Project Description: Evolution of Time in Simple Neural Architectures

Revision Notes: This proposal is a major revision of a proposal previously submitted in 2008 to the NSF CISE IIS RI program. The main criticisms were (1) lack of innovation [in technique, especially the use of the inefficient genetic algorithms], (2) not clear how the PI intends to figure out [what] the [neural] network has learned and why: [again, a limitation of genetic algorithms], (3) there is no attempt to identify causal relationships [between emergent network function and task performance], (4) the plan of study is not well developed [i.e., lack of step-by-step progression in the proposed tasks], and (5) There were no direct implications for neuroscience, psychology or robotics. (The text enclosed in brackets above are added or edited to give the proper context.) In the proposal text, where appropriate, we indicated in **bold** where we specifically addressed the above issues and included brief notes to further clarify (**[Revision 1], [Revision 2]**, etc.). To give an advance summary, (1) we provided rationale for using genetic algorithms and emphasized the novelty in experimental design, going beyond evolution of neural networks, (2) we included plans for the analysis of evolved neural networks, (3) we proposed how to measure such causal relationships, (4) we dropped tasks that are only remotely related and took a step-by-step approach, from task 1 to 4 (section 4), and (5) we made explicit connection to neuroscience.

1 Introduction

This project will investigate the evolutionary emergence of memory and prediction in simple neural architectures. The **two main ideas** we will test are (1) interaction between the internal nervous system and the external material environment is key to the evolution of memory and (2) prediction naturally emerges from memory due to selective pressure in evolution.

The function of the brain is intricately weaved into the fabric of time. Functions such as (1) storing and accessing *past* memories (Shastri 2002), (2) dealing with immediate sensorimotor needs in the *present* (Rossetti 2003), and (3) projecting into, predicting, and/or anticipating the *future* for goal-directed behavior (Gross et al. 1999; Henn 1987; Kozma and Freeman 2003) are good examples of how key brain processes are integrated into time. Moreover, it can even seem that the brain *generates* time (in the psychological sense, not in the physical sense) since, without the brain, a living organism cannot have the notion of past nor future (see Dowden 2001 for a discussion on time and mind/brain function). When combined with an evolutionary perspective, this seemingly straight-forward idea that the brain enables the conceptualization of past and future can lead to deeper insights into the principles of brain function (see our prior work: Chung and Choe 2009; Chung et al. 2009, 2011; Kwon and Choe 2008).

Key gap: Most current investigations on the temporal aspects of brain function are focused on specific tasks such as temporal coding, binding/segmentation, or prediction (see, e.g., Fortune and Rose 2001; Fuhrmann et al. 2002; Natschläger et al. 2001; von der Malsburg and Buhmann 1992). **[Revision 1]** Therefore, broader questions from an evolutionary perspective are rarely asked, e.g., can memory evolve from simple feedforward neural architectures, or can predictive function evolve from simple recurrent neural architectures? See Suddendorf and Corballis (2007) for a rare exception to this, where the authors talk about evolution of foresight and "mental time travel", albeit at a higher, cognitive level than what we will focus on in this proposal.

Goal: The goal of this project is to systematically investigate, through simulated evolution of neural networks, conditions for the emergence of functions that enable the notion of past and future (i.e., memory and prediction) in simple neural architectures.

Novelty and Rationale: [Revision 1] Studying specific mechanisms of memory and prediction can only give us a clue on how these final products of evolution work. It cannot tell us (1) why

is it inevitable that memory and prediction emerge through evolution, (2) what kind of evolutionary steps it could have taken and how each step relates to various brain subsystems, and (3) how memory and prediction are related in an evolutionary sense. These are important questions we will ask that can lead to new insights for the understanding of brain function. Questions from such a perspective and the novel experimental design including genetic encoding schemes going beyond weight adjustment and topology change are the **main innovations** of this project. Furthermore, since we are investigating the **evolution** of memory and prediction **in simple neural architectures**, **we are bound to use genetic search on neural networks**, rather than using principled learning algorithms that optimize on specific task criterion. We want to observe the emergence of functions that are not explicitly expressed in the fitness (e.g., avoid criteria such as maximize memory capacity, maximize information, maximize predictive performance, etc.).

Objectives: [Revision 4&5] The objectives of this project are as follows (see Fig. 1). The first three objectives below pertain to memory, with a step-by-step progression, and the fourth objective pertains to prediction, based on the recurrent architecture from objective three.

1. Evolution of external memory use in reactive, feedforward neural architectures: Feedforward architectures only support reactive behavior (i.e., they reside in the eternal present). (See Bell 1999 for a critique of feed-forward systems.) This architecture will be minimally extended, while maintaining the feedforward topology, to allow dropping and detecting markers in the environment (Chung and Choe 2009; Chung et al. 2009, 2011), a form of stigmergy (Beckers et al. 1994). Memory-like behavior is expected to emerge from this simple augmentation. This type of agent-environment interaction is analogous to *olfaction*.

2. Internalized marker interaction: Once external markers are found to be effective in implementing memory, the next step is to test if such external marker interaction can be internalized, without introducing recurrent circuits. This could be analogous to the *neuromodulatory system* (see Krichmar 2008 for a review of the neuromodulatory system).

3. From internal marker interaction to recurrent circuits: The next step is to test if internal marker interaction can lead to actual recurrent circuits that support fully dynamic internal memory, such as in the *hippocampus* (cf. Amaral and Witter 1989; Wallenstein et al. 1998).

4. Evolution of predictive dynamics in recurrent circuits: Recurrent neural architectures are generally associated with memory (of the past). Whether such recurrent circuits have the potential to evolve predictive internal dynamics projecting into the future will be investigated (Chung et al. 2009, 2011; Kwon and Choe 2008, 2010).

Intellectual merit, broader impact, and transformative potential: Please refer to the project summary.
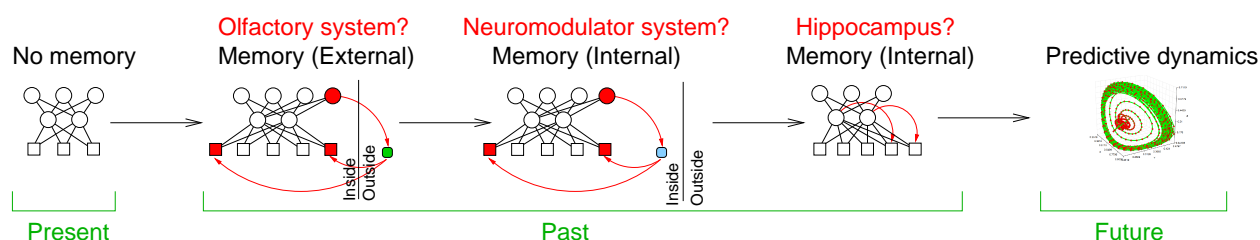

Figure 1: **From the present to the past, and forward to the future.** Initially, only reactive behavior mediated by feedforward networks may have existed (left-most panel). (Note: "No memory" here means that the network is oblivious of its past input patterns.) By evolving external dropper/detector capability while maintaining the feedforward topology, simple memory function may have emerged (second panel), reminiscent of olfaction. Then, this kind of dropper/detector mechanism could have been internalized (third panel), leading to a full-blown recurrent architecture (fourth panel). The final step is predictive activation dynamics emerging from the recurrent architecture (fifth panel).

2 Background

In this section we will review works that provide background and motivation for this project. First we will review the neural architectures of simple, primitive animals. Next, we will look at literature related to stigmergy, i.e., alterations of the environment to affect future behavior (Beckers et al. 1994), and its relation to memory. Finally, we will discuss literature on predictive functions in the brain.

2.1 Neural architectures of primitive animals

It is instructive to look at the origins of the nervous system and what steps it took to become the complex networks that we see today in advanced animals like mammals. Here, we will focus on the first few steps, as shown in Fig. 2. One of the simplest animals is the sponge. The sponge lacks a nervous system, where independent effectors are actuated by direct stimulus (Fig. 2a). The next step up is the simplest animals with a nervous system, such as corals, jellyfish, and hydra. In these animals, e.g., in the hydra, a single neuron (sensorimotor neuron) links between the sensory surface and the effector (Fig. 2b) and these neurons form a sparse, distributed network. Finally, a more advanced form can be found in animals like the flatworm, where interneurons are introduced and cell bodies are organized into nervous ganglia along the length of the body (Fig. 2c-d). In all cases, the neuronal network of the animals are distinctly *feedforward*, thus their behavior is largely reactive. Such animals can only respond to the moment-to-moment stimuli, oblivious of the inputs they received in the past (i.e., they live in the eternal present). In this sense, they do not have memory. Note that synaptic plasticity can be seen as a form of memory, but for simple animals like the flatworm, adjustment of synaptic efficacy can only change how the animal reacts to a certain given stimulus. **[Revision 1]** How can such primitive animals further evolve to become sensitive to the past or the future? This is one of the central questions we will address in this project.
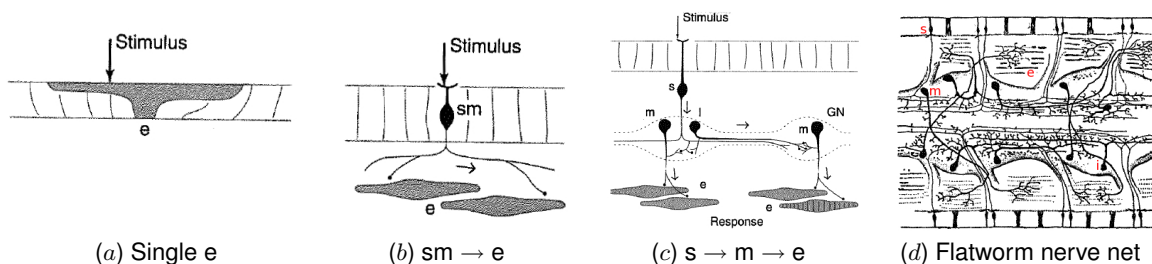

(a) Single e   (b) sm → e   (c) s → m → e   (d) Flatworm nerve net

Figure 2: **Progression of neural architectures in simple animals.** A progression of neural architectures is shown, from (a) a single effector (= e) that also senses the stimulus, to (b) a sensorimotor neuron (= sm) innervating the effectors (e.g., muscle cells), to (c) a sensory neuron (= s) innervating a motor neuron (= m), which in turn actuates the effectors. (d) Part of the flatworm nervous system showing a basic plan similar to (c) (i = interneuron, GN = ganglion). In all cases, the basic architecture is *feedforward*. Adapted from Swanson (2003). (d) is from Cajal (1909), as shown in Swanson (2003).

2.2 Stigmergy and its transition to memory-like function

Stigmergy refers to "the production of a certain behaviour in agents as a consequence of the effects produced in the local environment by previous behaviour" (Beckers et al. 1994). Altering the environment in any way that affects future behavior falls under this category, such as dropping and detecting some type of marker. For example, humans and many other animals use external objects or certain substances excreted into the environment as a means for spatial memory (see Chandrasekaran and Stewart 2007; Chandrasekharan and Stewart 2004; Rocha 1996 for theoretical insights on the benefit of the use of inert matter for cognition). In this case, olfaction

(or other forms of chemical sense) serves an important role as the "detector". Olfaction is one of the oldest sensory modalities, shared by most living organisms (Hildebrand 1995; Mackie 2003; Vanderhaeghen et al. 1997). This form of spatial memory resides in the environment, thus it can be seen as external memory. On the other hand, in higher animals, spatial memory is also internalized, for example in the hippocampus. Interestingly there are several different clues that suggest an intimate relationship between the olfactory system and the hippocampus. They are located nearby in the brain, and genetically they seem to be closely related: (Machold et al. 2003; Palma et al. 2004) showed that the Sonic Hedgehog gene controls the development of both the hippocampus and the olfactory bulb. Furthermore, neurogenesis is most often observed in the hippocampus and in the olfactory bulb, alluding to a close functional demand (Frisén et al. 1998). Finally, it is interesting to think of neuromodulators (Krichmar 2008) as a form of internal marker dropping, in the fashion explored in this project.

[Revision 1] In this project, we will focus on the use of stigmergy as a primitive form of memory in reactive agents. This is a distinctly *individual* use of stigmergy, as opposed to most existing works on stigmergy that focus on the *social* aspect of it, such as in social insects and ant colony optimization (Bonabeau et al. 2000a; Carroll and Janzen 1973; Dorigo and Blum 2005; Dorigo and Gambardella 1997; Theraulaz and Bonabeau 1999), and in many cases involving structure-building in the environment (Bonabeau et al. 2000b; Theraulaz and Bonabeau 1999).

2.3   Predictive function in the brain

Rosen (1985) is one of those few who saw early on the importance of prediction in intelligent systems, and called these "anticipatory systems". Rosen argued that anticipatory systems depend on an internal predictive models of the agents themselves and the environments are used in predicting the future for the purpose of control in the present. Rosen's work was more theoretical in nature, but it was soon followed by more concrete investigations (Bongard et al. 2006; Diedrichsen et al. 2003; Gross et al. 1999; Kawato 1999; Möller 1997; Rao and Sejnowski 2000; Witney et al. 1999; Wolpert and Flanagan 2001; Wolpert et al. 1995, 1998). For example, Wolpert and his colleagues have shown how internal models in the brain (cerebellum, to be specific) can be used for prediction in motor behavior (Kawato 1999; Wolpert and Flanagan 2001; Wolpert et al. 1995, 1998). On the other hand, Bongard et al. (2006) has shown that through the use of an internal self model, physical sensorimotor agents can show resilient behavior when part of the agent becomes damaged (such as amputated limbs, etc.). There are more instances of prediction being detected in brain function. Rao and Ballard (1999) showed that the interaction between feedforward and feedback connections between cortical regions plays a predictive role. Rao and Sejnowski (2000) also showed that predictive sequence learning can occur in recurrent cortical circuits. Finally, Hawkins and Blakeslee (2004) also argued that the neocortex may have prediction as its primary function. In general, any work that cites anticipation, internal model, and goal-directed behavior all implicitly (or explicitly) involve prediction as a key part of their investigation.

[Revision 1] As mentioned in Sec. 1, most of the existing works on prediction focus on specific tasks or mechanisms (see Sec. 3.2 as well), and rarely question the evolutionary origin of such a function. Furthermore, how memory (past) is related to prediction (future) is not considered in these works. In this project, we will build up on our prior work on the evolution of predictive internal neural activity dynamics (Chung et al. 2009, 2011; Kwon and Choe 2008) (Sec. 3.2).

3   Prior Work

Here, we will present preliminary results that directly support objectives 1 and 4. Objective 1 is the key part in the initial development of memory in feedforward, reactive neural architectures,

and objective 4 is the main part on prediction, so, these results lend solid support for the whole proposal. We will also briefly discuss results from prior NSF support.

3.1 Evolution of memory in reactive neural networks with dropper/detector

Can feedforward neural networks express memory-like behavior? In principle, this is not possible, but we found that when material interaction with the environment is allowed (basically a form of stigmergy), it can be possible.

Fig. 3 summarizes the task, methods, and results. Fig. 3a illustrates the ball catching task (Beer 2000). equipped with a fixed number of range sensors (radiating lines), is allowed to move left or right at the bottom of the screen while trying to catch two balls falling from the top. The goal is to catch both balls. The balls fall at different speeds, so a good strategy is to catch the fast-falling ball first (B and C) and then the go back and catch the slow one (D and E). Note that in C the ball on the left is outside of the range sensors' view. Thus, a memory-less agent would stop at this point and fail to catch the second ball. In sum, this task requires memory.

Fig. 3b shows a feedforward network with a slight modification (dropper and detector of external markers). This kind of modification can be trivial to implement from an evolutionary sense, since existing sensors can be extended to serve as detectors and excretion and other bodily discharge (e.g., pheromones) can become the dropper. The basic internal architecture of the network is identical to any other feedforward network, with five range sensor (I_1 to I_5), and two output units that determine the movement (O_1 and O_2). The two added input units (I_6 and I_7) signal the presence of a dropped marker on the bottom plane, and the one additional output unit (O_3) makes the decision of whether to drop a marker at the current location or not. Note that there are no recurrent connections in the controller network itself. We used genetic algorithms (Mitchell 1998) to evolve the network weights. The fitness was calculated based on the number of balls caught. The success in this kind of agent will critically depend on whether the markers are dropped at the right moment, and appropriate behavior generated when certain markers are detected,
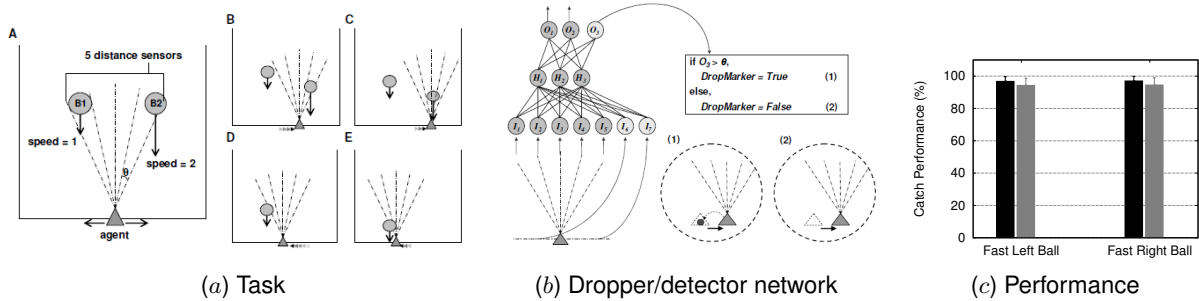

(a) Task   (b) Dropper/detector network   (c) Performance

Figure 3: **Dropper/detector network's performance in ball catching.** (a) The ball catching task is illustrated. (b) The dropper/detector network is shown (it is basically feedforward). Genetic search is conducted on the connection weights. (c) Performance comparison between dropper/detector network (gray) and a recurrent network (black) is shown. See text for details. Adapted from Chung et al. (2009).

In Fig. 3c, the average ball catching performance of the dropper network is presented (gray bar), along with that of the recurrent network (black bar). The recurrent network was a standard Elman network (Elman 1991). Both types of networks were trained using genetic algorithms, where the connection weights were adjusted over the generations. The error bars indicate standard deviation. The results are reported in two separate categories: fast left ball and fast right ball. This was to show that the network does not have any fixed bias for catching the ball to the left or to the right. Both networks perform at the same high level (above 90% of all balls caught). This is quite remarkable for a feedforward network, although it had the added dropper/detector mechanism. The dropping/detecting strategy also seems consistent with an interpretation that the agent

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has memory (see Chung et al. (2009) for details). We also tested purely feedforward networks, but they were only able to catch only ~50% of all balls dropped.

3.2 Evolution of predictive dynamics in recurrent neural networks

Once a recurrent neural architecture is made available (through some route in evolution), what can it achieve? It can clearly behave based on stimuli that have passed along into the past. So, in a sense, recurrent neural networks have memory of the past, but that is only half of the story.

Do these recurrent networks have the ability to forecast the future? In fact, recurrent networks have been used extensively for time series prediction (Barbounis et al. 2006; Connor et al. 1994; Kuan and Liu 1995). However, these works are based on training the recurrent networks on time-series data that explicitly contain future information. Thus, the predictive capability emerging in these networks are due to the information provided to them from the beginning through the supervised training set.

We take a different stab at this question, by assuming no prior data that contains information of the future, nor a built-in optimization criterion that explicitly measures prediction performance. The idea is to evolve recurrent neural network controllers in a dynamic task where prediction is not an immediate task requirement (Fig. 4a-b). **[Revision 1]** The **key innovation** here was to simply measure the inherent predictability of the internal state trajectory (i.e., the time-series made up of hidden neuron activations over time; see Fig. 4b-c), and see if those with higher predictability spontaneously evolve, just based on the task demand (in this case, pole balancing). Note that here the predictability of the trajectory is a *post hoc* quantity only used for analysis, so it does not feed back into fitness calculation.

An immediate question is, how can predictability be measured? Fig. 4c shows how. Again, we do not want to impose a preconceived notion (such as smoothness, low curvature, etc.) to muddy our analysis, so we take a data-driven approach. Given n past data points ($n = 4$ in the figure), we want to know if the $n+1$-th data point can be easily predicted. To measure this, we can construct a supervised learning training set consisting of n inputs and 1 target value, by sliding this small window along the entire trajectory. Then, we can use any suitable supervised learning algorithm to learn the mapping, from n past data points to the $n+1$-th data point. Trajectories that lead to lowest training error can be said to have high predictability (i.e., the data set itself has this property).
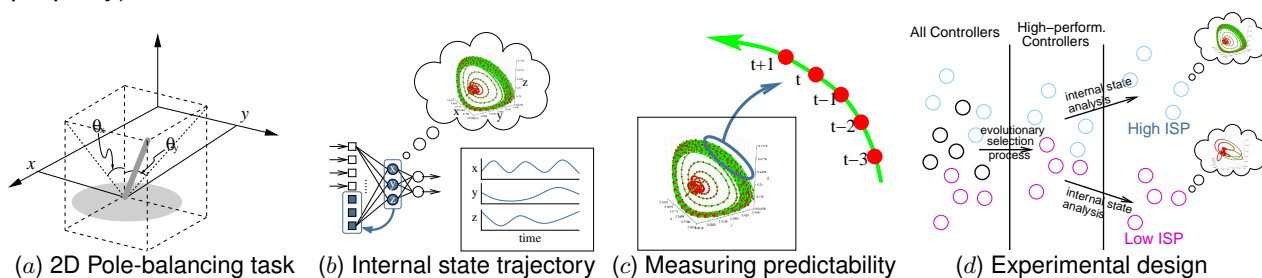

(a) 2D Pole-balancing task   (b) Internal state trajectory   (c) Measuring predictability   (d) Experimental design

Figure 4: **Predictability of internal state trajectory in a pole-balancing controller network.** (a) 2D pole balancing task. (b) A recurrent neural network controller for (a), illustration of its hidden-unit activations (internal state) over time (lower right, three neurons x, y, and z), and a 3D plot of the internal state trajectory. The connection weights are adapted using genetic search. (c) Measuring predictability of internal state trajectory. Given a few past data points as input ($t - 3$ to t), how well can the next data point ($t + 1$) on the trajectory be predicted? (d) Experimental design showing population (left), selection (middle), and post-selection analysis (right). Individuals that pass the selection stage have equal task performance, but analysis of their internal state can show different characteristics: Some with highly predictable internal state trajectory, and others with much less predictable trajectory. (ISP = Internal State Predictability)

Why should this be of interest? We have found that among equally high-performing individuals (Fig. 4d, middle), some have highly predictable internal state (i.e., hidden unit activation value) trajectories (Fig. 4d, right, top group [high ISP]) while some are not so predictable (low predictability, Fig. 4d, right, bottom group [low ISP]). Since individuals from both groups passed the same performance threshold, they actually show equal performance. However, we discovered that when the initial condition of the task is made harder, those with high predictability retain their performance while those with low predictability lose much of their performance! (See Sec. 4.4 for more preliminary results.) **The implication of this finding is profound.** First, *predictable* internal state dynamics turned out to have a high selective value in evolution. This can an important precursor to full-blown predictive function. **[Revision 3] Note that this is where previous reviewers raised their concern: How can we ascertain that predictability was causal in raising the task performance? We will address this issue in Sec. 4.4.** Second, certain properties that are *internal* to the agent can affect the course of evolution (examples of such internal properties include subjective phenomena like consciousness: see Sec. 5 for more discussion on this).

These (including results in Sec. 3.1) are exciting discoveries that we intend to further develop in this project. The main questions lie in the generalizability of the results in Sec. 3.1 to more complex tasks (Sec. 4.1), how dropper/detector architecture can evolve into fully recurrent architecture (Sec. 4.2–4.3), and how to establish causality and generality of the predictability result (Sec. 4.4).

3.3 Results from Prior NSF Support

The PI has one NSF grant on a subject relatively remote from the current proposal: "CRCNS data sharing: Whole Mouse Brain Neuronal Morphology and Neurovasculature Browser" (#0905041), which started in September 2009. Publications resulting from this grant are Choe et al. (2010a,b) (abstracts). Three conference papers are currently under review (IEEE International Symposium on Biomedical Imaging). A major journal paper is under preparation and will be submitted soon. A public web-based mouse brain atlas is also under development (`http://kesm.cs.tamu.edu`). **We would like to note that the theoretical works by the PI (including those presented in this proposal) have been continually developed over the past 9 years without funding, albeit with multiple close calls ("competitive, fund if possible").**

4 Research Plan

The project will be carried out in four major tasks, corresponding to the four objectives in Sec. 1.

4.1 Evolution of External Memory Use

Our preliminary results in Sec. 3.1 lay a solid ground work for this task. Our main focus will be to test whether the results in Chung et al. (2009) are generalizable to more complex tasks and environments. We propose to test the dropper/detector network by evolving them in a 2D foraging task requiring memory. Fig. 5 shows an overview of the task, the agent, and the controller network. The agent starts from the nest, and goes about looking for food sources. The agent has sensors with a limited range, and a limited food carrying capacity, so it needs to remember what it has seen during its exploration and be able to come back later after dumping the food at the nest. For example, after initially visiting food source #1, food source #2 comes within sensor range. However, the agent has to return to the nest to deposit the food from source #1. In order to retrieve more food, it has to remember and come back to the remembered location of food source #2. Fitness is calculated by the amount of food the agent brings back to the nest. This is a substantially more difficult task than the ball catching task in Sec. 3.1, due to the freedom of movement and more complex task semantics. (See the work by Chandrasekaran and Stewart
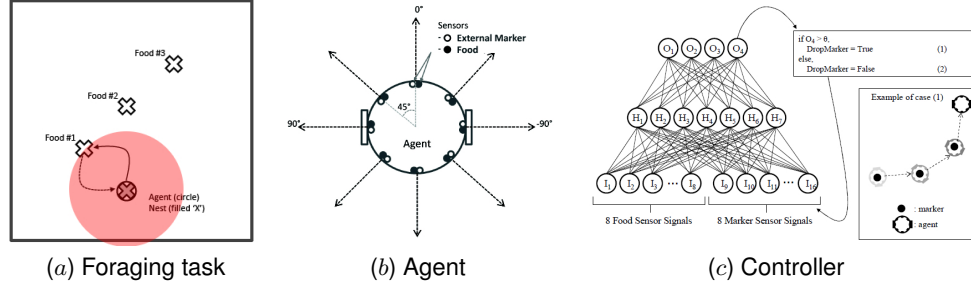
(a) Foraging task   (b) Agent   (c) Controller

Figure 5: **2D foraging task and dropper/detector network.** (a) 2D foraging task is shown. The x mark at the bottom is the nest, and the top three are food sources. The foraging agent, shown as a circle, is overlaid on top of the nest. The sensor range is shown in red. (b) The foraging agent is shown with its food sensors and marker sensors. The three outputs are for x, y, and orientation displacement, and the fourth output is the dropper decision unit. (c) The controller network for the foraging agent is shown. The network is again a feedforward network, with additional sensors for marker detection and an added output for marker dropping.

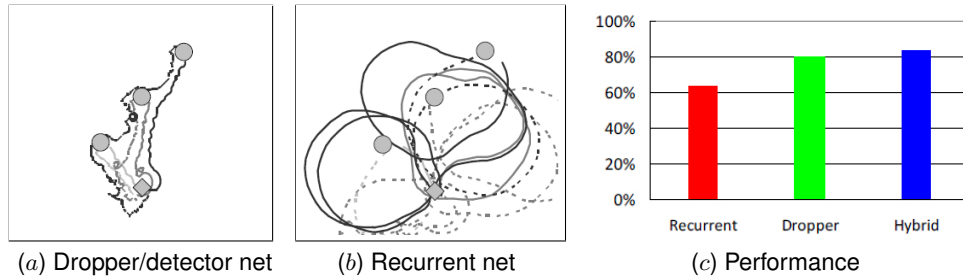(a) Dropper/detector net   (b) Recurrent net   (c) Performance

Figure 6: **Preliminary results in 2D foraging task.** (a) Sample trajectory of a dropper/detector network. (b) Sample trajectory of a recurrent network. Solid lines are trajectories toward food, and dotted lines are away from the food. Grayscale represents time lapse: the darker, the more recent. In general, the dropper/detector network exhibited tighter, more goal-directed trajectories than the recurrent network. (c) Performance comparison is shown for three types of networks, recurrent network (red), dropper/detector network (green), and hybrid (recurrent network with dropper/detector, blue). The performance is comparable in all cases.

[2007] where marker dropping behavior was examined in reactive agents, albeit without much memory demand [single food source].)

Our initial results are promising. Fig. 6 shows preliminary results. Again, we compared the performance of the dropper/detector network with that of recurrent networks. Interestingly, the dropper/detector network slightly outperforms recurrent networks. This may be due to the fact that the use of external markers effectively expands the memory capacity by utilizing the external map itself as a canvas to draw on.

Research issues: (1) Although our preliminary results are promising, we need more robust performance under more general conditions. For example, for the results in Fig. 6, we fixed the nest and food source locations across trials and generations. We will amend this by randomly varying the location of the food sources and the nest. (2) We will also analyze why the dropper/detector network outperforms recurrent networks. We will compare the hidden unit activation dynamics in both network types, and correlate those to the behavior. Also, we will test if systematic removal of markers dropped by the dropper/detector network affect performance, to make sure that the markers are indeed playing a key role. (3) Furthermore, we will test if a hybrid (recurrent + dropper/detector) network will utilize both the internal and external memory (see Fig. 6c). Since advanced animals tend to depend on both, this experiment can give us new insights. (4) We will attempt a formal analysis of the dropper/detector network's capability. This will include memory

capacity, VC dimension, and other standard machine learning metrics. (5) The neuromodulator system is also known for its major role in reward and reward-based decision function. In some sense, the external markers can be thought of as surrogate rewards. This view will be further explored. **[Revision 5] (6) We will make explicit connection to the olfactory system in animals (especially insects) by introducing into our experiments olfactory characteristics such as diffusion, evaporation, and use of multiple olfactory cues. We will also investigate the literature for specific uses of the antennae and conditions under which different pheromones are released by insects, and systematically compare these patterns with our agent's behavior (Brian 1983; Parry and Morgan 1979; Pierce et al. 2002). Especially, Pierce et al. (2002) discuss *cost* of various forms of chemical communication between insects, which can be helpful when calculating the fitness.**

4.2 Internalized Marker Interaction

[Revision 5] Explicit connection to neuroscience is made throughout this section. In the previous section, we have seen how external material interaction can confer memory-like capability to feedforward neural architectures. This can be a good model for primitive animals, but dependence on such dropping/detecting behavior may decrease as the animal becomes more advanced. The most advanced form would be where memory is implemented in recurrent circuits. However, a jump from a feedforward architecture to a heavily recurrent architecture is unlikely. What could be a reasonable intermediate stage? Our view is that the neuromodulatory system, with its broad diffuse targeting and large variety of signaling molecules, can serve as a possible intermediate stage (for reviews, see Krichmar 2008; Sporns and Alexander 2002), where neuromodulator secretion within the brain can serve as a surrogate of external marker dropping.

The neuromodulatory system consists of subcortical structures in the (mammalian) brain projecting to major cortical targets and to each other. Main functions of the system are thought to be (1) threat assessment, (2) attention effort, (3) novelty and saliency, and (4) reward prediction and wanting. The major subsystems, their influences, and associated neurotransmitters are shown in Fig. 7 (Krichmar 2008). Among these, we will focus on the attentional role, since combined with an internal "cognitive map" (Jacobs 2003), attention can play a role similar to marker dropping (attentional "trace").
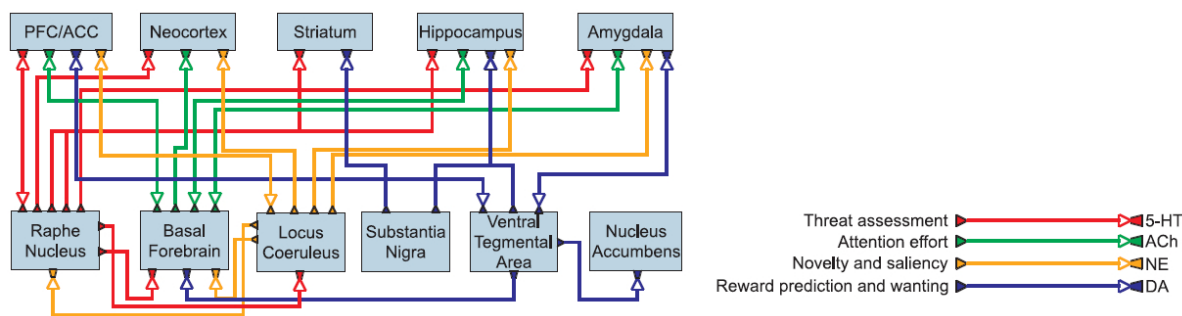

Figure 7: **Neuromodulatory system in mammals.** A schematic diagram of the neuromodulatory system and the theorized roles (and associated neurotransmitters) are shown. PFC = prefrontal cortex, ACC = anterior cingulate cortex, 5-HT = serotonine, ACh = acetylcholine, NE = norepinephrine, DA = dopamine. Adapted from Krichmar (2008).

We realize that mammals are a huge departure from primitive animals like the flatworm we discussed in Sec. 4.1. However, there is strong evidence suggesting similarities between insect- and vertebrate sensory organization (e.g., olfaction) and subsequent processing, which is our

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focus (Kay and Stopfer 2006). Furthermore, acetylcholine (ACh), which is a major neuromodulator for attentional function in mammals (e.g., Fletcher and Chen 2010), is also widely used in insects (Fresquet et al. 1998) and other invertebrates such as the terrestrial slug (Watanabe et al. 2001).

In this project, we will construct an internal map modeled loosely after hippocampal place cells (O'Keefe 1979; O'Keefe and Reece 1993) to serve as an internal, relative map of the external space, and mimic the neuromodulatory system to generate traces within the grid. ACh-like action will be used to direct attention on the internal grid as a feedforward neural network controller behaves in the 2D foraging task from Sec. 4.1. Recent findings suggest that this kind of attention is necessary for stable representation in the hippocampus (Kentros et al. 2004; see Moser [2004] for an overview). Fig. 8 shows an overview of the proposed model. Note that the food sensors and marker sensors are now segregated rather than sharing the same space as in Sec. 4.1.
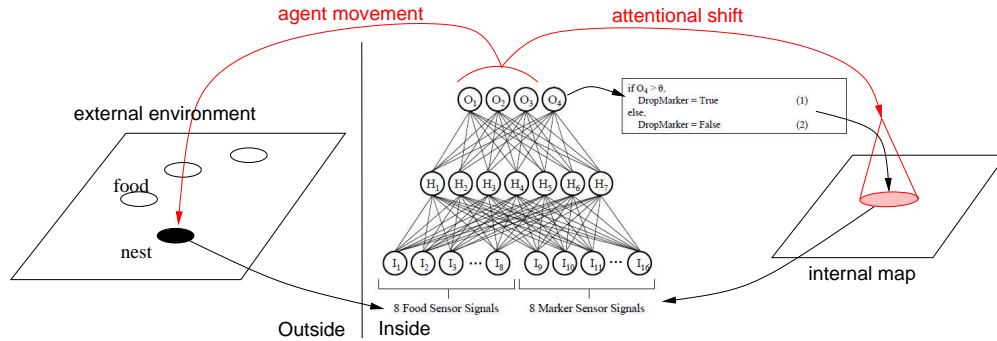

Figure 8: **Neuromodulator-based attention and marking.** A feedforward network controller for the 2D foraging task is shown. It is the same as the one in Fig. 5, except for an added internal map and attentional mechanism. Note that the internal map can be *significantly smaller* than the external environment it is modeling. See text for details. Cf. Chandrasekaran and Stewart (2007) where Q-learning was used along with a backpropagation network as internal memory (instead of internal marker sensors).

Research issues: (1) How the agent movement-related output of the controller network should affect the attentional focus in the internal map needs to be determined. There are a couple of options: (a) move the attentional focus in the internal map based on the controller output on a 1-to-1 scale, and allow boundless map size, or (b) do an arbitrary mapping (linear or nonlinear, e.g., using manifold learning (Choi et al. 2008)), and restrict the internal map size. In the second case, if attentional focus goes outside of the boundary, immediately bring it back. We will reference Wyss et al. (2006) to construct a dynamic map, and compare the results. (2) Several parameters need to be determined as well, such as radius of the attentional focus, which will in turn determine the size of the area where the internal markers are secreted. (3) We will also test hybrid controllers that combine both internal- and external-marker sensors. Running evolutionary trials on this type of hybrid network will allow us to identify conditions where internal, external, or both markers are used. Analyzing the marker sensor to hidden unit weights will help us answer this question. (4) Finally, we will begin to look into how morphological evolution can be modeled to account for the emergence of the internal map itself (for work on evolution of morphology as well as controller, see Sims 1994).

4.3   From Internal Marker Interaction to Recurrent Circuits

Up to this point, it was sufficient to conduct genetic search on the connection weights of a fixed-topology feed-forward neural network. However, in order to model the emergence of recurrent connections, we need to go beyond evolving the connection weights, to adapt the network connection topology. Neuroevolution of Augmenting Topologies (NEAT) is perhaps the best known
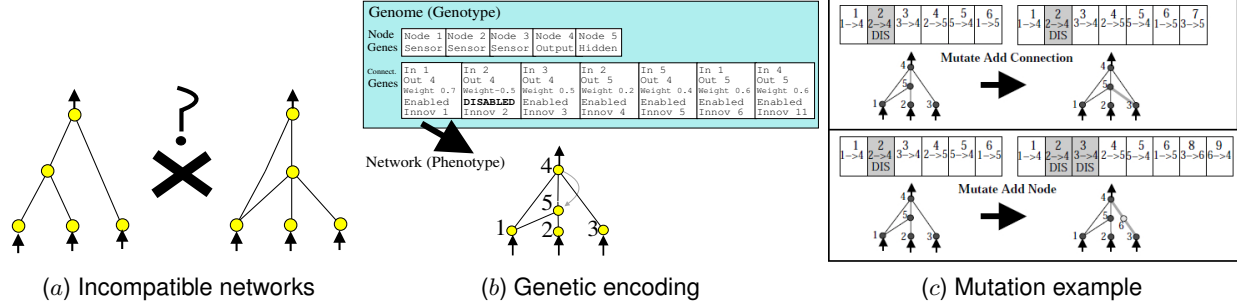
(a) Incompatible networks   (b) Genetic encoding   (c) Mutation example

Figure 9: **Neuroevolution of Augmenting Topologies (NEAT).** (a) Two neural networks with a different topology cannot be crossed over unless the genetic encoding is compatible. (b) NEAT solves this problem by individually representing nodes (node genes) and connections (connection genes), and by using "innovation numbers". Only connections that have the same innovation number can be swapped during cross over. (c) How "augmentation" happens is illustrated. Either connections (top) or nodes (bottom) can be added freely, hence the chromosome representation is variable length. Adapted from Stanley and Miikkulainen (2002b).

algorithm for this (Stanley and Miikkulainen 2002a,b), so we will adopt and extend this algorithm for the current task. Fig. 9 shows the basic idea behind NEAT.

[Revision 1] As part of this task, we will **significantly extend** NEAT in two steps: (Step 1) implement the internal map environment and the neuromodulator mechanism from Sec. 4.2, and (Step 2) introduce new genetic encoding elements so that internal marker dropping/detecting through the internal map can be interchangeable with direct recurrent connections.

Step 1 is fairly straight-forward. We can simply implement the internal map, and hook it up to the input/output interface of an initial NEAT network that contains only input and output nodes. So, it is basically adding a second environmental simulation to the NEAT network, on top of the original 2D foraging environment.

Step 2 is non-trivial and needs careful thought. The existing NEAT genetic encoding in Fig. 9b needs to be updated. New entries (other than nodes and connections) need to be introduced, and new forms of mutation introduced so that connections can be replaced with a loop through the internal map and vice versa. For the convenience of representation, the internal map can be considered a 2D array of nodes, so that the definition of node and connection can be preserved and be compatible with the rest of the NEAT network.

Research issues: (1) The key question we have to answer in this part is whether the step in Sec. 4.2 (and subsequent elaboration in the current section) was necessary and indeed an easier alternative to a direct jump from Sec. 4.1 to Sec. 4.4. In order to answer this question, we will develop a parallel experiment where the dropper/detector mechanism is directly linked to the environment, rather than to the internal map. For this, genetic encoding elements similar to the above will be developed. (2) In recurrent networks like the Elman network that we used in our prior work to compare with the dropper/detector network, links between hidden layer units are fully connected (e.g., Fig. 4b). Is this kind of full connectivity required for competent performance in memory tasks like the 2D foraging task? This is an interesting question since the recurrent feedback through the internal map (or the external environment) is local. We will first test if full connectivity is required by cutting down on the connections in the recurrent network to form local receptive fields. In converse, we will try expanding the attentional window in the internal map. This kind of exercise can help us tune the genetic encoding and mutation operations. (3) Finally, we will investigate the similarities between our work and existing works on the evolution of body morphology (Sims 1994) or grammatical encoding and other methods for patterned neural circuit

formation (Jung 2005; Stanley 2007), and adopt their approach if appropriate.

4.4 Evolution of Predictive Dynamics in Recurrent Circuits

In order to investigate the emergence of predictive capability at the network level in a sensorimotor agent, we will investigate the internal state dynamics of a recurrent neural network controller in the pole balancing task. The basic premise here is that before specific predictive mechanisms can come about, the internal state dynamics first needs to be predictable. See Fig. 4 for the basic experimental protocol.

Our approach is to collect individual controllers that reach a particular performance threshold, and compare their internal state properties (Fig. 4). It turns out that controllers that have evolved to have the same level of performance can have dramatically different internal state dynamics (Fig. 10). The question is, would this internal difference have any effect on fitness? An initial answer to this question is "no" since all these controllers are from the same high-performance population.

The only way to differentiate between these two groups, high predictability and low predictability, is to put them in a more testing environment. We can make the pole balancing task harder by increasing the initial tilt of the pole, removing certain information (such as velocity input), or introducing noise. We expect the controllers with more predictable internal state dynamics will show more robust behavior under harsher environmental conditions. As our pilot data suggest, there is a smooth gradient in the internal state predictability among controllers that are successful in the initial, easy task (Fig. 11a). The plot shows that the 130 controllers that evolved to meet the 5,000 step performance threshold have a wide range of internal state property, quantified by the predictability in their internal state trajectory. When the top 10 and the bottom 10 in the predictability scale are compared in a harder task, the performance deteriorates in those with low internal state predictability (Fig. 11b).

Again, the importance of these preliminary results is that agents with more predictable internal state trajectory have a better chance of surviving in a changing environment, thus they are more robust. This hints at how prediction could have evolved, without having predictability explicitly represented in the fitness function.
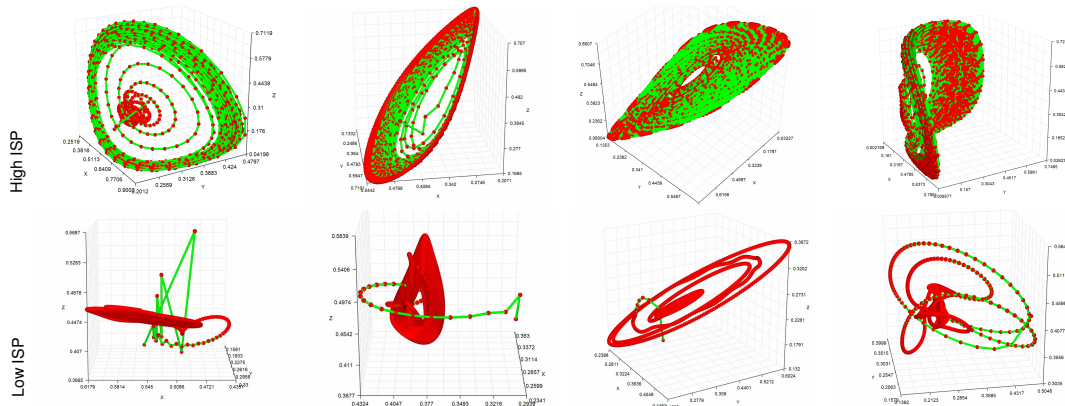

Figure 10: **Internal State (Hidden Unit) Trajectories.** Examples are shown for highly predictable (top row) and hard to predict (bottom row) internal state trajectories. The highly predictable group shows smooth and periodic orbits, whereas the hard to predict group shows sudden turns and tangled trajectories. Adapted from pilot results in Kwon and Choe (2008).

Research issues: As part of this task, we will address the following research questions. (1) Can the robust performance in the high predictability group hold in tasks that are made harder in different ways, such as added delay in the input, noise, and/or missing information? (2) Does

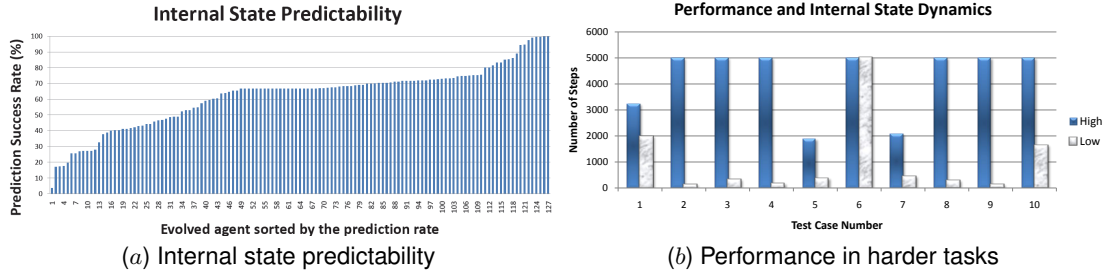(a) Internal state predictability   (b) Performance in harder tasks

Figure 11: **Internal State Predictability and Task Performance.** Pilot results from the analysis of internal state predictability and subsequent performance in harder task environments are shown. (*a*) The internal state predictability measured with a supervised learner is shown for 130 highly successful pole balancers. All of the controllers were able to balance the pole for 5,000 or more steps. (*b*) Initial comparison of the top 10 (blue bar) and bottom 10 (white bar) controllers in (*a*) are shown. In this comparison, the pole balancing task was made harder by increasing the initial tilt angle of the pole. We can see that the controllers with high internal state predictability mostly retain their performance, those with low predictability lose most of their performance. Adapted from pilot results reported in Kwon and Choe (2008).

the internal state dynamics correlate to behavioral dynamics, thus indirectly providing a hint to the selection process? **[Revision 3] This question directly addresses the causality issue.** We will check if the hidden-to-output weights contribute to the internal-external discrepancy. (3) Can the approach be applied to different task domains? We will test the same experimental design in a different domain such as the predator-prey domain (Gomez and Miikkulainen 1997) or competitive co-evolution tasks (Stanley and Miikkulainen 2002a). The key question is if predictable internal state dynamics gives the agents a competitive edge in a changing environment, on a wide variety of tasks.

5 Deeper Implications

Finally, we would like to discuss some deeper implications of our work. (We admit that this part is rather speculative and philosophically loaded, so please read below at your own risk!) We think that through our approach we can get closer, in a scientific manner, to one of the deepest mysteries in modern science, i.e., that of *consciousness* (Searle 1997). Here, we will talk about two aspects of consciousness that relate to our proposed work (especially material from Sec. 4.4): (1) subjectivity and (2) self-perspectival organization (Van Gulick 2004).

Subjectivity basically means that consciousness is a first-person property and is inaccessible by a third-person (Van Gulick 2004). This immediately raises questions regarding the evolutionary value of consciousness. For example, consider Fig. 12. If two equally functional individuals exist, one with subjective consciousness and the other without, why would natural selection favor the conscious one? Our preliminary results in Sec. 4.4 shed some light on this. As shown in Fig. 4*d*, at some point in time, individuals with equal performance but with different internal properties (internal state predictability) can coexist. However, certain internal properties can at a later time (e.g., when circumstances change) turn out to be beneficial to survival. (Part of our work in Sec. 4.4 is to establish this kind of causal link.) Thus, our work shows how *apparently* subjective properties can bias natural selection.

Self-perspectival organization means that conscious experience does not stand alone, but rather, it belongs to a subject or a self (Searle 1997, p. 183; Van Gulick 2004). How can we scientifically study something that is so subjective as the notion of self? We propose that we need to track back by considering the properties and necessary conditions of these phenomena.
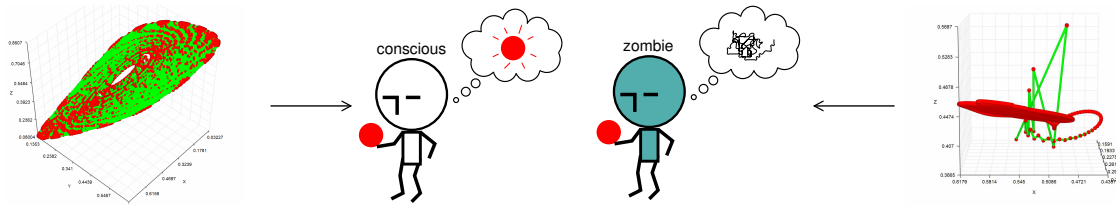
Figure 12: **Conscious being vs. zombie.** From the outside, a conscious being and a zombie (a philosophical zombie) may seem indistinguishable. However, internally (or subjectively), one might have phenomenal experience (left) while the other might lack this kind of experience (right). These internal characteristics may be determined in part by the internal state dynamics (see the text for details).

For example, authorship (of own action) is a prominent property of the self. Authorship means I am the owner of my actions (Millgram 2005). A distinct property of self-authored actions is that they are 100% *predictable*. It does not make sense to say, e.g., "I think there is a 90% chance that I will type the letter 'A' after this." A necessary condition for such an accurate prediction is the predictability of the internal state dynamics, i.e., the underlying dynamics should lend itself to prediction (see Fig. 12). This is where it suddenly becomes objective, detached from the notion of self. There is no agreement on how to measure the subjective aspect of consciousness or self, but we can experimentally (and hence objectively) measure the predictability of neural (or population) dynamics. Furthermore, our preliminary results in Sec. 4.4 showed that there is an evolutionary edge for agents that have more predictable internal dynamics. So, our work can provide important clues on how certain necessary conditions of consciousness could have evolved.

This last part (Sec. 5) may have sounded overly philosophical, but we want to emphasize that our intent was to operationalize these concepts so that we can study them within experimental science, especially with an evolutionary perspective (cf. Humphrey 1992). Finally, it is interesting to note that two major mysteries in modern science, time and consciousness, seem to be so tightly entangled (Koch 2007, chapter 15).

6 Broader Impact Plan

Curriculum development and graduate education: An important aspect of the research component of this project is that the subject requires an interdisciplinary approach, ranging from computer science, cognitive science, to neuroscience. The new interdisciplinary course the PI designed and taught in spring 2003 (Intelligent Neural Systems) and offered again in spring 2004 and spring 2005 (as Computations in Neural and Biological Systems) was received very well among students. For that course, the PI was awarded the departmental graduate teaching award in spring 2004. The course contained interdisciplinary material from artificial intelligence to cognitive science and neuroscience, and in the course the close relationship among these fields and their mutual relevance were made explicit. Now, the course is being taught as a regular course (CSCE 644 Cortical Networks). As part of this project, the PI will incorporate the research methodology and outcome resulting from this project into the interdisciplinary curriculum, with an emphasis on "prediction".

Undergraduate research and under-represented groups: The PI is also committed to equally motivating and mentoring underrepresented groups, and acknowledge that this mission is best carried out in the undergraduate classroom. This is because stirring interest in this group of students at an early stage will help them stay in school and continue on to pursue a career in research and education. In this vein, the PI has been participating in the Undergraduate Summer

Research Grant (USRG) program sponsored by the College of Engineering at Texas A&M. The program attracts excellent undergraduate students from across the country, and many of these students are from minority-serving institutions. The PI supervised two undergraduate students (one minority) under this program (2003 and 2005). The PI also mentored eight students supported under the NSF Research Experience for Undergraduates program (REU; #0353957, PI: Valerie Taylor) in 2004, 2005, 2006, 2007, 2008, and 2009, and two students (one minority, both female) under the CRA-Women Distributed Mentor Project (DMP) for undergraduate women in computing research. Four of the above students applied to and were accepted by top graduate programs in the US. The PI will continue mentoring undergraduate students under NSF REU, TAMU USRG, and CRA-Women DMP. The PI is planning to apply for REU supplements to continue providing such excellent research opportunities to undergraduate students. The methodology and tools developed as part of the proposed project will be organized into a toolkit that will allow summer research students to have a hands-on experience in cutting-edge research in robust intelligence.

K-12 outreach: Sparking an initial light of excitement in the younger generation of scientists and engineers is quite important. In line with this commitment, the PI has been participating in departmental events where the research labs are showcased to high school students, teachers, and parents. Since 2003, our lab hosted six lab tours to high school student groups and other interested parties. The PI also gave a guest lecture at the Summer Honors Invitational Program (SHIP) at Texas A&M University in 2004, where top high school students (national merit scholars) from around the country were invited to experience the atmosphere of the university. The PI will go beyond participation and take an active role in these and other events to reach out to the general public, especially the younger generation.

As part of this effort, a set of web-based interactive tutorials will be authored, which illustrate the basic principles of the proposed research (cf. `http://www.whyville.com` spearheaded by James Bower at the University of Texas). **The web tutorial will include interactive realtime evolution experiments where visitors can get hands-on experience on steering the direction of evolution in a micro ecosystem by adjusting environmental factors. The experiments will highlight the emergence of unexpected properties, i.e., properties that are not directly expressed in the fitness function. This kind of computational experiments can provide deeper insights and appreciation for evolution.**

Software and data dissemination: All software and data resulting from this project will be publicly released under the GNU Public License (`http://www.gnu.org`) and the Open Database License (`http://www.opendatacommons.org/`). We will set up a dedicated web page for this purpose. (See `http://topographica.org` and `http://computationalmaps.org` for similar web pages contributed by the PI.)

7 Management Plan

Personnel: Please refer to the PI's bio-sketch for his accomplishments. The PI will work with one Ph.D. student of his (Timothy Mann) on this project. Timothy Mann is a former NSF Research Experience of Undergraduates program participant (the PI was the mentor), who subsequently joined the PI's lab. He is a highly insightful and technically capable student who is currently funded as a teaching assistant by the PI's department. A dedicated research award to support him as a research assistant can be of great assistance.

Timeline: The four tasks in Sec. 4, 4.1 to 4.4, will be carried out in linear order. In year 1, task 4.1 and task 4.2 will be completed. In year 2, task 4.3 will be completed. In year 3, task 4.4 will be completed. Starting from year 2, we will work on the specific broader impact activities in Sec. 6, including the web-based tutorial.

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