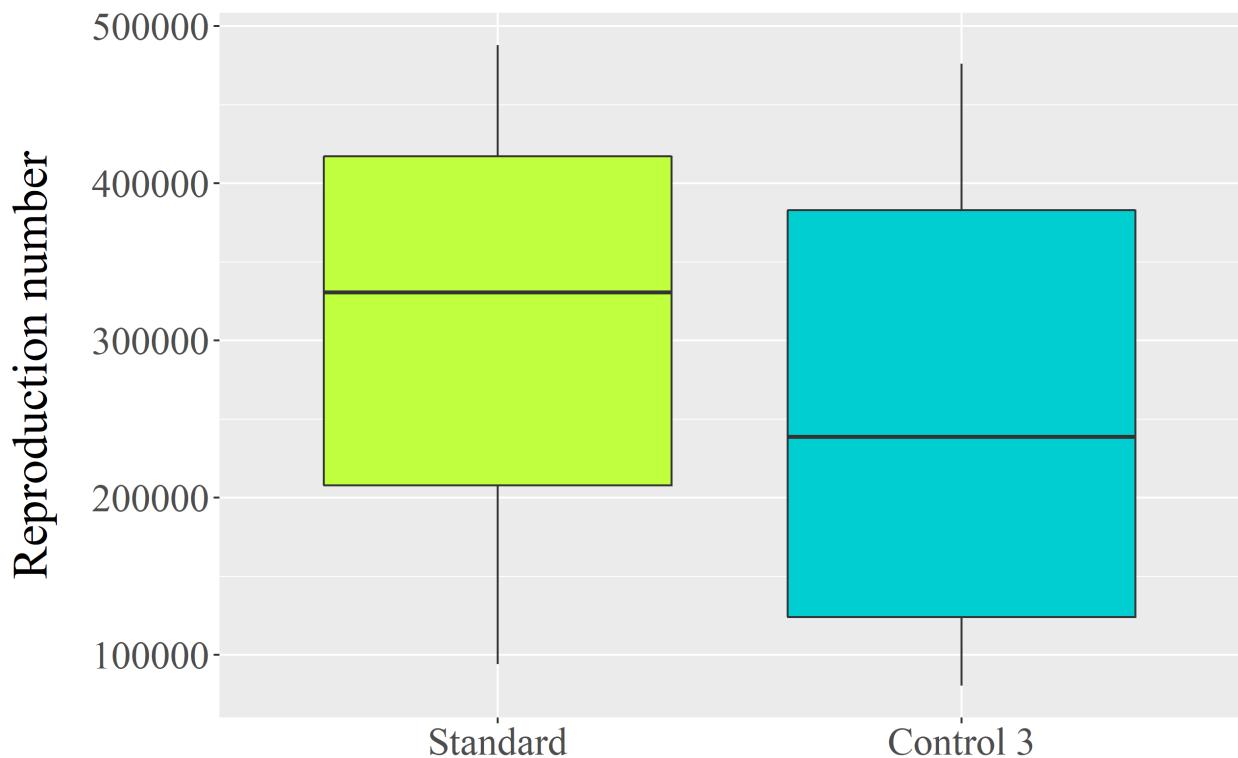


Figure 8.5: **Median last new species reproduction number, Control 3.** The last species in this world emerges at median reproduction 238,000 when individuals cannot decide for themselves where and how to interact with the environment, compared to reproduction 330,750 in the standard world ($p=6.29 \times 10^{-8}$). This quantitative result is consistent with the emergence of a pervasive and somewhat chaotic dark color throughout the worlds in the visual snapshots (Figures 8.1 and 8.2) and suggests that these worlds have either converged to a stable state or have begun to converge.

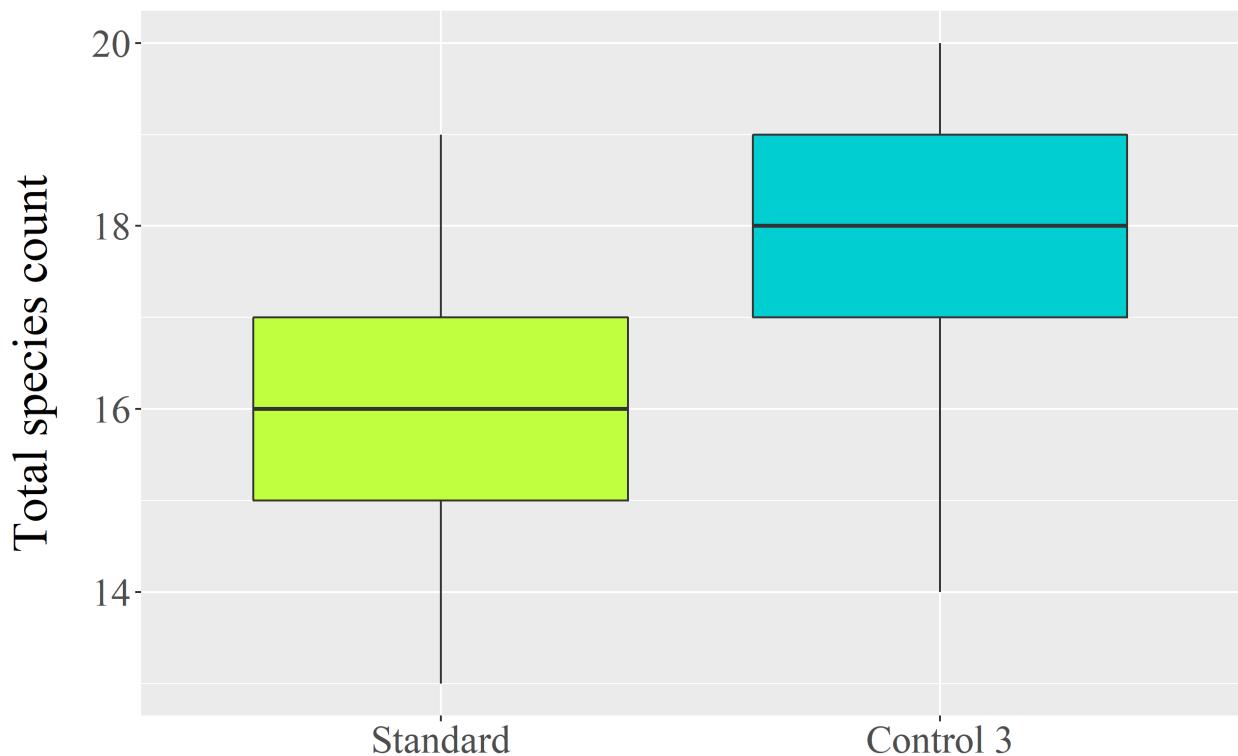


Figure 8.6: **Median total species, Control 3.** The number of species found in this world (18) is significantly different but only slightly greater than in the standard world (16; $p=0.01017$). Considering this result in tandem with the time of last new species emergence (Figure 8.5) indicates that a higher volume of species are found earlier in these runs compared to the standard world. However, this elevated degree of generativity is not sustainable.

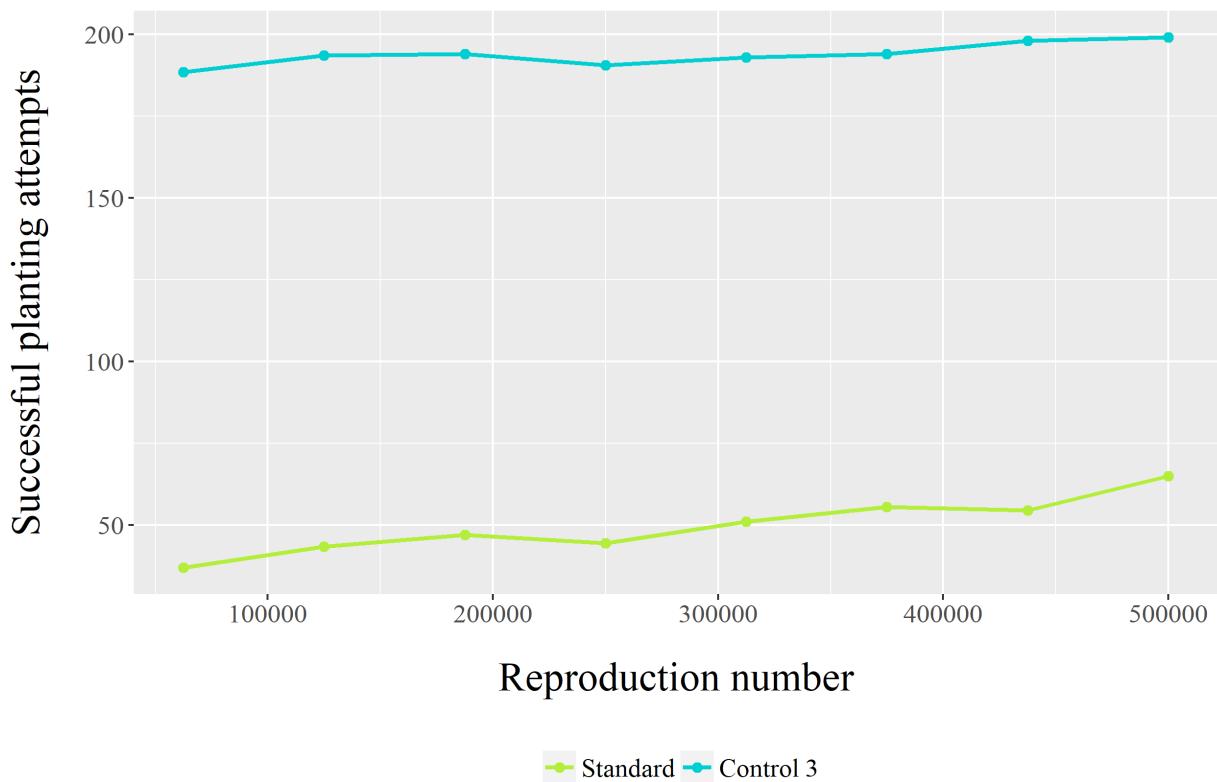


Figure 8.7: **Median successful planting attempts, Control 3.** These rates are atypically high because every individual is forced to attempt to plant once its location has been (semi-randomly) determined. However, a planting attempt can still fail if the individual is either placed in a location that is not adjacent to colors matching the individual's morphology or if the individual's heading is incorrect. Note that planting attempt success rates increase slightly as the runs progress and the world becomes visibly more homogeneous.

CHAPTER 9: SYNTHESIS: ASSESSING OPEN-ENDEDNESS IN CHROMARIA

The purpose of the experiments in the previous chapters is to test the validity of four conditions hypothesized to be necessary for open-ended evolution. While its definition is often the subject of discussion (Bedau, 1998; Maynard-Smith and Szathmary, 1995; Ruiz-Mirazo et al., 2008; Taylor, 1999), at its core open-endedness refers to a process that can in principle continue to innovate forever.

One of the challenges with open-ended evolution is to avoid conflating biological evolution (which is a specific instance of evolution) with evolution in general (which is an abstract process that could be implemented in many different domains). The properties and dynamics of biological evolution are not necessarily essential to open-ended evolution even if they are observed phenomena in nature. For example, concepts such as relative fitness, competition, and adaptation may be features of some specific instances of evolution, but they have not been hypothesized here to be necessary for all possible realizations of open-ended evolution. Because we are interested here in all possible realizations, these phenomena incidental to nature have been intentionally omitted from the proposed theory and methodology, leaving the set of necessary conditions for open-ended evolution as minimal as possible.

Open-endedness here means that a process lasts *approximately* forever. Somewhat more technically, exhausting an open-ended domain should be computationally intractable (possible in theory, but impossible in practice due to the finite nature of time). Turing (1936) famously proved that it is impossible to determine a priori whether a generic computational process will halt in a finite amount of time. Given the obstacles to formally determining that an evolutionary process will last forever, the most viable option so far in the field has been to examine the phenomenon in simulated

experiments.

The experiments with control 1 (wherein no minimal criterion had to be satisfied for a planting attempt to succeed) showed that there must be *some* minimal criterion, because otherwise evolution fails to produce any nontrivial innovations. Passive drift alone does not lead to innovations that are interesting (i.e. both novel and complex); if a system is to evolve open-endedly, it must incorporate some sort of selective pressure. However, the other implication is that we should be open-minded as to the implementation of such selective pressure and not necessarily default to modeling evolution as survival of the fittest (as many gradient-based evolutionary optimization algorithms do). Instead, it may be better to view evolution as “survival of the fit enough”, where “fit enough” is determined by the minimal criterion. These experiments with Chromaria show that an evolutionary process can indeed produce nontrivial innovations even in the absence of traditional competition-based fitness and selection pressures. In fact, a method for manually adjusting the difficulty of satisfying the minimal criterion turns out to be a useful tool for controlling the pace of evolution in artificial systems (Soros et al., 2016). However, it is only in the complete absence of any nontrivial minimal criterion that evolution completely collapses.

From the experiments with control 2 (wherein individuals were blind to each other), we learned that the innovations produced by prior individuals must be accessible to the current population to provide sufficient resources to fuel further innovations. That is, the current population must be able to interact with the successful innovative strategies of the past for their own potential innovations to be realized. While any particular individual may be innovative in its own right, greater novelty and complexity result from the interaction of many individual innovations.

By the same token, individuals will only continue to innovate if they are given the ability and opportunity to decide where to do so. In the experiments with control 3, the system as a whole shows signs of premature convergence when fixed rules and randomness alone determine individuals’

actions. When fully embodied and given a neural network controller, Chromarian behaviors were better able to adapt to an evolving world. Premature convergence to a “safe” state then becomes less likely because when it is less necessary.

There was a fourth condition hypothesized to be necessary for open-endedness: that complexity should have room to increase indefinitely. In principle, this requirement seems to be almost tautological. However, Chromaria proved unsuitable for validating this condition because morphological and behavioral complexity and innovation occur with a minimal genome size even without artificially restricting the size of the genetic encoding. However, while the Chromaria experiments do not empirically validate this condition, they instead show that there exist sufficiently expressive genetic encodings (such as CPPNs) such that only minimal resources are needed to represent complex behaviors and forms. Then, allowing these encodings to grow indefinitely (as many neuroevolution methods do) should in principle indeed allow complexity to increase unboundedly. Nevertheless, researchers can infer from the particular experiments with Chromaria that *in practice* sometimes a fixed-length encoding may be sufficient to support the appearance of open-ended dynamics at least for a sufficiently long duration of time that a dynamically growing encoding may not always be necessary, contingent on the aims of the experimenter. That insight is also a useful and perhaps surprising outcome of this study.

What we have learned about open-ended evolution in general is that its success requires a somewhat fragile synergy between multiple interacting components, and that if just one of the hypothesized necessary conditions goes unmet then evolution will stagnate. Thus it is clear that it will be important in future investigations to make sure that the major conditions are satisfied carefully before moving to more complicated hypotheses. Of course, it is possible that further conditions may be identified, and their interactions may add new layers of complexity to the current understanding, but at minimum it is safe to conclude that the presence of certain conditions cannot be ignored in any concerted attempt to investigate the phenomenon of open-endedness.

So, then, we address the question looming large over this whole discussion: Is Chromaria open-ended? The answer of course depends on what is meant by “open-ended”. As mentioned earlier, open-ended evolution researchers have moved away from a binary concept of open-endedness in favor of more continuum-based, and perhaps more nuanced, definitions. It is instructive at this point to consider how Chromaria may or may not overcome the various barriers to OEE defined by Dolson et al. (2015).

As discussed in previous chapters, there is reason to believe that each of the control runs fails to overcome either the change or novelty barriers of Dolson et al. (2015). Yet, what about Chromaria without artificial constraint placed upon it?

Chromaria clearly overcomes the change and novelty barriers as evidenced by the emergence of new species (marked by the successful planting of an individual with sufficiently novel color ratios) even in the later portions of a run. The contrast with the control runs further underscores this point. It is of course impossible to determine *a priori* whether a run will continue forever, but in the span of time in which it is possible to run experiments evolution appears to still be productive.

In considering the complexity barrier, it is perhaps instructive to consider what it would look like if a system *failed* to overcome the complexity barrier, meaning organisms hit a limit on the amount of environmental information they can incorporate into their genomes. Genome size in such a system might plateau, indicating that a ceiling has been reached. If genome size can serve as a proxy for complexity, then it is clear from the strictly decreasing controller genome size that Chromaria is not blocked by a complexity barrier. The explanation for the decreasing genome size is that CPPNs, the genetic encoding for individuals in Chromaria, are capable of representing an effectively inexhaustible (for the purposes of these experiments) space of viable Chromarians. Perhaps when even longer experiments are able to be undertaken, it will become possible to empirically investigate evolution’s ability to overcome the complexity barrier.

The ecological barrier is met when ecosystem diversity stagnates. It is clear from visually examining Chromaria snapshots that there are different kind of Chromarians in the world and, more significantly, that the population as a whole is changing. Overcoming the ecological barrier requires more than overcoming the novelty barrier, which simply requires that a new kind of individual (species) emerges at some point. Overcoming the ecological barrier requires that the population as a whole demonstrates some kind of innovation. Indeed, in Chromaria we see the population innovating, moving, and expanding its reach as illustrated in Figures 9.1 and 9.2.

Whether or not we conclude that Chromaria is open-ended, it is clear that evolutionary dynamics essential to open-endedness are adversely affected when any of the three testable conditions hypothesized necessary for OEE are not satisfied. It is also important to remember that the proposed conditions were hypothesized to be *necessary*, not *sufficient*. We should additionally remember that the goals of these experiments were not necessarily to positively observe open-endedness, but to validate a theory about what is necessary to even come close to achieving it. One of the tangible outcomes of these experiments is a predictive framework that can be applied to artificial life worlds and other evolutionary computation domains. By evaluating evolutionary domains in the context of the validated conditions, we are able to clarify the limits of these systems and then offer ways to increase their open-endedness.

We should also careful to note that while the experiments reported in this dissertation showed that the testable conditions are indeed necessary for open-ended evolution in Chromaria, they do not conclusively prove that this particular set of conditions is necessary for open-endedness in arbitrary evolutionary systems. However, remember that the conditions were written generally and not in terms of any particular evolutionary system (such as Chromaria, or even Earth). In terms of artificial life, it has already been established that achieving open-ended evolution is a holy grail for this particular research community. Constructing a domain-independent theory of open-endedness is progress towards the increasingly important goal of unifying the often disparate fields of the

artificial life community. It is our hope that these experiments with Chromaria are not the end, and that these experimental results might motivate testing the theories contained herein in other alife research areas, including more physically constrained domains such as “wet” alife.

Beyond validation

A nontrivial MC is necessary for continued evolution, but it is the “unnecessary” yet intentional behaviors enacted on the way to satisfying the MC that make things really interesting. This insight invites an important question: why not make interestingness itself constitute at least a portion of the MC?

Incorporating interestingness into the MC is promising because it identifies a particular location within the algorithm where it becomes possible to constrain search to those kinds of behaviors that we deem interesting. However, we must take into account that whatever we deem interesting must admit a wide breadth of behaviors from simple to complex (e.g. from single cells to human beings). That is, we want to be careful not to overly constrain the MC or we will not get anywhere (perhaps as a result of discarding simple but necessary stepping stones). If our goal is to generate gaits, for instance, we cannot simply filter out robots that only take one step before falling over because taking that one step is the foundation of more complicated behaviors such as running, jumping, and skipping.

Furthermore, even if it admits interestingness, the minimal criterion alone does not ensure open-ended proliferation of interesting behaviors. Comparing control 3 (wherein the function of individuals’ neural networks was replaced by a random movement scheme inspired by the artificial life world called Avida) to the standard world, it is true that individuals satisfied the same minimal criterion and reproduced. However, the standard world exhibited a much wider variety of possible

life forms and world states than the control world.

What would the world look like if creatures' movements were not random, but more rule-based? To answer this question, and to demonstrate the importance of this question in the context of artificial life, we might consider deterministic alife models such as L-systems (Prusinkiewicz and Lindenmayer, 1990) and Conway's Game of Life (Gardner, 1970). In L-systems, the evolution of a component of a system (such as a character in a string) is determined by the state of its neighbors. Conway's Game of Life implements this idea in a two-dimensional grid world, where the binary state (alive/dead, or black/white) of a single grid cell is a function of the state of its neighboring cells. Both L-systems and the Game of Life exhibit regular and repeating patterns, even if these patterns only repeat at large scales.

We could expect a similar outcome from a deterministic version of Chromaria (i.e. one in which movement rules are a function of either sensor field contents or colors surrounding an individual). In this world, the final state would be fully determined by initial conditions; only time and the limits of computational power would stop us from instantly skipping ahead to an arbitrary future world state. Evolution at least admits the possibility of surprise.

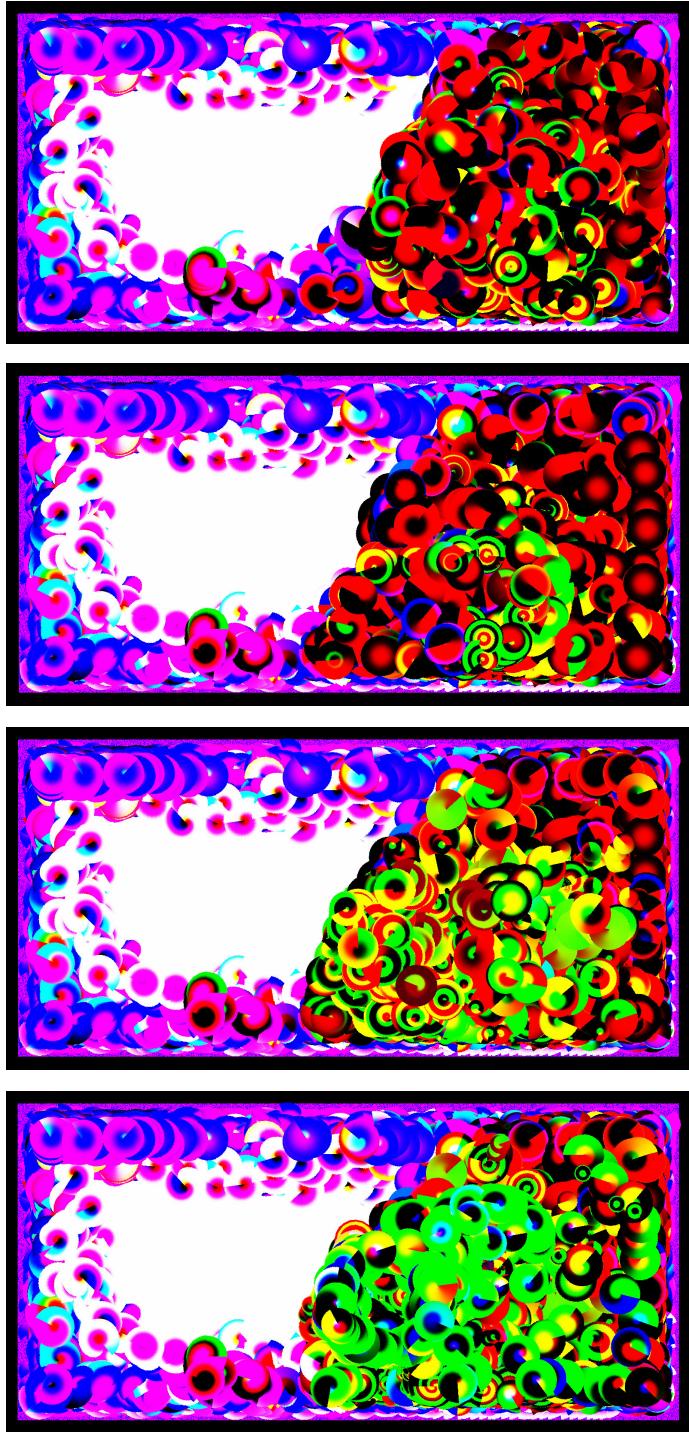


Figure 9.1: Snapshots from a single run of the standard world demonstrating ecosystem diversity. Small flashes of green on a few individuals at reproduction 150,000 lead to the emergence of primarily green Chromarians by reproduction 187,500. (Continued in Figure 9.2.)

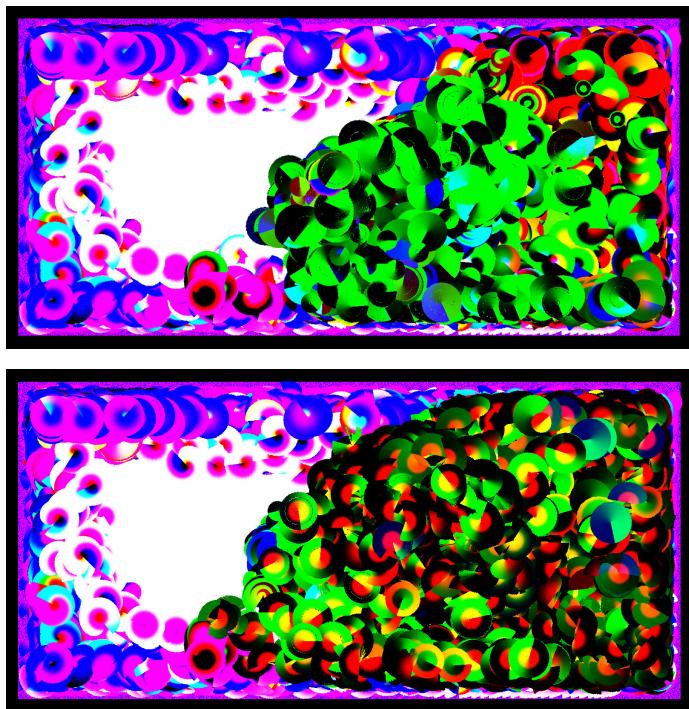


Figure 9.2: Snapshots from a single run of the standard world continued from Figure 9.1

CHAPTER 10: DISCUSSION AND FUTURE WORK

Chromaria is unlike any other alife world to date. One of its most useful and distinctive feature is that it was designed to be visually intuitive. While quantitative analyses can be performed to rigorously study its dynamics, an observer can also simply view the world to appreciate and understand general patterns and shifts that occur in the world. Visual feedback can also provide information about the experimental runs in real time, before post hoc run statistics are calculated. For instance, in the experiments wherein at least one hypothesized necessary condition went unmet and evolution collapsed entirely, a lack of visual change in the world indicated an obvious algorithmic pathology. Additionally, when all of the hypothesized necessary conditions were satisfied, runs differed from one another in terms of trajectory through color space, making it obvious to a human observer that innovation was still taking place.

It is also interesting that this outcome (that many of the standard run end states displayed starkly different colors, indicating unique evolutionary trajectories) was not obvious or predictable from the preliminary experiments reported in Chapter 4. This result, and specifically the disparity between the end states reached in the preliminary experiments and the full dissertation experiments, illustrates the necessity of running alife experiments for vast numbers of iterations. Chromaria was designed to be memory efficient so that it could run for a longer amount of time than alife worlds are usually run. Given that open-ended evolution is in principle supposed to last forever, it was important to test the hypothesized necessary conditions at the upper bounds of computational feasibility.

The results presented in Chapters 5 through 8 validated three of the four conditions hypothesized to be necessary for open-ended evolution: that a nontrivial minimal criterion is necessary for selective reproduction, that new ways of satisfying this minimal criterion should become possible as

new individuals evolve, and that individuals should control their own interactions with the environment. However, the results that validated these conditions also showed that Chromaria cannot offer empirical evidence to support the hypothesis that individual complexity must be able to increase without bound. Still, validating even one of the hypothesized necessary conditions would be a useful step towards a comprehensive theory of OEE because of the lack of any systematic empirical study verifying hypothesized conditions. The knowledge gained from this study is interesting because it can provide concrete suggestions for increasing open-endedness in a variety of different kinds of systems. It is different from previous works on OEE because there is an actual empirical study conducted instead of merely a theory proposed.

The theoretical knowledge gained through these experiments can inform the design of systems both in alife and outside of alife. To make this point clearer, the rest of this chapter explores implications of the conditions proposed and evaluated in this dissertation to nontrivial problem domains in the specialized area of alife, then also discusses the framework more broadly in terms of complex systems and computer science.

Implications for artificial life

As discussed in the Background chapter, demonstrating and understanding open-ended evolution has been an open problem for the artificial life community since the birth of the field (Langton, 1988). Though many alife worlds have been constructed with the aim of replicating open-ended evolutionary dynamics (Channon and Damper, 2000; Miconi and Channon, 2005; Ofria and Wilke, 2004; Ray, 1992; Spector et al., 2007; Yaeger, 1994), none have unequivocally demonstrated bona fide open-ended evolution. These worlds can potentially be made more open-ended by revisiting convergence-inducing design decisions illuminated by the proposed conditions.

For instance, consider the results from control 3 in Chapter 8, which showed that evolution in Chromaria became more predictable when individuals in the system could not decide for themselves when and where to interact with the world. Also recall that this control was inspired by design choices in the Avida digital evolution system (Ofria and Wilke, 2004), wherein new offspring spawn in a random location. To achieve more open-ended dynamics in Avida, the proposed conditions would suggest modifying the world such that position in the world is less dependent on fixed rules and chance. If the proposed conditions generalize beyond Chromaria, the evolutionary dynamics in Avida would be predicted to become more open-ended as a result of allowing individuals more control over their points of interaction.

An example of a different alife model that could benefit from the proposed conditions is the Swarm Chemistry artificial chemistry system (Sayama, 2009, 2010a,b). In Swarm Chemistry, individuals are simulated particles, each with different kinematic parameters such preferred speed and local perception range. Interactions between these individuals (which exist and move about in a finite 2D space) occur when they collide with each other, permanently changing the particles' kinematic parameters. Initial evidence that this system can be modified to target OEE is found in Sayama (2011).

It is also interesting and important to consider the impacts and applicability of this work on non-simulated alife domains. The systems covered in this dissertation so far largely encompass an area of alife called *soft alife* (Komosinski and Adamatzky, 2007) – alife systems that are implemented in software. However, software is not the only substrate for alife research. The two other main research areas are *hard alife* (Adamatzky and Komosinski, 2007), which encompasses hardware-based systems (i.e. robots), and *wet alife* (Bedau, 2007), which includes biochemical domains such as synthetic biology. Though these research areas perform experiments in vastly different media, they all aim to address the same questions fundamental to understanding the origins of life and the evolution of complexity.

Implications for complex systems

The implications of the completed experiments extend beyond artificial life; the question of what gives rise to open-ended evolutionary dynamics is an open question not just for evolutionary computation and artificial life, but for science in general. It is possible to apply the proposed conditions to domains outside of artificial life as well, as long as the domain can be described in terms of individuals and interactions between/among them.

Complex systems are defined by the fact that they cannot be understood in terms of individual units; the interactions between individuals must also be taken into account. However, sometimes these interactions are so intricate that they are difficult to represent as mathematical equations. Thus, as in Chromaria, creating a simulation that incorporates a minimal abstraction of the domain of interest and observing it over long timescales is often the most empirically sound strategy. These simulations, known as agent-based models (Abar et al., 2017; Bonabeau, 2002) have long been a useful tool for computationally studying the natural and social sciences. Though agent-based models are not necessarily evolutionary in the Darwinian sense (meaning they do not include one of the following: reproduction, inheritance, or variability), it is instructive to consider them in terms of individuality and interactions for the purpose of understanding how the proposed conditions could be applied to domains beyond artificial life.

In natural systems, including domains from the sciences such as biology and chemistry, “individuals” are often simple units that enact only simple behaviors. In chemical systems, the individuals might be molecules that can attach to other molecules (subject to rules about which attachments are valid). This organizational structure could be applied both to natural chemistry, wherein combination rules are determined by the laws of physics and electromagnetism, and artificial chemistries, wherein molecules or particles are simulated and combination rules are determined by a programmer. Rising to the level of biology, the notion of individuality is expressed intuitively as a plant,

animal, or other higher order life form. Interactions, then, can include a variety of behaviors including mating and resource consumption. The social sciences often make use of agent-based modeling as well to describe and simulate human systems. In the context of economics, for instance, individuals are people who interact with each other by buying and selling goods.

This list of systems that can be conceptualized in terms of individuals and interactions is of course not exhaustive. For instance, it does not include applied domains such as technological innovation and cultural innovation (the development of new art, music, fashion, etc). Technological innovation in particular has been proposed as a non-biological domain that evolves open-endedly (Taylor et al., 2016), with populations consisting of technology adopters, technology designers, technological innovations, and technological products. We might consider other creative domains this way too in the context of open-ended evolution, with creators and creations both serving as individuals that can interact with each other in domain-dependent ways.

The benefits of applying the proposed conditions to natural and artificial systems are threefold. First, analyzing whether such systems are potentially open-ended, or evolutionary, or both, can help validate whether the proposed conditions actually describe open-ended evolution or instead some other related class of process. Second, considering a variety of historically disparate domains from a unified ecological perspective may inspire new hypotheses about the mechanisms underlying those systems. Third, we will increase our ability to build simulations of these real-world systems, thereby improving tools for empirical analyses of these domains.

One particularly interesting research question is what mechanisms underly the human brain. Obviously the brain is made up of neurons, but other animals' brains are made up of neurons too. What is it about the neurons of the (typical) human brain that give it higher, or at least different, capabilities than other animals? More importantly, what processes caused the human brain to become different in this way? If the brain can be conceptualized in terms of individuals and interactions,

then perhaps the development of the brain can also be thought of as an open-ended process. In fact, Fernando et al. (2012) and Fedor et al. (2017), building on the work of Edelman (1987), develop a model to this end wherein neural firing patterns constitute individuals that combine and reproduce in a Darwinian fashion. It is possible that continued experimentation will deepen our understanding of human intelligence.

Implications for computer science

The question of whether a machine can think, famously posed formally by Turing (1950), lies at the heart not just of artificial intelligence, but at the heart of computer science. The main difficulty in answering this question lies in the ambiguity and underspecificity of the term “think”. “Thinking” generally denotes what intelligent people *do*, but it is nearly impossible to come up with a general yet precise definitions of what behaviors exactly intelligence encompasses. A reasonable concept of intelligence, implemented in computational processes or otherwise, should probably incorporate both focused problem solving and more open-ended creativity. Balancing the two characteristics is currently an area of significant interest in evolutionary computation. Quality Diversity algorithms (Pugh et al., 2016) in particular, reviewed in Chapter 2, aim to blend these characteristics optimally to solve problems outside the traditional realm of optimization problems. It is interesting, then, to consider how the proposed conditions can inform the design of evolutionary algorithms.

Different engineering applications may best be served by different degrees of freedom with respect to the conditions shown to be necessary for open-endedness. As such, the goal here has not been to establish a firm prescription for designing such systems but instead to provide at least somewhat of an understanding of how changing certain (sometimes implicit) variables affects the behaviors of the system being constructed. Instead, the framework should be thought of as revealing what *bad* design choices to avoid rather than prescribing a one-size-fits-all solution to computational

problems. The conditions are designed to be minimal, so one approach might be to experiment with relaxing design constraints to only reach that minimal threshold and then building out from there. Of course, this recommendation assumes that we want to maximize creativity. In fact, for most practical considerations there likely exists a continuum with convergence and optimization at one end and open-ended creativity at the other end. The extent to which you want to drive system design towards or away from the conditions specified in this dissertation depend on the aims of the domain, but both aims are informed by this work.

One application to consider is machine learning and artificial intelligence writ broadly. A common criticism of AI throughout its history is that there has not yet emerged a true “general” intelligence; intelligent systems are mainly built to achieve a single, specific purpose. This situation results from a few combined factors, but much like the goal of achieving open-ended evolution, the goal of open-ended artificial intelligence – AI that can continue to develop an arbitrarily large number of behaviors and capabilities that are both interesting and increasingly complex – has proven unexpectedly elusive.

It may be interesting to consider the recent emergence of deep learning (Bengio, 2012; Hinton, 2007; Hinton et al., 2006) as a popular methodology for artificial intelligence. Deep learning at first seemed to be, possibly, an important part of the solution to the problem of artificial general intelligence. Though the seeds of hierarchical processing schemes had been identified as important and useful (particularly in the context of image processing, mirroring the hierarchical organization of the visual processing pathways in mammalian brains) as far back as the 1960’s (Hubel and Wiesel, 1965), only recently, with the advent of cheap and high-performing GPUs, has it become possible for hierarchical models to process information on a large enough scale to really accomplish anything interesting. Deep learning models, using the same underlying concept of gradient-following training algorithms as the early connectionist models, suddenly began achieving previously impossible performance on classical pattern recognition datasets such as MNIST.

The past decade has seen an intense focus on machine learning models both in academia and in industry.

One area that has been particularly interesting to observe is style transfer (Gatys et al., 2016). Popularized by DeepDream (Mordvintsev et al., 2015), this class of algorithms is trained on a massive dataset of creative works such as art, music, or writing and then the model learned by the system is used to compose “new” works in the style of the works in the training set. The products of these systems have certainly been amusing. However, once you have seen one plate of spaghetti grotesquely deformed into a dog with too many eyes, you have effectively seen them all. The main problem with DeepDream, and with most convergence-oriented machine learning systems, is that once the model is trained, new *kinds* of transformations are not possible. There’s no real creativity here. However, just as divergent search algorithms such as novelty search (Lehman and Stanley, 2011a) challenged and improved upon the gradient-following paradigm in the domain of evolutionary algorithms, perhaps it is similarly possible to reconsider deep learning systems in the context of OEE to make them more creative.

The field of digital entertainment seems particularly able to benefit from studies of highly productive generative processes, as evidenced by the promise and then disappointment of the 2016 video game *No Man’s Sky*¹. The game was advertised as a space exploration game so large that no player could ever explore the entirety of the universe. The main problem was that, while impressively large, the environments created by the (procedural) generation system were repetitive riffs on the same general theme. What people hoped for with respect to that game was what many of us want from life: a seemingly endless source of novel experiences. We do not want to be bored, subjected to the trivial, the totally predictable, the mundane. At the same time, we do not want chaos and we do not want things to change too abruptly; we want things to make sense when considered

¹Copyright ©2016 Hello Games

in hindsight. We want to be able to construct a cohesive narrative around our life experiences. A validated set of necessary conditions can potentially guide the design of games like No Man's Sky so that they can be truly open-ended.

Evolution offers a unique and paradoxical combination of controlled constraint while also being out of our control. Implemented in nature, it has demonstrated the capacity for unparalleled breadth of creativity at scale. Of course, evolution is not the answer to every problem, and many problems are solvable with much simpler and more controllable methods. For instance, procedurally-generated systems were instrumental in expanding the scope of early video games such as *Rogue* and *Elite*², which were highly constrained in terms of physical memory and as a result used mathematical functions to reliably and deterministically generate consistent environments on the fly instead of having to store them in persistent memory. The claim in this dissertation is not that evolution, open-ended or otherwise, is a panacea for computer science. However, for a certain class of very interesting problems requiring some degree of creativity, evolution seems uniquely capable of success where other algorithms have proven ineffective.

There has of course been continual discussion over the years about whether a computer can even be creative in the first place (Boden, 1990; Colton and Wiggins, 2012; Jefferson, 1949; Turing, 1950). These discussions ultimately reduce to a debate over whether or not humans are fundamentally special in some way, which is outside the scope of this dissertation. What is more salient to the discussion of open-ended evolution is the fact that no creative AI has thus far produced artifacts that are sufficiently interesting, novel, and complex to put an end to this debate.

It should hopefully be clear at this point that the questions of open-ended evolution (in artificial life), artificial general intelligence, and computational creativity are different flavors of the same fundamental question about the limits of computational processes. The recent successes (and

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shortcomings) of deep learning highlight the importance of hardware, independently of algorithmic innovations, on our ability to answer from a computational perspective the big questions about ourselves and the world we inhabit. AI research serves many purposes for many people, and one of those purposes is not just to achieve human-competitive performance on some task but to understand (as a result of building such a system) something about the black box of ourselves, our minds, and our experiences.

As stated at the beginning of this dissertation, the experiments summarized herein are not about biology even though they focus on evolutionary dynamics. In fact, the results speak to a canonical problem not just for artificial life, but for computer science in general: is it possible to construct a process that never ends? Exploring the question of what components might be necessary for an open-ended process with an empirical methodology has required exploring the limits of modern computation. The question of what makes certain processes tractable versus intractable, regardless of the domain, is a question at the heart of computation theory and it is exactly that question that this dissertation speaks to. It just so happens that the particular class of processes explored in this dissertation are inspired by biology.

While Chromaria may not implement the same level of scale as Earth, performing experiments in a systematic way still allows us to explore questions about both life on Earth and creative processes in general with tools beyond pure speculation and theory. In a sense, the core issue addressed by this dissertation is what evolution *is*. It does not always serve as an optimizer, nor does it intentionally reflect and design. Instead, it meanders. It ignores what does not work and otherwise stays open-minded. It is an intrepid adventurer, always blazing trails through the unexplored. Understanding open-ended evolution informs our understanding of life, and though the completed experiments may not be the final word on this understanding, they are a much-needed stepping stone along the way. While limited by the current state of technology, it is important to recognize that we have at our disposal tools that were not accessible to Darwin, Turing, and the other revolutionaries

whose ideas laid the groundwork for the research being done today. While we might not be able to answer these questions definitively at present (insofar as we ever will), we can certainly make some progress with what resources we have.

CHAPTER 11: CONCLUSION

This dissertation described the first scientific endeavor to systematically test an OEE framework in an alife world and thereby contribute to the solution of an unsolved mystery about evolutionary systems. It first (1) enumerated a set of conditions hypothesized to be necessary for OEE and (2) introduced an artificial life world called Chromaria that incorporates each of the hypothesized necessary conditions. It then (3) described a set of experiments with Chromaria designed to empirically validate the hypothesized necessary conditions. The results of these experiments supported the hypotheses that open-ended evolutionary systems must implement some minimal criterion for reproduction, must allow opportunities for new ways of satisfying the minimal criterion to be created via interactions between individuals, and must allow individuals to control how and where they interact with the world. These results advance the field of artificial life toward its long-standing goal of finally developing an empirically validated theory of what is necessary to implement an open-ended evolutionary process in a computational domain.

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