# Creativity Evolution in Simulated Creatures: A Summary Report

Hrafn Th. Thórisson & Kristinn R. Thórisson

h.thorisson@gmail.com, thorisson@ru.is

Center for Analysis and Design of Intelligent Agents
& School of Computer Science
Reykjavik University

**Reykjavik University – School of Computer Science**

## Technical Report

**Abstract**

This report summarizes work on a research framework for studying the evolution of human and animal creativity. The work has resulted in a method for quantifying creativity, a simulation apparatus for constructing complex, deterministic, evolving worlds, and a methodogogy for exploring the mechanisms of creative behavior in simulated creaturs. The theoretical foundation of the framework is also described, including the relationship between creativity, randomness and logic. The primary questions addressed in the first steps of this work are the relationship between environmental complexity and the evolution of cognitive mechanisms underlying creative behavior, and to what extent creativity is bound by rules embedded in the environment in which cognition evolves.

Keywords: *Creativity, Intelligence, Intelligent Agents, Artificial Intelligence, Emergence, Simulation, Evolution, Autopoiesis, Deterministic Systems, Cellular Automata, Complexity*

# 1   Introduction

Through creativity the human race has learned to build complex technology far beyond that of any other species on the planet (Figure 1). However, the scientific study of creativity, as a feature of both natural and artificial intelligence, has a spotty history. Although creativity is an enormously important aspect of our existence, few artificial intelligence (AI) studies have been directly aimed at understanding the general underlying mechanisms of creativity. The field of AI has so far been focused on logic as a foundation of intelligence, resulting in creativity often being considered a by-product of logic. Creativity is, in short, generally perceived as the ability of an intelligent system to invent things. Since one can invent important, impressive, idiotic and irrational things, it stands to reason that creativity is not a Boolean feature, it comes in shades of gray. Where logic and intelligence go together there is room for creative thought: Only with non-obvious, deep insight can the hardest problems be solved. It is these types of insight that are generally referred to as "creative".

Exploring cognitive mechanisms in animals is difficult for the simple fact that it is hard to elucidate their cognitive processes. Complex processes underlying intelligence cannot be readily explored in natural animals – and thus neither the evolution of the mechanisms involved. Artificial intelligence presents an optional approach to gaining a detailed understanding of intelligence.

The original goal of this project was to explore ideas about the relationship between environments with emergent properties and evolution of creative tendencies in species. This resulted in a series of follow-on projects that included both experimental and software development efforts. One result is the creation of a simulation platform for use in studying the relationship between evolution and environmental complexity (each of the points are discussed in more detail in the appropriate sections below):

- *Cellular automatons as environments.* Traditional explorations of agents in cellular automatons have been carried out by having the cells themselves represent the agents (e.g. Conway's Game of Life [Berlekamp et al., 2001]). The approach taken in this project is to have cellular automatons represent emergent environments for a close estimation of our own, real environment in which organisms evolve. This approach is new, and cannot be found in similar research.

- *Abstract cell architecture.* The Vélaldin engine uses cellular automatons as a foundation for producing emergence. The cells, however, are architectured in a unique way which allows them to take virtually any form and features. We have named this design the Vélaldin Extended Cell Architecture. Details on this framework are given in the Appendix.

- *Methods for measuring environmental complexity.* By varying the rules and number of different kinds of patches, the diversity of the environment can easily be measured since the variation of patches and the number of their rules constitute the worlds complexity/diversity. This approach is entirely new to complexity measurements, and to cellular automata research.

- *Methods for measuring creativity.* The methods of measuring creativity presented in this project are based on the presented theory of creativity and offer a completely new approach to studying and understanding the roots of creativity.

- *Vélaldin Emergence Engine as a cognitive system.* The abstract cell architecture of the Vélaldin engine opens up possibilities of using the engine itself as a creative cognitive system. This concept requires further exploration and is not detailed in this report.

In this report we thus summarize our work done to date that uses simulation to explore the morphogenesis of creative behavior and the cognitive skills underlying it [Thorisson, 2004]. To this end we propose a formalization of complexity, based on cellular automata, to compare the effects of evolution on the cognitive skills of simulated creatures whose cognitive capacity for solving problems is controlled by genetic algorithms. According to the formalism, causal chains are represented with rules: A large world with many possible states – both local and global – is more complex than one with few states and few causal mechanisms. We have used this to compare the emergent cognitive skills of simulated creatures as a function of their environment. The results so far indicate a connection between the cognitive skills associated with problem solving chosen by evolution and the complexity of the world.

This paper is organized as follows: First we discuss the background for this work, related research, and the hypotheses that we have proposed for the relationship between creativity and environmental complexity. We then describe the world, the creatures we implemented and the experimental setup.



Figure 1: Comparing creative constructs from animals to those of humans. The human constructs on the right are perhaps not considered prime examples of creative output, yet are based on numerous creative insights without which they would not exist. Compared to some of the structures considered very creative in the animal kingdom the difference in creativity becomes obvious. Notice that the constructs on the left are by two distinct species, the ones on the right by the same one.

Finally, we present the results of two simulation runs. The Appendix details the software platform developed for this work.

## 2    The Phenomenon of Creativity

In ultra high-dimensional problem spaces such as Earth's nature, solutions to a vast majority of an individual creature's problems are non-obvious; to solve them requires some amount of creative behavior, and creativity requires the coordination of a number of mental faculties. Runco's [Runco, 2004] review of creativity research covering the past 20 years mentions many processes studied in cognitive sciences including memory, knowledge, attention, tactics, strategies, metacognition and many other intellectual skills. It seems that creativity affects behavior to such a high degree that it is difficult

to discern the difference between it and what we would (intuitively) call "intelligence" — the skills needed to guide everyday behavior of animals in a natural environment. This would include for example the skills that enable an animal to make plans for survival in a given environment. Considering the high number of cognitive features that creativity has been associated with, it has been suggested – and indeed seems likely – that creativity is not a specific (sub-)mechanism of the brain but rather an aspect of human intelligence in general [Boden, 2004].

By 1988 over 50 different definitions of creativity had already been proposed ([Taylor, 1988]). A common thread among many of them is a primary distinction between creativity displayed in an artifact (e.g. poems, paintings, architecture, music) and processes that might result in a creative product [Gero, 1996]. The characteristics of "creative" artifacts are generally considered to be (1) novelty, (2) unconventionality or unexpectedness, and (3) value of the product (value to whom remains undefined). These have often been the pillars from which creative artifacts are evaluated (c.f. [Boden, 2004], [Wiggins, 2006], [Gero, 1996], [Liu, 1996]).

Some attempts have been made to explain the origins of creativity in terms of evolution (most of which are presented in relation to human creativity), and it has been suggested that exploring creativity's evolutionary roots might give us a holistic picture of how and why it emerges in relation to other processes (c.f. [Gabora, 2005], [Thorisson, 2004]). Carruthers [Carruthers, 2002] has proposed that the function of the extensive creative play of children, also evident in the behavior of other mammalians where the young engage in pretend-play such as hunting and fighting, is to train the young in imaginative thinking for use in adult activities. Again we see attempts to explain creativity in the context of mammals. If we could study creativity in simpler animals, even such as insects, perhaps the pursuit would become easier.

Since evolution is responsible for producing all natural intelligence the same will be true of *creative behavior*. The environment will have had an impact and may possibly have left an imprint – a reflection of itself – in animals' potential for creative behavior. Whether this is the case there are, at the very least, reasons to believe that the nature of the environment for an evolving species will have a tremendous effect on the evolution of the species' behavioral repertoire; that it will to a large extent be responsible for producing the potential for creative behavior in the species as a whole, and expressed in each individual.

Our stance is that creativity is *a necessary component of intelligent behavior*, that *in order to be intelligent* a system will *necessarily* harbour skills that we would categorize as "creative". The strong view along this line of thought states that for a system to be intelligent it **has to be creative** – that creativity is in fact as a necessary component of intelligence. Should one choose this view, the study of creativity in nature is simply a different take on the study of natural intelligence.

Compared to other animals humans are cognitively complicated. However, our tendency to associate creativity with (extraordinary) human abilities is undoubtedly too strong: If creativity is tightly coupled with intelligence the notion must be entertained that creativity will also play a role in the intelligence of simpler animals. This has proven to be the case. Beavers, birds and squirrels, for example, have all shown a propensity for creating physical constructs. Going even further, crows have exhibited an ability to for bend strings of wire into various shapes to use as tools for retrieving food from places that are difficult to get to ([Weir and Kacelnik, 2006]). Research indicates that this is a true skill — the crows did not solve problems by repeating previously learned patterns but rather by generating new plans to solve each specific problem, using higher-level abstractions of the problem space. When humans do this we refer to the behavior alternatively as "intelligent", to some level, or "creative", to some level. If creativity is a phenomenon evident in all intelligences creativity's evolutionary roots must be tightly related to the evolution of planning mechanisms, e.g. as used by the crow to retrieve food.

Despite simple nervous systems, insects apply different strategies to identify landmarks, detect objects, and plan courses of action. They are not mere reflex machines, but instead use memory, evaluation methods, and perceptual mechanisms, including the detection of geometric shapes and route-segmentation, to function in their environment, depending on previous experience [Giurfa and Menzel, 1997] [Collet and Collet, 2002]. Some might find it difficult to accept that insect behavior has anything to do with creativity, and to our knowledge there have been no serious attempts to shed light on creativity in terms of simpler animals than mammals. However, exploring the general concept of cognition in animals lower in the phylogenetic tree has gained some attention in recent years [van Duijin et al., 2006].

Godfrey-Smith [Godfrey-Smith, 2001] recently proposed that cognition evolved to cope with environmental complexity, and Maturana and Varela [Maturana and Varela, 1973] introduced theories of the origins of cognition with the concept of autopoiesis; a network of component-processes that perpetually generate themselves.

In the following work we assume the following general definitions:

(i) *Creativity* is an agent's ability to vary and adapt processes in order to fulfill its goals. Processes can be internal (mental functions), or an externalization of internal processes (physical actions and interactions with the environment), where an agent is a living or autopoietic agent, be it organic or artificial. Creativity is a third-party's judgement of the agent's behavior in the context of its environment. Creativity can be exhibited by an agent without it explicitly understanding the environment and without necessitating existence of internal goals in the agent.

(ii) *Logicality* is an organism's ontogenetic ability to produce actions which are coherent with the organism's goals and structural organization of the environment. Environmental organization imposes itself on organisms as they evolve and is reflected in logical behavior; insanity is the inverse of logicality, resulting in behavior which is not relevant in the context in which they are realized, failing to fulfill the agents' goals and are consequently illogical or nonsensical. Creativity exists in the space between that which is (easily and obviously) logically deducable and that which is truly random. No creativity is without logic; randomness is not creative. According to our view, even basic logical behavior is creative, only to a minimal extent.

# 3   Operationalizing Creativity

Goal-directed creativity as especially evident in humans is generally very hard to measure since it is expressed in such highly diverse manners. By giving simulated creatures a single goal – that of survival – new behaviors can be directly related to that particular goal, and hence, be operationalized and measured as simply the longevity of the creatures. The number of distinct plans in memory at the time of death, produced to fulfill that goal, can also be measured to further quantify creativity.

According to the hypothesis that creativity is governed by environmental diversity, creatures in complex, rule-driven environments should evolve to become noticably more creative than those who evolve in simple environments (as judged by the measure of creativity proposed above). Creatures who have a goal to surive in a world will evolve abilities to make plans for survival: this could include, for example, eating food and avoiding poison. If the world is simple and static enough the creatures will evolve plan making mechanisms that produce plans of limited variability (perhaps only capable of producing a single plan). For complex, dynamic worlds, however, the individuals will not be able to produce standardized plans for every potential life-and-death situation. Instead of evolving simple mechanisms focused on particular types of plans, and passing these on between generations, these creatures will have an evolutionary pressure to evolve generalized l *plan-making skills*. For creatures in dynamic worlds, repetitive behaviors are thus less likely to persist between generations. In other words, creatures evolving in dynamic worlds will produce cognitive mechanisms able to exhibit more creative behavior.

## 3.1   Environmental Complexity

Before we can define creativity we need to define the complexity of the environment, as this, according to our model, is key to the development of creative behavior. We use a cellular automaton ([Wolfram, 2002]) to define the world of the creatures. Cellular automata (CA) are discrete, dynamical systems which have been used frequently in research on artificial life (ALife). The term refers to discrete dynamical systems in which patches or cells on a grid layout are given local rules to abide ([Wolfram, 2002]) – these rules provide instructions as to what state a cell should take depending on its neighboring cells. Typically in such work the emergent organization of the cells themselves result in agent-like behavior, i.e. the cells are programmed to organize themselves to form patterns which behave like creatures [Anthony et al., 2004].[1]

---

[1] The work of Anthony et al. [Anthony et al., 2004], [Anthony et al., 1998] is a good example of these kinds of artificial life simulations. In this prior work the lifeforms that emerge are fairly primitive – allowing a very limited

By varying the rules and number of cell types/states in the CA, the diversity of the environment's behavior can be scaled in complexity: Increasing the number of possible cell states and ruleset results in a wider range of possible patterns and variations. The combined cardinality of cell and rule types controling their states can be used as a quantitative measure of a world's diversity. As the rules are explicitly represented we can thus quantify the complexity of different environments and compare them in a consistent way. Formally, we define a single rule as:

*rule := a set of conditions that can cause a cell state transition*

As each rule, by this definition, represents a cell's potential for interaction with other surrounding cells, this can be used as the basis for an estimate of the behavioral complexity of a world: The worlds complexity is quantified by cardinality of (a) the total number of (perceptually distinct) possible cell states ($C$) and (b) the number of rules ($R$), using the above definition, that controls the state transition of the cells. At this point we do not quantify the rule complexity (which could of course be arbitrarily complex) but instead keep all rules at one or two IF-conditions at most.

We define a Complexity Quotient ($Qc$) for quantifying world complexity as:

$$Qc = RC \qquad (1)$$

where $C$ represents the number of simultaneous cells perceivable by a creature and $R$ the number of rules pertaining to these cells. $Qc$ represents a continuous scale of complexity, from simple to complex. At the low end we have one rule and two possible and perceivable cell states (a single rule would prevent cyclical transitions); at the high end we have (apparent) noise.[2] For our purposes the interesting complexity level lies somewhere above 2 and below 20 – in this range one can easily see that gradual increases in $R$ and $C$ gradually increase the visual complexity of the resulting patterns.

A more comprhensive version of forumula 1 would include the size of the area that enters into the rules, i.e. the number of neighbouring cells whose states can enter into determining each cell's next state ($N$):

$$Qc_2 = RCN \qquad (2)$$

This modification produces a somewhat more accurate estimate of the emergent complexity of the world. Other improvements are certainly conceivable; however, these were not deemed necessary for the purposes of the present work, and in fact our experiments were done using the simpler version of this equation.

## 3.2   Plan Complexity

A series of logical decisions is what we typically call a "plan". Before the decisions in such a plan get executed they are "merely steps in a non-executed plan", after they are executed they are part of a fully or partially "implemented plan". A plan which achieves its intended results is a good plan; a plan which does this while being non-obvious (to produce and/or execute) is more "creative" than one that is more obvious.[3] In a world where a creature produces more offspring if it lives long has an evolutionary bias for longevity; plan-making capabilities which enable creatures to live longers are thus selected for. Longevity can thus be used as a measure of the goodness of the plans produced by the creatures – and by extension their plan-making mechanisms. According to our view creativity is not a binary or a semi-binary feature: Creativity is a continuum, where an increased ability to solve problems is evidence of increased creativity. As plans become more complex they become less obvious – the relative complexity of the plans made by a species, therefore, can be used as a measure of the species' creativity.

---

spectrum of association with higher functioning organisms. This is because most approaches limit the *whole system* to a CA framework, explicit rules governing everything. The work presented here should not be confused with ALife work based solely on CAs; our "agents" are not cells but rather fully-simulated creatures inhabiting a CA world.

[2]At the noise end there are, of course, underlying rules, as the changes would still be driven by the rules, but at say 1 million rules we could probably not detect any regularity with standard methods of pattern detection such as autocorrelation or other known pattern analysis methods.

[3]In this sense, how "creative" a plan is is certainly a relative concept.

Daily usage of the concept of creativity does not typically involve a comparison between species but rather a comparison of individuals of the same species. When we do this we typically use the results of executed plans – artifacts – as the basis on which to make this comparison. However, equating creativity with plans (or the results of executed plans) means that we have a basis to compare *creative potential* between species. In our simulated creatures we have formalized this as the difference between species evolved in worlds of varying complexity. Creativity is defined as the ability of the specie's creatures to make plans for survival. Meta-planning, i.e. the use of complex rules or mechanisms to generate plans, can produce plans more creatively than e.g. a method that siply copies and/or mutates old plans. A species where offspring inherit *plan-making mechanisms* has evolved more creative planning mechanisms than one where offspring inherit a set of static or semi-static plans – the plans *themselves*.

## 3.3   A Measure of Creativity

Given the above operationalizations of environmental complexity and plan complexity, the ratio between environmental complexity ($Qc$) and plan-making capability ($Cp$) is proposed as a definition of creativity:

$$Mc = \frac{Cp}{Qc} \tag{3}$$

where $Mc$ is our measure for creativity. Since creativity is always relative to the complexity of the task at hand, which is always bounded by the possible complexity of the world, we must take the environment into consideration in measuring creativity. (The assumption here is that simple environments do not need to – and thus will likely not – result in high levels of creativity.) The above definition assumes that the creatures perceptual abilities are held constant; clearly a more complex measure could be proposed where variable perception can be accomodated (see Discussion).

We operationalize plan-making capability $Cp$ as the fraction of complex plan-making methods over simple plan-making mechanisms:

$$Cp = \frac{Pc}{Ps} \tag{4}$$

where $Pc$ is the relative (and average) use of complex planning methods and $Ps$ is the relative (and average) use of simple planning methods.[4] As the creature uses more complex methods for planning $Pc$ increases, as does the Creativity Measure $Mc$, for a constant-complexity world.

## 3.4   Hypotheses

All non-reactive animals (e.g. mammals) have mechanisms for dynamic planning. What we count here as the basic "creative artifact" is a *plan*; more specifically, a plan for survival. Creativity's roots, according to this line of thought, derive from the interaction of the environmental structures and their sub-parts: Unless the interactions of these structures are obvious to the organism (via some fairly direct transformation of readily-available environmental patterns or signals), and thus easily perceivable and relatively repetitive, evolution must provide creatures with a cognitive system capable of producing diverse behavior in response to the diversity of the environment. As the unpredictability of the environment increases – as the interactions between the causal chains in nature – become so complex that causation is hidden from direct perception the creatures must evolve an ability to mentally represent and link unobvious causations.

In our simulation, the agents evolve to learn to predict the environment. They do this by generating random action plans to begin with, and over a lifetime, learn to associate the correct plans/actions to the various perceptual stimuli. A more complex world has two major implications for the agents: The diversity of perceptual stimuli greatly increases, meaning that the domain of plans with which the agents can associate perceptual cues increases. Secondly, as the environment is not highly repetitive,

---

[4]We propose to measure the average plan method usage for the total individuals in the Xth generation that is chosen for measurements.

the agents must produce behavior to meet this diversity, exctracting the invariants, yet classifying them and grouping them such that different different problems call up different plans and produce different behaviors. With respect to this relationship between the environment and plans it can be said that *the plans reflect the architecture of the environment.* Over time, evolution provides the agents with mechanisms to produce plans (without evolution having direct control over the plans themselves). Over the lifetime of a species, therefore, these mechanisms become increasingly fine-tuned to match the specific circumstance and reflect the environment more accurately. If the plans are not coherent with the specific circumstance they are selected and executed in they fail to comply with the agent's goals and are therefore illogical or irrational. It can consequently be stated that logic and rationality is bound in the coherence of the plans (behavior) and the goals (or environmental conditions) that the plans are intended to fulfill.

Our background hypothesis in this work is thus that

> *the evolution of mechanisms behind creativity are directly related to the complexity/diversity of an emergent environment: The co-evolution of creativity and external environmental logic could result in internal "visualizations" (imagination) that arrange components and structures corresponding to the structural "rules" of the environment.*

From an evolutionary perspective it can be assumed that, with increased complexity, natural organisms evolve more advanced methods of prediction, allowing them to represent structures internally and simulate or imagine environmental events. An internal representation of an emergent structure enables a deeper understanding of that structure, and hence, a more accurate prediction and increased chance of survival. Understanding can be equated with that of explanation ([Baas and Emmeche, 1997]). To be useful these simply have to produce a prediction that then can be verified or falsified by the creature via its actions in the world. Over time the predictions start to more closely match reality, and we say that the creature has learned to "understand how the world works." Nevertheless, in order to continue to be equipped to expand its mind to a wide array of phenomena, the creature's mind needs to continue to be "imaginative" – otherwise the creature's mind would become increasingly less capable of adapting to new situations and contexts. We thus theorize that

> *creativity is evolutions answer to perceptually apparent unpredictability: As a particular perceptually recognizable pattern is presented, the creature comes up with "stories" about how this pattern can be "disected" – and subsequently tests these stories, to see if the disection hypothesis holds up.*

As the creature gains in experience it collects evidence about how particular disections – essentially models of causal chains – relate to certain patterns; these causal chain models then become increasingly more easily and directly evoked as the creature gains more experience and the context-model pairings become more robust. One way to see this is that the causal models that once were "wild fantasy" in a creature's head become "reality" with experience. Perceptual unpredictability is different from some hypothetical or "actual" unpredictability - the discussion here revolves around predictability from the standpoint of a situated individual creature, perceiving the world in particular circumstances, via its particular perceptual apparati and cognitive faculties: As it is an *individual's* probability of survival that determines its chances of producing offspring, it therfore also determines a species' chances of survival.

> *We assume that the **complexity** of the environment and an organisms ability to **perceive** environment are equally important aspects of the evolution process of a species, since varying complexity of the environment will make no difference if the members of the species are unable to perceive the variation.*

Given creatures with different kinds of planning mechanisms, the complexity of the planning should vary with the complexity of the world that the creatures evolve in: Given a relatively high $Qc$ (i.e. worlds with more complex underlying rules) we should see more reliance on complex planning methods; lower $Qc$-worlds should see lower $Pc$ and higher $Ps$; i.e. given a set of plan-making capabilities, $Cp$, the simpler ones will suffice for simpler worlds and more complex ones will be required for survival in more complex worlds.

# 4   World Implementation

Our worlds are thus a 2-D cellular automata where the cells – or patches – represent physical phenomena such as grass and rocks. The rules are evaluated and the whole world is reset per cycle, upon which the state of a patch could change; for example, grass grows and dies according to preset rules of interaction between patches. An important aspect of using cellular automata in this work is that the patterns expressed by the creatures' environment are based on regularities controlled by explicit underlying rules. Even though the rules for each type of patch are unknown to an observer that inhabits the world all regularities in the environment's behavior are the result of interaction between rule-based patches, completely deterministic, and a part of this regularity is visually inspectable at any point in time by the creatures' sensors. Using as few as five or six rules can nontheless produce relatively complex environmental behavior without losing the determinism and logical results in terms of the world's overall behavior. Rule examples used in the following experiments can be found in Table 1.

While the modification introduced in equation 2 (above) produces a somewhat more accurate estimate of the emergent complexity of the world than equation 1, in the present experiments we are only comparing three fairly distinct levels of compleixty and the difference in accuracy does not matter for the questions under consideration. We therefore use formula 1 in the following experiments.

| Simple World ($Es$) $Qc = 18$ | Complex World ($Ec$) $Qc = 91$ |
|---|---|
| <ul><li>If EATEN: turn BROWN</li><li>If GREEN and green patches around $> 20$ and lifetime $> 30$: turn BROWN.</li><li>If GREEN and green patches around $< 12$ and lifetime $> 20$: turn BROWN.</li><li>If GREEN and number of green patches around $= 25$, turn BROWN.</li><li>If GREEN and lifetime under any circumstance $> 60$: turn BROWN.</li><li>If BROWN and green patches around $> 8$ and their lifetime combined ¿ 80 and brown patches around $> 10$: turn GREEN.</li><li>If GREEN and lifetime $> 53$: turn DARKBROWN.</li></ul> | <ul><li>If EATEN: turn BROWN</li><li>If RED and lifetime $> 15$: turn BROWN.</li><li>If GREEN and green patches around $> 23$ and lifetimes $> 30$: turn MAGENTA.</li><li>If GREEN and green patches around $< 12$ and lifetime $> 20$: turn BROWN.</li><li>If GREEN and red patches around $> 6$: turn RED.</li><li>If MAGENTA and lifetime $> 30$: turn YELLOW.</li><li>If MAGENTA and lifetime $< 30$ and brown patches around $> 19$: turn GREEN.</li><li>If BROWN and green patches around $> 6$ and brown patches $> 10$ and their combined lifetime $> 25$: turn GREEN.</li><li>If DARKBROWN and magenta patches around $> 4$: turn YELLOW.</li><li>If DARKBROWN and green patches $> 6$ and dark brown patches around $> 4$: turn RED.</li><li>If YELLOW and lifetime $> 30$: turn MAGENTA.</li><li>If YELLOW and lifetime $< 50$ and magenta patches around $> 8$: turn BROWN.</li><li>If YELLOW and lifetime $> 70$ and brown patches around $> 19$: turn GREEN.</li></ul> |

Table 1: Rules of the example worlds shown in Figures 4a and 4b, Simple ($Es$), and Complex ($Ec$), respectively.
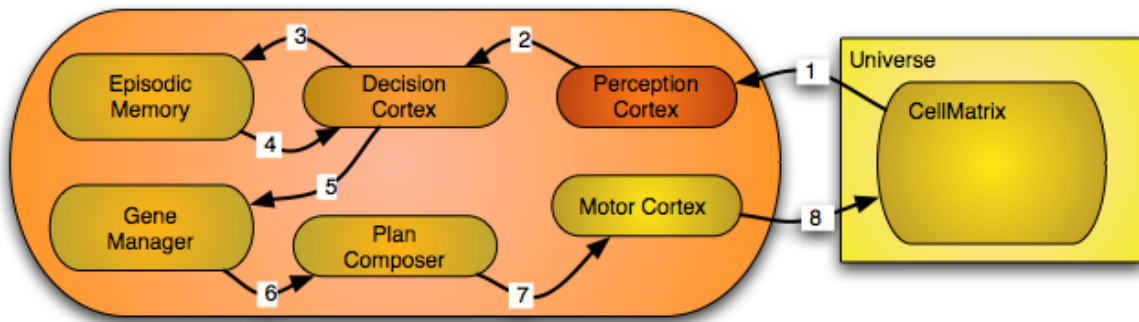
Figure 2: Creature components.

# 5   Creatures

According to our thesis, complexity of the environment and an organisms ability to perceive the environment are equally important aspects of the evolution process of the individual, since varying complexity of the environment will make no difference if a creature is unable to perceive the variation. Further, an ability to perceive is tied to an ability to make use of that perception: If motor control cannot produce the needed behavior to respond to perceptual events in a way that is useful for the individual then of course the perception is useless to that individual; therefore, to some extent perception must co-evolve with motor planning and control. We assume that such co-evolution has a primary relation to time-sensitive planning abilities, as vision constitutes a significant proportion of information reception in most mammals.

The artificial species is designed to bear a resemblance to natural insects found on Earth, based on the research of Collet and Collet ([Collet and Collet, 2002]). The simulation of insect memory and navigational abilities has been attempted before using a physical LEGO robot ([Chan and Wyeth, 1999]). The authors showed a method for reducing the degree of prior knowledge required about the environment, compared to other more classical approaches. The learning method they used was comparable to the one proposed here: Insects associate visual cues with their plans to navigate to and from nest and food sources. However, the method for associative learning and cognitive apparatus used here is a greatly simplified version of the one applied in the LEGO robot.

In this framework a creature has a body comprising a vision system, mobility, a mouth for feeding and a mental apparatus. A memory system provides the basis for forming repeatable plans that enable them to interact with their environment. The cognitive mechanisms are divided into parts as described in the next sections. The parts of the creature are:

```
1. Perception Cortex
2. Decision Cortex
3. Episodic Memory
4. Genetic System
5. Plan  Composer
6. Motor Cortex
7. Digestive System
```

We will now look at two examples of how components in a creature could be implemented. These are not part of the platform itself but rather are described here to give an idea of the level of complexity and functionality of these key components.

## 5.1   Episodic Memory

The Episodic Memory is the storage area for all perceptual input, the creature's actions and the consequences of those actions. In my example, memories are stored in the form of chunks which integrate these various components together into a package. The packages include a particular visual field, the plan that was associated with the perceptual input, the score - in particular the energy expenditure which was registered during the execution of the plan, along with a normalized plan score.

During each step, the Decision Cortex sends a message to the Episodic Memory to find all memories that the creature might have of similar situations.

The procedure is as follows:

Find all similar memories by first rating them along three semi-independent feature dimensions:

1. Image Matching (dimension one). The visual field in general: Compare each patch of the current visual field to each patch of a particular memory $M$. Similarity scoring is incremented with each patch that corresponds precisely to a patch in the precisely same location in memory $M$, based on the creature's coordinates (thus, if a patch in the upper left-hand corner is green, and the upper-left hand patch in memory $M$ is green, the memory gets a point for similarity). This score is normalized, so the increment for each patch that's identical is 1 divided by the total number of patches in the visual field. The final score is the sum of all identical patches.

2. Dominant Zone Similarity (dimension two): Compare the current visual fields dominant color and the zone the dominant color is mostly evident in to all memories. The score is normalized, but is either on or off (i.e. 1.0 or 0.0).

3. Patch in Front of Mouth (dimension three): Compare the patch in front of the creature's mouth to that same patch in all existing memories. This is similar to the Zone Similarity scoring – if the current patch in front of the mouth corresponds to that same patch in a memory, the similarity is turned on (again, 1.0 or 0.0).

For each of these features, the memories are arranged in descending order according to each feature's similarity score. The plan associated with each memory (there is either a plan or a "primitive move" associated with each memory) is retrieved for the top three memories – one for each dimension.

Plan scores are normalized by

$$Sf = \frac{1}{Sp(S_{max}S_{min})} \tag{5}$$

where $Sf$ is final score, $Sp$ is plan score, $S_{max}$ is the maximum score of any plan retrieved from memory, and $S_{min}$ is the minimum score for any pLan retrieved from memory.

The normalized plan scores of memories in the sorted dimensional arrays are multiplied by the similarity measurement of the memories, providing a "winner" which then determines which plan is used.

## 5.2   Genetic System

Following the terminology introduced by Holland ([Holland, 1998]), covering natural and artificial adaptive systems, a gene is denoted $A$, composed of set of alleles is $A = \{a_1, a_2, ...a_n\}$. In the example in this paper, $A$ denotes a unique component within the genetic structure to which genetic operators, $\Omega$, are applied. In our work these structures are implemented as "control boxes". Here the structures corresponding to Holland's alleles are connections between these control boxes. The combinations of control boxes and their connections are defined by the adaptive plan $\tau$ which uses the genetic operators (e.g. mutation, crossover, etc.). The criterion for comparison of $\tau$ will is denoted as $\mu$; the measurement when comparing adaptive plans is the age a creature reaches by the use of a particular adaptive plan. The set of structures attainable by the adaptive plan can represented by the following equation:

$$a = A_1 \times A_2 \times ...A_n = \Pi_{i=1}^{n} A_i \tag{6}$$

Since the environment, $E$, selects over time which control boxes survive between generations, an evolving, adaptive plan is defined over time by a particular environment $E$.

The Gene Manager is the part of the program that gets passed on and mutated between generations by genetic operators ($\chi$); it holds the creature genome which constitutes a set of control boxes and the connections between them, these two components constitute the Control Network. The control boxes consist of two inputs $I_1$ and $I_2$, an output $O$ and an operator which determines what to do with the inputs received. There are no initial connections between control boxes for the first generation in all worlds, and the initial outputs of Static Boxes are set to zero. After the first generation, all settings of control boxes and their connections are changed by mutation.

The types of boxes in the Control Network are:

```
Static Box: fixed output - a constant.
NOR box: returns 1 if both inputs are zero.
NAND box: returns 1 either inputs receive numbers but not both.
Input Gate Box: I1 IFF I2 > 0.
```

## 5.3   Control Network

Each of the boxes serves as a node in a Control Network. Outputs from the boxes are connected to none, some or all of the other box inputs. This is implemented by using a matrix to represent the outputs and inputs of all of the boxes (Static Box inputs excluded). The exact routing of the control box inputs and outputs is determined entirely during reproduction of the creatures. That is, the creatures' genetic configuration is responsible for using received inputs efficiently for plan composition.

For each box, a total of 4 possible connection configurations are possible. Given an example setting of 39 boxes that each can receive two inputs (static boxes have no input) and provide one output, the number of possible connection structures attainable by the network are 439.[5]

On every step during execution the Control Network receives a request from the Decision Cortex for updating its outputs. The outputs feed into the Plan Composer and set control parameters as the creature decides how to plan its actions. There are five main ways for planning the next step, as explained in the next section.

## 5.4   Plan Composer

The Plan Composer receives instructions from the Control Network during each turn regarding what to do and specifically how to do it. The instructions are in the form of integers that are deciphered by simple logic gates applied to the Control Network inputs in the Plan Composer.

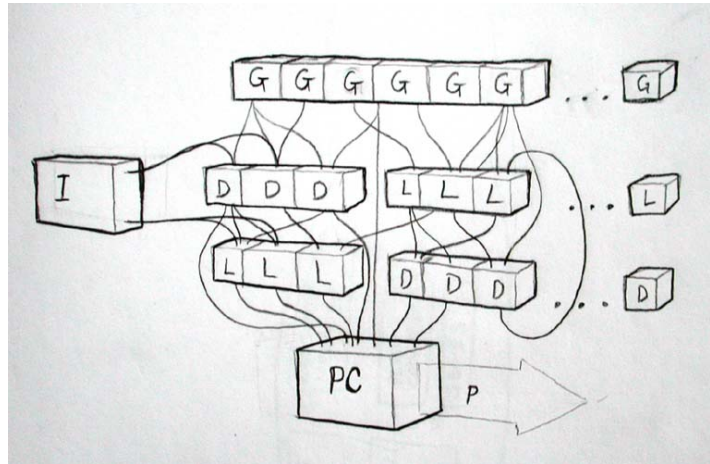The methods that the Plan Composer can use to create the next plan include:



Figure 3: Control Network. Output flows from the bottom of the boxes into none, some or all inputs of the other boxes (except for Static Boxes, see text). Boxes can connect to themselves. ($G$: Static Box, $D$ = NOR Box, $L$ = NAND and Input Gate Boxes, $I$ = inputs from perception and internal state, $PC$ = Plan Composer, $P$ = plans.)

```
a. Create a new plan from scratch.
b. Combine halves of two old plans.
c. Sequenced composition (combine two
   whole plans, executed in sequence).
d. Mutate an old plan (randomly change
   primitive actions of an older plan).
e. Use an old plan unmodified.
```

When creating a new plan from scratch, the Plan Composer randomly selects the length of the plan and how many instances of each primitive action are to reside in it. With random distributions of actions, the other four methods become very important since they provide a much more controllable way of making sensible plans. Also, by using combine and mutate, the individual development will become more evident as the creature is bound to use the methods on plans that have provided good results.

---

[5] An interesting question is the relationship between the this number and the minimum number of generations required to develop sustained existence. An even more interesting question is the relationship between the complexity of the world and the size of the Control Network.
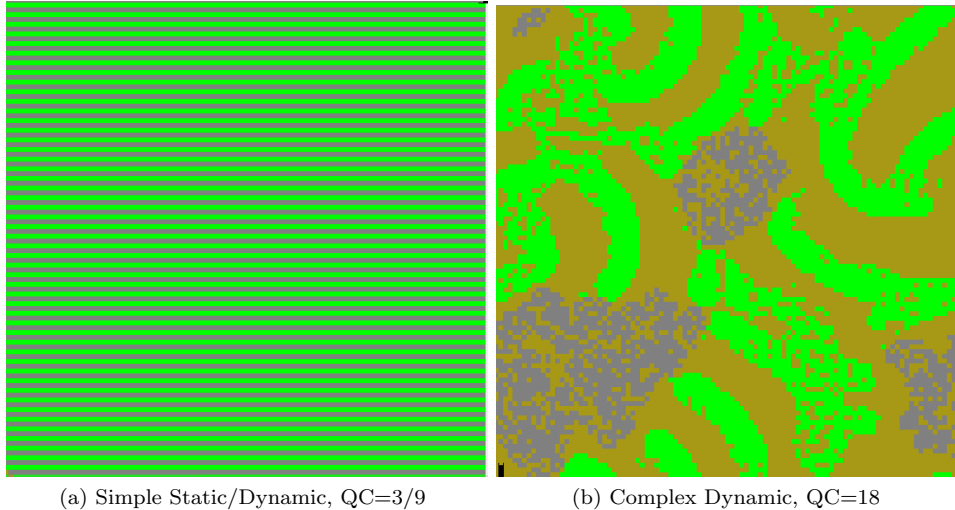
(a) Simple Static/Dynamic, QC=3/9    (b) Complex Dynamic, QC=18

Figure 4: Cellular automata worlds of varying complexity.

# 6 Experiments

A number of unique worlds were proposed as a testing ground, two of which can be seen in Figures 4a and 4b. To make worlds comparable on the measure of how world diversity affects the creatures' plan composition an appropriate balance between the quantity of food in each type of world must be kept. This will ensure that environmental niches ([Holland, 1998]) are kept at a minimum, giving the different worlds equality in everything besides diversity.

In the experiment we use three versions of the world. Simple ($Es$), which is made up of stripes alternating green and gray (Figure 4a). Green is grass (food), gray is rock and brown is mud (if the creature eats a green cell, the cell turns brown). $Es$ has $Qc = 3$. Simple Dynamic ($Esd$) is the same as $Es$ with the seemingly small change that the stripes change regularly from gray to green and green to gray, increasing the worlds $Qc$ to 9. Update frequency of $Esd$ is every 50 steps. Both $Es$ and $Esd$ reset for each new individual. The third world, Complex Dynamic ($Ecd$) presents more landscape-like structures; $Qc = 18$ in $Ecd$ (Figure 4b). $Ecd$ begins with initial random placement of cells, but is updated 500 times to eliminate the initial randomness before creatures are introduced to the world.

Each generation is made up of 100 creatures ($Ng = 100$), natural selection is implemented by sorting the creatures according to age; the top ten individuals (C1, C2 ... C10) are selected as the basis for the next generation. The selection criteria for inheritance, $\mu$, is the creatures age reached. The creatures only goal is to survive. Having a single goal simplifies comparison between the different worlds and plans. Because the creatures only have one goal, all plans that the creature creates are geared towards reaching that goal. And thus, coming up with alternative plans for reaching a goal is a form of creativity.

# 7 Results and Interpretation

The results show a high similarity between simple ($Es$) and simple dynamic ($Esd$) environments in the creatures planning behavior. In both environments the creatures used all of their available mechanisms for plan creation (Create-new-plan from scratch, Mutate-old-plan and Combine-old-plans). Figures 5 and 6 show the average use of the 3 mechanisms for plan creation over the lifetime of the creatures in each of the 100 generations (see section on creatures for details about the mechanisms). While the creatures are producing new plans from scratch relatively often, they compensate for plan randomness by using the other mechanisms. The creatures evolving within these simple worlds are maintaining a balance between innovation and logic: creating new and untried plans as well as learning from their previous experiences by using and combining plans that have proven efficient and useful.
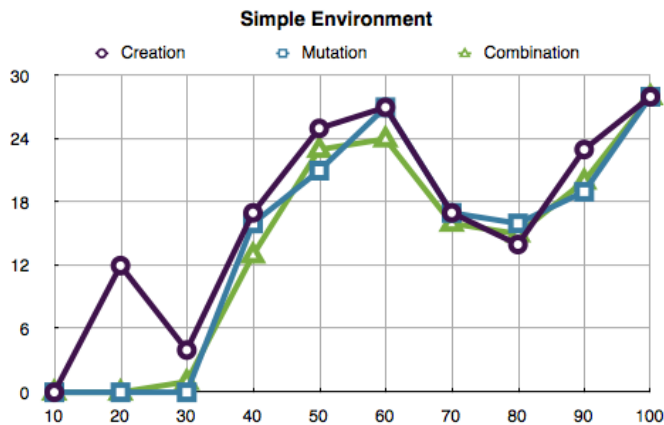
Figure 5: Simple (static) Environment ($Es$). Average use of create new plan (circles, purple), mutate old plan (boxes, blue) and combine old plans (triangles, green) X-Axis: generation; Y-Axis: average use of planning method.

In terms of our hypotheses, it would not have been surprising to see more difference in the results of the two worlds. Looking at the two simple worlds only, the main hypothesis, that an increase in environmental diversity results in a larger set of plans, is not clearly supported or disproved. This similarity might be due to structural likenesses between the two worlds. When compared to the results from the Complex Dynamic World ($Ecd$), however, the hypothesis is clearly supported. Figure 8 shows the average use of the plan-making mechanisms over the 100 generations. With $Qc = 18$, the creatures resorted to using the creation mechanism (creating a new plan from scratch every turn), while leaving the other mechanisms relatively unused. The plans and behavior of the creatures was therefore very diverse but the lack of learning from previous experiences resulted in their plans maintaining no logicality.[6] The creatures had shorter lifespans in more complex worlds and could therefore not use the plan-making mechanisms as often. In $Es$ the creatures' average age reached is 28; in $Esd$ it is 25, and in $Ecd$ it is 21.
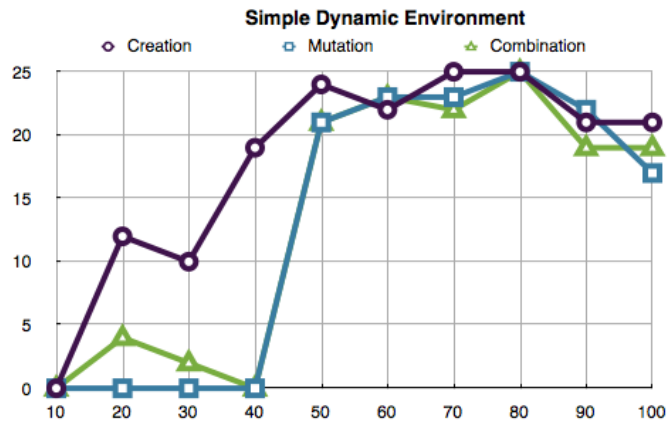


Figure 6: Simple Dynamic Environment ($Esd$). Average use of Create-new-plan (circles, purple), Mutate-old-plan (boxes, blue) and Combine-old-plans (triangles, green) X-Axis: generation 10-100; Y-Axis: average use of planning method.

Figure 5 shows an example of how the creatures' plan maintains logicality by eating only the food (green) while skipping the rock-lines (gray) which, if eaten, result in a substantial loss of energy. Similarly, 6 shows a creature having turned to eat a row of food in a consecutive manner. Such behavior would not have been possible were it not for the fact that the creatures in $Es$ and $Esd$ were using the mechanisms that build on previous experience. In the $Ecd$ (Complex Dynamic Environment), the creatures showed little logicality in their behavior due to their frequent usage of the random plan-making mechanism (Figure 7 shows a creature within the $Ecd$). To find food in $Ecd$ is not as simple as finding food in $Es$ and $Esd$ the agents have to produce behavior that allows them to cope with the complexity of their environment. The agents work relatively mechanically in $Es$ and Esd because the visual cues are few and provide accurate accounts of what will happen if the agents execute a certain plan. If the agents encounter a gray cell-structure (a stripe) in $Es$, they can depend on the fact that

---

[6]Note that we speak of logicality and not of efficiency, as plans can potentially be logical but still inefficient.
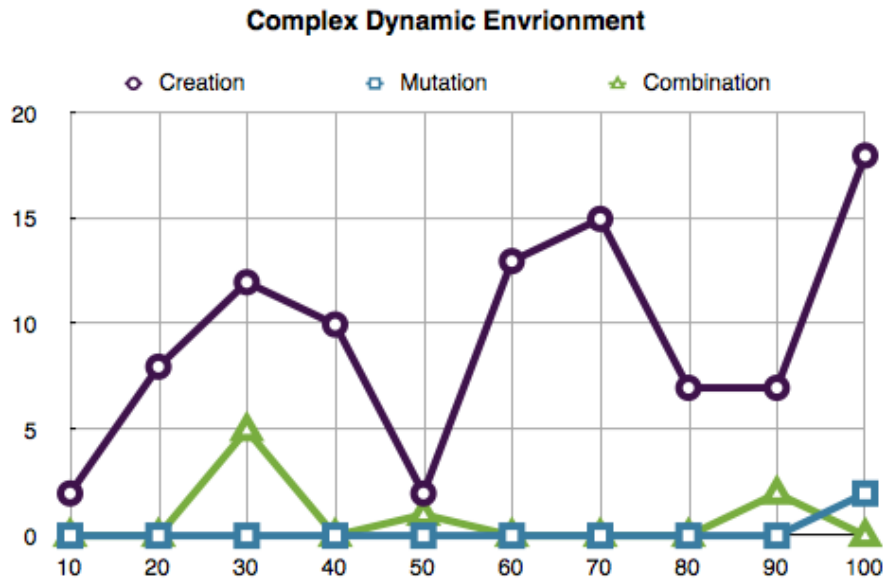
b



Figure 7: Complex Dynamic Environment (*Ecd*). Average use of Create-new-plan (circles, purple), Mutate-old-plan (boxes, blue) and Combine-old-plans (triangles, green) X-Axis: generation; Y-Axis: average use of method per generation.

if they use the plan move forward once, then eat they will gain energy, as the cell they will eat is guaranteed to be green (food). However, in *Ecd*, the green structures' behavior is much more diverse, and hence harder to predict.

In summary, the results strongly suggest that creativity is governed by environmental complexity, and that structural coherence dictates logicality of produced plans. Particularly, agents whose cognitive system evolve in overly complex worlds tend to create diverse (random) plans, but simple ones impose plans that maintain novelty and diversity without venturing into randomness supporting the stated hypothesis.

# 8    Future Work

The present results are clearly indicative that the evolution of planning mechanisms – and thus the creatures' understanding/modeling of the environment – is influenced by environmental complexity. However, as graphs 6 and 7 indicate, there is clearly more to the story. The causal relationship between environment and the evolution of creative mechanisms in creatures needs to be studied further to reveal its robustness under varying conditions, its precise relationship with complexity as opposed to other factors (e.g. dynamics). This can be done by testing more variations of environments, as well as more variations on the creatures' cognitive makeup. Moreover, our particular measure of complexity needs to be investigated to reveal its ability to predict variations in the evolution of cognitive capabilities, in particular planning and creativity, as defined here. The usefulness of our complexity measure in alternative settings should also be investigated, e.g. by trying to map non-CA worlds to CA-type rules. Lastly, the relationship between randomness, complexity, creativity and logicality should be further studied, to map out the full scope of these concepts and how they relate to each other.

# References

[Anthony et al., 1998] Anthony, A., Salzberg, C., and Sayama, H. (1998). A closer look at the evolutionary dynamics of self-reproducing cellular automata. *Selection*, 2(june).

[Anthony et al., 2004] Anthony, A., Salzberg, C., and Sayama, H. (2004). Evolutionary dynamics of cellular automata-based self-replicators in hostile environments. *BioSystems*, 98(1-3):119–134.

[Baas and Emmeche, 1997] Baas, N. A. and Emmeche, C. (1997). On emergence and explanation. *Intellectica*, 25:67–83.

[Berlekamp et al., 2001] Berlekamp, E. R., Conway, J. H., and Guy, R. K. (2001). *Winning Ways for your Mathematical Plays (2nd ed.)*. A. K. Peters Ltd.

[Boden, 2004] Boden, M. A. (2004). *The Creative Mind: Myths and Mechanisms*. Routledge.

[Carruthers, 2002] Carruthers, P. (2002). Human creativity: its evolution, its cognitive basis, and its connections with childhood pretence. *British Journal for the Philosophy of Science*, 53.

[Chan and Wyeth, 1999] Chan, P. and Wyeth, G. (1999). Self-learning visual path recognition.

[Collet and Collet, 2002] Collet, T. S. and Collet, M. (2002). Memory use in insect visual navigation. *Nature Review*, 3.

[Gabora, 2005] Gabora, L. (2005). Creative thought as a non-darwinian evolutionary process. *Journal of Creative Behavior*, 39(4):65–87.

[Gero, 1996] Gero, J. S. (1996). Creativity, emergence and evolution in design: concepts and framework. *Knowledge-Based Systems*, 9(7):435–448.

[Giurfa and Menzel, 1997] Giurfa, M. and Menzel, R. (1997). Insect visual perception: Complex abilities of simple nervous systems. *Current Opinion in Neurobiology*, 4(7):505–513.

[Godfrey-Smith, 2001] Godfrey-Smith, P. (2001). *Environmental Complexity and the evolution of cognition*, pages 233–249. Lawrence Elrbaum Associates.

[Holland, 1998] Holland, J. (1998). *Adaptation in Natural and Artificial Systems*. M.I.T. Press.

[Liu, 1996] Liu, Y. (1996). 'What' and 'where' is design creativity: a cognitive model for the emergence of creative design. In *IDATER'96*.

[Maturana and Varela, 1973] Maturana, H. R. and Varela, F. J. (1973). *Autopoiesis: The organization of the living*, pages 59–138. Reidel.

[Runco, 2004] Runco, M. A. (2004). Creativity. *Annual Review of Psychology*, 55:657–687.

[Taylor, 1988] Taylor, C. W. (1988). *Various approaches to the definition of creativity*, pages 99–124. Cambridge University Press.

[Thorisson, 2004] Thorisson, H. T. (2004). A framework for exploring the evolutionary roots of creativity. In *Proceedings of the European Conference on Case-Based Reasoning 2004 (ECCBR 2004)*, pages 179–190.

[van Duijin et al., 2006] van Duijin, M., Keijzer, F., and Franken, D. (2006). Principles of minimal cognition: Casting cognition as sensorimotor coordination. *Adaptive Behavior*, 14(2):157–170.

[Weir and Kacelnik, 2006] Weir, A. A. S. and Kacelnik, A. (2006). A new Caledonian crow (corvus moneduloides) creatively re-designs tools by bending or unbending aluminium strips. *Animal Cognition*, September 2006.

[Wiggins, 2006] Wiggins, G. (2006). A preliminary framework for description, analysis and comparison of creative systems. *Journal of Knowledge Based Systems*, 19(7):449–458.

[Wolfram, 2002] Wolfram, S. (2002). *A New Kind of Science*. Wolfram Media, Champain, IL: Wolfram Media.

# 9    Appendix: The Vélaldin Engine

The software we have developed is called the *Vélaldin*. The software can produce emergent environments based on cellular automata framework, and allows externally-developed agents to traverse these environments. The software also includes artificially intelligent agents capable of sensing and acting within these emergent worlds. We have also implemented methods for gathering statistical information from the environment and the agents.

The software is quite flexible and allows alternative setups of experiments than the ones we discuss here. The platform is developed on Sun Microsystem's Java programming language, making the Vélaldin software capable of running on the major computer operating system (MacOS, Windows, Linux).

The architecture of Vélaldin contains multiple features, some of which are completely unique in comparison to similar software architectures. The features of Vélaldin include means to:

- (i) Create 1D, 2D and 3D worlds through a single interface

- (ii) Maintain an abstract and open representations of cells

- (iii) Allow software agents to sense and act within Vélaldin's universes

- (iv) Gather statistical information about the universes through simple means

- (v) In addition to the above features, the system can do everything that a conventional cellular automaton simulator is capable of.

The Vélaldin Engine facilitates the creation of 1D, 2D and 3D worlds composed of cell-like objects, which are updated in discrete time steps. The cells determine their next state through use of rules they carry internally and govern their behavior in accordance to the state of their neighboring cells. This format of cell-composed worlds is known as cellular automatons. A Vélaldin cell can be defined as:

$$cell = s, r, n | s \in S, r \subseteq R, n \subseteq N \tag{7}$$

where s is a state from the set of possible states the cell can take on, r is the set of rules that govern the cell and n is the set of the cell's neighbors (other cells). All of which, except for the current state, are subsets of the superset of available States, Rules and Neighbors (capital letters). See xxx for a graphical representation of a cell.
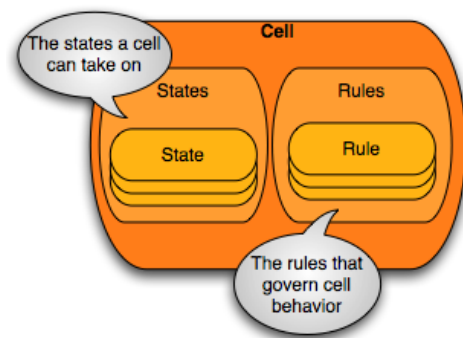


Figure 8: Graphical representation of a cell in Vélaldin.

It follows that a statechange of a cell can be defined as a function f, which maps a cell's current state, rules, and neighbors to a new state:

$$f : s, r, n \rightarrow S \tag{8}$$

Vélaldin takes this format of cellular automatons to a new level by introducing the concept of abstract cell representation, that is, within Vélaldin a state, a rule and a cell can be virtually anything the developer/user can imagine. To explain further: while a conventional CA state might for example be a type of color, the Vélaldin architecture makes no distinction between whether the state is a color, an alphabetical letter, 500 pages of text, or something completely different. The same applies to rules and the general cell architecture. The only requirements made by the Vélaldin Engine is that a state is something that can be computationally represented, and a rule is something capable of instructing the cell what to under particular circumstances. We have dubbed this abstract-architecture the Vélaldin Extended Cell Architecture, or $VECA$. VECA is the component responsible for referring to Vélaldin as an "emergence engine". In addition to the mentioned features of VECA, the architecture also allows for rules and states to exist independently, meaning

that it's possible to construct cells that generate new rules or states, opening up new dimensions for experimentation with emergence. This does not only allow conventional cellular automatons to be run but can produce an emergent effect with anything that fulfills the aforementioned requirements (see more on VECA in the Vélaldin Manual).

The cells within Vélaldin are represented as a matrix, each cell connected to its neighbors at runtime to allow neighbor-checks. The matrix of cells is contained in cell-placeholders called Cocoons at any given time during simulation. A Cocoon stores cells and is responsible for collecting neighbors and passing them to each cell. Together the cocoons represent the actual matrix of any Vélaldin simulation, being linked to each other via references to their immediate neighboring cocoons. This architecture adds a new layer of flexibility to cellular automaton simulations. Two examples are that cells can move from one position to another[7] and cocoons that serve as cell-observers (notifying the user or system when a certain cell appears at a certain position, for example).



Gathering statistical data at Vélaldin runtime is easy due to yet another architectural feature. We created a specific object, a Morpher, whose sole purpose is to update the worlds created with Vélaldin. During each update of a particular world, the Morpher object iterates through the Universes list of cocoons and call for each cell to morph according to his specified set of rules, and the states of his neighbors. This implementation gives the user an ability to collect

Figure 9: Vélaldin Cocoon connectivity (only some of the connections are shown, for simplicity).

information from the world instantaneously, such as state changes or counting the number of a certain type of cells currently available. A basic implementation of a Morpher is provided in this first release of Vélaldin which exemplifies it's usage and fulfills the requirements for basic cellular automaton simulations.
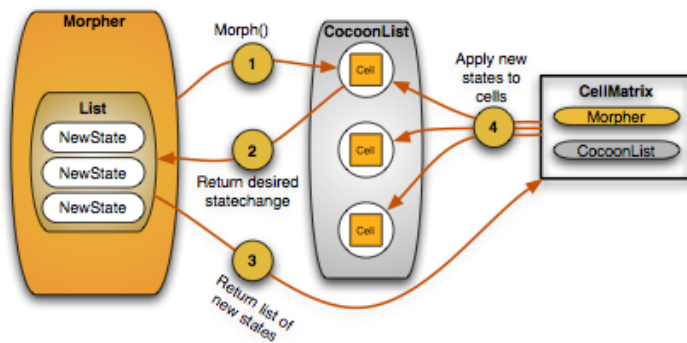


Figure 10: The Synchronous morphing process in the Vélaldin Engine.

Another benefit of the Morpher architecture is efficient synchronized updating of cells. Cells in a conventional cellular automaton update synchronously (all change state at the same time). For this to be possible, a state change can not be allowed to occur until all of the cells have been allowed to decide their next state. (If this were not so each cell might potentially be looking at their neighbors future state instead of their current state.) A standard method of solving synchronicity is to maintain a duplicate universe in memory which is kept unchanged while the cells update, the neighbors of each cell being fetched from the duplicate and not from the actual universe (which might contain new states). As two worlds have to be maintained at all times, this method is memory consuming. In Vélaldin this problem was solved through an algorithm in a Morpher: If a cell's rules dictate a state change, the cell does not change state immediately. Instead, the new state is stored in a temporary list in the Morpher. When the Morpher has completed morphing the whole Universe of cells, the list of changed states is returned to the CellMatrix which, in turn, applies the new states to the cells. This solution requires no duplicate universe, and only has to maintain a list of changed states. It can be added that should the user of Vélaldin so wish, they can set the system up to allow cells to update asynchronously. The CellMatrix also allows external processes to access the cell content and states, such as when simulated agents can perceive and affect cell states through their actions.
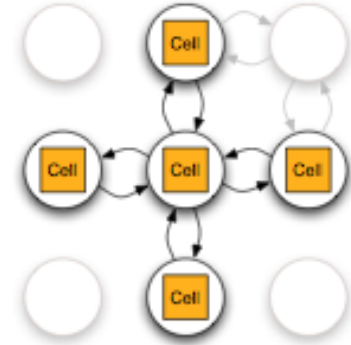
---

[7]In contrast, in standard cellular automatons the cells do not move and the only changes allowed are state changes.