

CHAPTER 2

SELECTED SELF-ORGANIZATION AND EVOLUTIONARY CONSTRUCTIVISM

1. Selected Self-Organization²

1.1 Self-Organization

Self-organization is seen as the process by which systems of many components tend to reach a particular state, a set of cycling states, or a small volume of their state space, with no external interference. All the mechanisms dictating its behavior are internal to the system: self-organization as opposed to externally imposed organization. Thus, it is reasonable to further demand that for a system to observe self-organizing behavior, its order cannot be imposed by special initial conditions, which would amount to a special creation. Therefore, to guarantee that a system is self-organizing, we start it with random initial conditions and see if it attains the desired order, or attractor behavior.

Thus, self-organizing behavior is the spontaneous formation of well organized structures, patterns, or behaviors, from random initial conditions. The systems used to study this behavior computationally are referred to as dynamical systems or state-determined systems, since their current state depends only on their previous state. They possess a large number of elements or variables, and thus high-dimensional state spaces. However, when started with some initial conditions they tend to converge to small areas of this space (attractor basins) which can be interpreted as a form of self-organization. Examples of computational dynamical systems are boolean networks and cellular automata. Since such formal dynamical systems are usually used to model real dynamical systems such as chemical networks of reactions, non-equilibrium thermodynamic behavior [Nicolis and Prigogine, 1977], or even mineral osmotic growths [Leduc, 1911; Zeleny, Klir, and Hufford, 1989], the conclusion is that in nature, there is a tendency for spontaneous self-organization which is therefore universal [Kauffman, 1993].

The existence of attractors is identified with the dissipation of some form of energy, therefore, self-organizing structures can only be maintained by a constant flux of energy through them, and are therefore not in equilibrium. These attractors may be chaotic in which case the emergent behavior becomes too disorganized to grasp (disorganized complexity). The behavior of interest is often found in the transition

² The ideas presented in this section were first developed in Rocha [1995c, 1995f, 1996a, 1997d], as well as on the lecture notes for the course “Evolutionary Systems and Artificial Life” [Rocha, 1995e].

between order and chaos — edge of chaos— and classified as a kind of organized complexity [Weaver, 1948; Langton, 1990]. This behavior — many parts working together to achieve some order — is also known as *synergetics* [Haken, 1977].

1.2 Emergent Classification and Constructivism

1.2.1 Cybernetics and Eigenbehavior

The cybernetician Heinz von Foerster [1981] equated the ability of a self-organizing system to classify its environment with the notion of *eigenbehavior*. He postulated the existence of some stable structures (*eigenvalues*) which are maintained in the operations of an organization's dynamics [Rocha, 1994b, 1995b, 1996a]. Following Piaget, he observed that any specific instance of observation of such an organization, will still be the result of an indefinite succession of cognitive/sensory-motor operations [von Foerster, 1977]. This reiterated the constructivist position that observables do not refer directly to real world objects, but are instead the result of a cascade of cognitive and sensory-motor operations in some environment/subject coupling. "Eigenvalues represent the externally observable manifestations of the (introspectively accessible) cognitive [operations]". [von Foerster, 1977, page 278, italics added]. Further, "Ontologically, Eigenvalues and objects, and likewise, ontogenetically, stable behavior and the manifestation of a subject's 'grasp' of an object cannot be distinguished." [von Foerster, 1977, page 280]. *Eigenbehavior* is thus used to define the behavior of self-organizing, cognitive systems, which through the closure of the sensory-motor interactions in their nervous systems, give rise to perceptual regularities as objects [Varela, 1979, chapter 13].

Notice that eigenvalues are specific to the particular cognitive operations and how they recognize observables, that is, to the system's structure and the corresponding dynamics³. Any system, cognitive or biological, which is able to relate internally, self-organized, stable structures (eigenvalues) to constant aspects of its own interaction with an environment can be said to observe eigenbehavior. Such systems are defined as *organizationally closed* because their stable internal states can only be defined in terms of the overall dynamic structure that supports them. Organizationally closed systems are also *informationally open* [Pask, 1992], since they have the ability to classify their constructed environment in what might be referred to as *emergent representation*

1.2.2 Complexity Theory, Emergent Representation, and Emergent Morphology

It is perhaps easier to think about these concepts in the modern terminology of dynamical systems and complexity theory. The coupling of many simple elements into a network allows the establishment of highly recursive dynamical systems which can observe a wide range of attractor behaviors. Kauffman [1993], for instance, has studied in detail the workings of random boolean networks and their attractor behavior ranges, showing that boolean networks can be made equivalent to most other computational models of self-organization such as cellular automata.

An eigenvalue of an organizationally closed system can be seen as an attractor of a self-organizing dynamical system. The global "cooperation" of the elements of a dynamical system which spontaneously emerges when an attractor state is reached is understood as self-organization [von Foerster, 1960; von

³ The structure of a dynamical system refers to the actual components and interrelations between components that establish the dynamics.

Foerster and Zopf, 1962; Ashby, 1962; Haken, 1977; Prigogine, 1985; Forrest, 1991; Varela, Thompson and Rosch, 1991; Kauffman, 1993]. The attractor behavior of any dynamical system is dependent on the structural operations of the latter, e.g. the set of boolean functions and connections in a boolean network. Speaking of an attractor makes sense only in relation to its dynamical system, likewise, the attractor landscape defines its corresponding dynamical system. Furthermore, attractor values can be used to refer to observables accessible to the self-organizing system in its environment, and thus perform environmental *classifications* (e.g. classifying neural networks). This classification capacity was identified in the cybernetic terminology as eigenbehavior. It is also the crux of the constructivist position [Glanville, 1981]. Not all possible distinctions in some environment can be “grasped” by the self-organizing system: it can only classify those aspects of its environment/sensory-motor/cognitive interaction which result in the maintenance of some internally stable state or attractor (eigenvalue). In other words, not everything “out there” is accessible; only those things that a particular physiology can construct with the stabilities of its own dynamics are.

A classifying self-organizing system is autonomous if all structural processes that establish and sustain its dynamics are internally produced and re-produced over and over again. Autonomy was previously referred to as organizational closure. A computational neural network by itself can classify an environment, but the processes (e.g. a backpropagation algorithm) that make it improve its classifying ability are external to the network. In this sense, the network itself is not autonomous, though the network together with the algorithm that changes its structure may be argued to be. It is precisely the ability of an autonomous system to change its structure in order to better classify a changing environment that defines *emergent representation*. For a classifying self-organizing system to change its classification ability, structural changes must be performed to alter its attractor landscape (this point is developed ahead). When the structure responsible for a given dynamics is changed, we obtain a new environmental classification (e.g. weight changes in a neural network).

Similarly, living organisms in order to adapt to their environment must be able to change the structure that establishes their own dynamic morphology. It is indeed a similar problem if we regard evolution as a search through a space of possible morphologies. In this case, living organisms must come up with mechanisms for evolving appropriate morphologies for a given environment: *emergent morphology*. This can be seen as the problem of classification of a morphological space given a certain changing environment, as much as emergent representation is a problem of classification of a space of cognitive representations given a certain changing environment. Natural selection is the living organism’s method of structural (genetic) perturbation of self-organizing networks of components. Computational models of this emergent morphology are often based on boolean networks standing for genetic regulatory networks [Kauffman, 1993], which can be coupled to genetic algorithms [Dellaert and Beer, 1994; Packard, 1988]. In these models, the structure of the boolean network (connections, functions and so on) is changed by the genetic algorithm, leading to different dynamic behavior which in turn stands for different morphologies, appropriate to a problem specified by the genetic algorithm’s fitness function. These morphologies self-organize from and are emergent to the boolean network’s dynamics, and can be regarded as the classification of an appropriate dynamic configuration for the given selective pressures.

The process of obtaining novel classifications of an environment, by an autonomous self-organizing system, can be referred to as *emergent classification*. Emergent because it is the result of the local interaction of the basic components of the self-organizing system and not from a global controller. This *bottom-up* definition of emergence [Langton, 1989] is generally accepted in artificial life and connectionist artificial intelligence as the guiding conceptual framework of models of life and cognition. In the following, I will refer to systems that are capable of emergent classification as *complex systems*. In section 1.3 I attempt to better specify the concept of emergence.

1.2.3 Self-Organization and Constructivism

Let me now make the connections between the terminologies of second-order cybernetics and complexity theory regarding self-organizing systems explicit by presenting figure 1. This relationship may be taken in some quarters as commonsensical, since most of the cybernetic principles of self-organization as defined by von Foerster and other participants of his program of research at the Biological Computer Laboratory in Urbana, Illinois in the 1960's and 1970's, were proposed within larger philosophical frameworks. In any case, the empirical basis for those theories depends on material and computational systems with the self-organizing characteristics outlined above. It is this empirical foundation of self-organization that I am exploring here, and not the related higher level interpretations of eigenbehavior. The single philosophical issue that I intend to pursue is that of the dependence of an autonomous system's environmental classification on its own dynamics, usually referred to as constructivism.

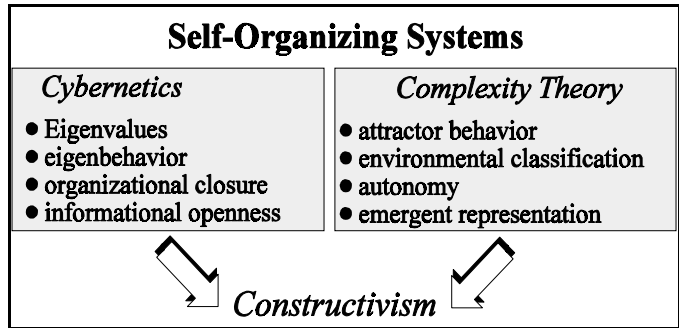


Figure 1: Terminologies of Self-Organization

Autonomous systems must construct their reality by using stable structures internally available. Objects are constructed by peculiarities of cognitive operators (the maintenance of stable structures) and are not accessible through a direct representation of real world categories. Constructivism, the philosophical cornerstone of second-order cybernetics, does not merely entail the idea that objects are not accessible but that objects are constructed by cognition and constitute its basic building blocks. Today, most of us agree one way or another with this principle which shall be discussed in more detail in section 2 of this chapter in the context of cognitive science. However, what must still be addressed is how do these stable eigenvalues become eigenbehaviors, in other words, what is the nature of the structural coupling (to use the autopoietic terminology [Maturana and Varela, 1987]) between an autonomous, self-organizing system, and its environment? How do the internally constructed eigenvalues refer to aspects of the environment? How can we increase the variety of eigenbehavior? Can this variety be open-ended?

1.3 Emergence and Levels of Description

There are three levels that need to be addressed when dealing with the notion of emergent phenomena in self-organizing systems, in particular, of emergent classification. First, there is the material, dynamical, substrate, which will be the causal basis for all other levels that we may further distinguish⁴. Second, we have the attractor behavior of this dynamics. Finally, we have the (possible) utilization of the set of attractors as referents for some aspects of the interaction of the dynamical system itself with its environment (e.g. the pattern recognition abilities of neural networks).

⁴ Causal in the sense that self-organization is considered to have exclusively a material substrate with no other processes are involved. It is not the scope of the present work to dwell into the issues of causation. Those who are more satisfied with Aristotelian classes of causation [e.g. Rosen, 1991, Minch, 1995], will find the previous expression vexed as material causality does not imply final causality. I thank Stan Salthe for pointing this out.

1.3.1 Explanatory Emergence

Robert Rosen’s concept of emergence defines it as the deviation of the behavior of a natural system from a model of it [Rosen, 1985, 1991, 1995]. Peter Cariani [1989] has developed this notion and renamed it *emergence relative to a model*.

“Emergence relative to a model, then is the result of the finite and hence incomplete character of all models of the world. At some point in time we can, if we are fortunate, construct a model which will deterministically capture the behavior of the physical system. The behavior predicted by the model will, for some period of time, correspond to the observed behavior of the physical system, because it was constructed to do so. But eventually, if one waits long enough, all physical systems will diverge from their models, but some will diverge before others. Physical systems can thus be sorted out according to whether they will exhibit emergence over some finite observational period.” [Cariani, 1989, page 164]

I prefer to see emergence relative to a model as an observer’s switching between different models offering different modes of explanation, rather than a temporal mismatch (and thus increasing lack of

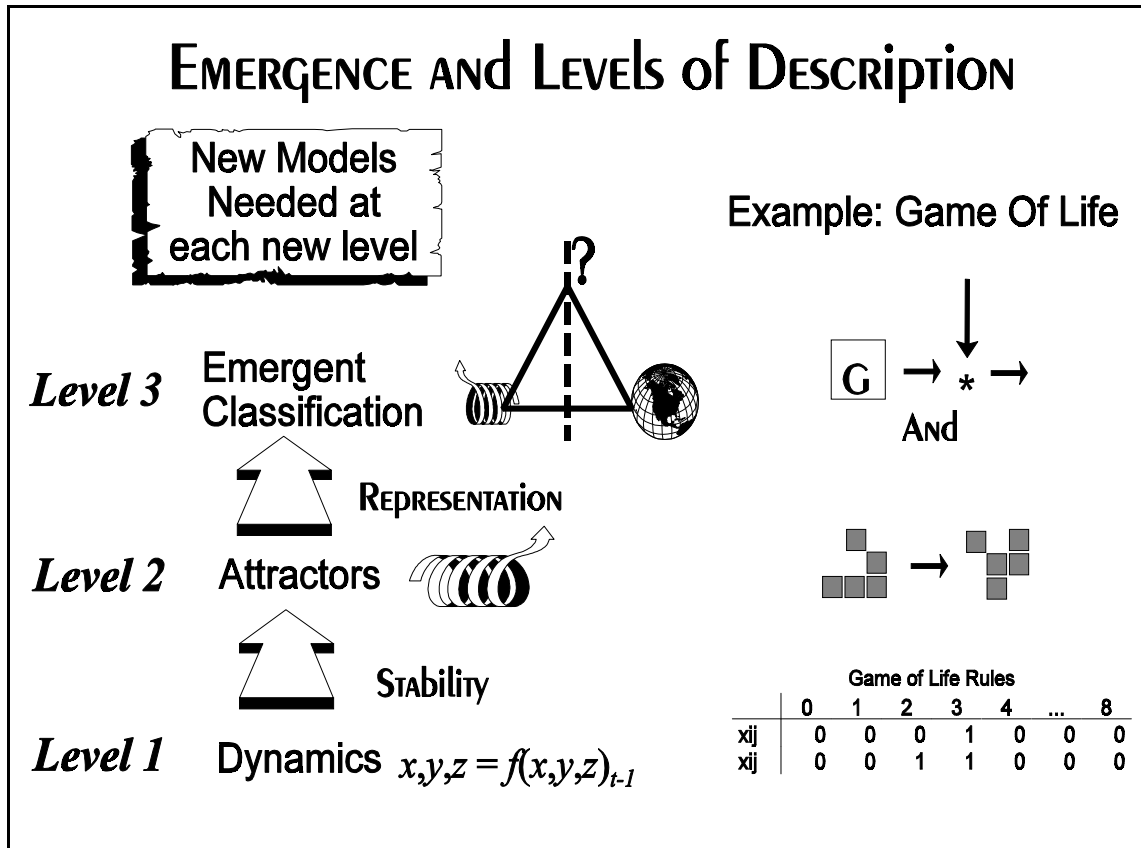


Figure 2: Classifications emerge from attractors, as attractors emerge from the dynamics. “Gliders” are not describable by the cellular automata rules of the Game of Life. Likewise, an “and” gate built out of a “glider gun” and streams of gliders is not describable by the stabilities of the Game of Life. A “standing-for” relation is required, which is depicted by a triangle representing an epistemic cut [Pattee, 1995b] between the world and the stabilities of the dynamic system through a system of representation.

explanatory power) between a model and the observed phenomena. As Howard Pattee [1978] has pointed out, due to the subject-object or observer-system dichotomy, a given observed phenomenon possesses several modes of description, none of which exhibits full explanatory power. In other words, models of physical phenomena explain only certain aspects of them, and to increase our understanding of the world we need complementary, at times irreducible, modes of description [Pattee, 1978].

Returning to the issue of self-organizing systems and emergence, we observe that the level of attractor behavior is emergent to the dynamics because it cannot be explained solely by a description of the latter. Stability of dynamical states is not expressed in the language of the interactions between the components of a dynamical system. At this lower level, there is no distinction between a stable and an unstable state, between attractor and transient states. For instance, the transition rules of Conway's *game of Life* cannot describe what "blinkers" and "gliders" are. Likewise, when the attractor landscape is utilized to classify an environment, a new level is created to define the representations necessary for this classifying function: a semantic relation is created. This self-organizing classification is emergent to the attractor landscape level since the latter can only describe stabilities of the dynamics and not any "standing for" relation with the environment. To continue with the previous example, the level of attractor behavior describes what a glider or a "glider gun" is in the Game of Life, however it cannot describe streams of gliders as information carriers in a universal computer built out of *Life* patterns [Poundstone, 1987]. The utilization of a glider as a bit of information requires a semantic relation imposed on the level of attractors.

1.3.2 Semantic Emergence

"We must distinguish the syntactical emergence of symmetry-breaking and chaotic dynamics from the semantic emergence of non-dynamical systems which stand for a referent." [Pattee, 1989, pp. 72-73]

No physical or formal description of the dynamical system and its attractors alone will completely explain the "standing-for", or semantic, dimension [Pattee, 1995a]. In figure 2, this third semantic level is depicted by a triangle whose left corner stands for a dynamic attractor, the right corner represents the world "out there", and the top corner represents the system of representation (denoted by a question mark) by virtue of which an internal attractor can be related to its environment. It is also a system of *reference*, as the representational link between dynamic attractors and an environment is established in reference to a third component. This system defines a cut between what is internal and external [Medina-Martins and Rocha, 1992] to the system, as Pattee [1995b] (following von Neumann [1966]) puts it, between the "knower" and the "known", that is, it defines an epistemic cut. We have then environmental events and a system's representation of those, by virtue of some representational relation. This triadic relationship is often equated in terms of Peircian semiotics [Salthe, 1995], and shall be explored in section 1.7.

The emergence of level 2 (attractor behavior) from level 1 (dynamics) and of level 3 (classification) from level 2 is based on explanatory emergence defined above as the existence of complementary modes of description. However, the emergence of classification from attractor behavior introduces a more specific form of semantic emergence as it establishes a representational relation between the classifying system and its environment. In the following, I shall argue that this emergent representation does not imply a commitment to open-ended representationalism, where symbols are free to represent everything in the environment of the classifying system. Rather, it implies an evolutionarily grounded constructivist stance.

The hierarchy of modes of description discussed in this section is very dear to systems-theoretic approaches to complex systems [Wuketits, 1990]. It requires a broader view of causality. As discussed before, I maintain that classification is materially caused by the attractor behavior of a particular dynamical system. The emergence of the third level of classification, which can also be referred to as a functional level, is often shown to require a more Aristotelian view of causation where final cause is interpreted as functional

or intentional cause [Minch, 1995; Salthe, 1995; Rosen, 1991]. Also, if classifying systems are autonomous, then they change their own dynamical structure in order to accommodate different classification abilities (as it will be explored in detail next). In a sense, we have then a closure of cause and effect. For this reason, some have defended that complex systems require a sort of network or feedback causality [Riedl, 1977, 1984, Wuketis, 1990]. At least, a distinction between functional/informational and dynamical causal systems descriptions must be made [Hooker, 1995]. This is precisely the goal of Pattee's epistemic cut and semantic emergence concepts. Recently, Clark [1996] has similarly defended the necessity of complementary models of description in artificial life and artificial intelligence which succumb to neither a pure dynamical systems, self-organizing, vocabulary nor a pure functional, homuncular⁵, description of classifying systems. It is precisely the necessity of emergence, or different levels of description, that makes systems with emergent classification complex.

1.4 Memory and Selected Self-Organization

“What do complex systems have to be so that they can know their worlds? By ‘know’ I don’t mean to imply consciousness; but a complex system like *E. Coli* bacterium clearly knows its world. It exchanges molecular variables with its world, and swims upstream in a glucose gradient. In some sense, it has a representation of that world.” [Kauffman, 1995, page 336]

“Metaphorically, life is matter with meaning. Less metaphorically, organisms are material structures with memory by virtue of which they construct, control, and adapt to their environment.” [Pattee, 1995b, page 24]

Self-organizing systems such as neural networks clearly have the ability to discriminate inputs. Generally, the attractors of their dynamics are used to represent events in their environments: depending on inputs, the network will converge to different attractors. If this ability to classify an environment is implemented by the self-organizing system itself, then we can say that it is an autonomous (classifying) system. As previously stressed, not all possible distinctions in some environment can be “grasped” by the autonomous system: it can only classify those aspects of its environment/sensory-motor interaction which result in the maintenance of some internally stable state (attractor). Another way of looking at this is to say that autonomous systems do not represent their environment, they construct it. Autonomous classification is not open-ended but dependent on a system's dynamics.

1.4.1 Variety of Classification and the Edge of Chaos

Self-organizing approaches to life (biological or cognitive), in particular second-order cybernetics [Pask, 1992], take chaotic attractors as the mechanism which will be able to increase the variety (physiological or conceptual) of self-organizing, classifying, systems. External random perturbations will lead to internal chaotic state changes; the richness of strange attractors is converted to a wide variety of discriminative power. However, for any classification to have survival value, it must relate its own constructed states (attractors) to relevant events in its environment, thus, similar events in the world should correspond to the same attractor basin. Chaotic systems clearly do not have this property due to their sensitivity to initial conditions. Ordered systems follow this basic heuristic. If on the “edge of chaos” Langton [1990], ordered systems may in addition allow for higher information exchange and perhaps more ‘clever’ (evolvable) categorization mechanisms.

⁵ Homuncular explanation occurs when “we explain the capacities of the overall system by adverting to the capacities of its components, and the way they interrelate” [Clark, 1996, page 263]

“Organisms and other entities which interact with their worlds are likely to couple to those worlds in such a way that smooth classification occurs, and the world is seen as relatively stable. Then the ‘knower’ should not be chaotic, nor should its classification, the ‘known’, be. It is a reasonable guess that both the knowing system and the known world are in the [ordered] regime, perhaps near the edge of chaos. [Kauffman, 1993, page 234]”

Kauffman [1993, page 232] further hypothesizes that “living systems exist in the [ordered] regime near the edge of chaos, and natural selection achieves and sustains such a poised state”. This hypothesis is based on Packard’s [1988] work showing that when natural selection algorithms are applied to dynamic systems such as boolean networks, with the goal of achieving higher discriminative power⁶, the parameters are changed generally to lead these systems into this transitional area between order and chaos. This idea is very intuitive, since chaotic dynamical systems are too sensitive to parameter changes, that is, a single mutation leads the system into another completely different behavior (sensitive to damage). By contrast, ordered systems are more resilient to damage, and a small parameter change will usually result in a small behavior change which is ideal for smooth adaptation (hill-climbing) in correlated fitness landscapes. However, even though very ordered systems can adapt by accumulation of useful successful variations (because damage does not propagate widely), they may not be able ‘step out’ of certain areas of their fitness landscapes. It is here that systems at the edge of chaos enter the scene, they are not as sensitive to damage as chaotic systems, but still they are more sensitive than fully ordered systems. Thus, some mutations will accumulate (by causing minor changes) and some others will cause major changes in the dynamics allowing more distant searches in fitness spaces. Simultaneous mutation buffering (to small changes) and dramatic alteration of behavior (in response to larger changes) has been shown to be ideal for evolvability [Conrad, 1983, 1990].

1.4.2. Structural Change and Emergent Classification

Chaotic classifications cannot grasp an ordered interaction with an environment, while point attractors and simple limit cycles may not allow enough behavior change for a good increase in variety. The edge of chaos regime seems to offer a good, intuitive, compromise. However, whatever the regime of a dynamic system, self-organization alone cannot escape its own attractor behavior. A given dynamic system is always bound to the complexity its attractor landscape allows. Even a strange attractor, though undoubtedly endowed with a much richer variety of behavior than limit cycles or point attractors, is restricted to a very small volume of the state space of the respective dynamic system. If the classification variety of the self-organizing system is restricted to such small volumes, then the ability to classify a changing environment is severely constrained, indeed, it is minimal.

For a dynamic system to observe genuine emergence of new classifications, that is, to be able to accumulate useful variations, it must change its structure. Creativity, or open-ended variety can only be attained by structural perturbation of a dynamical system. One way or another, this structural change leading to efficient classification (not just random change), has only been achieved through some external influence on the self-organizing system. Artificial neural networks discriminate by changing the structure of their connections through an external learning procedure. Evolutionary strategies rely on internal random variation which must ultimately be externally selected. In other words, the self-organizing system must be structurally coupled [Maturana and Varela, 1987] to some external system which acts on structural changes of the first

⁶ More on the coupling of dynamical systems and evolutionary algorithms to achieve higher discriminative power in chapter 5.

and induces some form of explicit or implicit selection of its dynamic representations: *selected self-organization*.

Explicit control of a classifying system's structure would amount to the choice of a particular dynamics for a certain task and can be referred to as *learning*⁷. Under implicit control, the self-organizing system is subjected to some variation of its structure which may or may not be good enough to perform our task. Those self-organizing systems which are able to perform the task are thus *externally selected* by the environment to which they are structurally coupled. If reproduction is added to the list of tasks these systems can produce based on their dynamic memories, then we have the ingredients for natural selection: heritable variation and selection.

1.4.3 Distributed Memory

The dynamical approach of von Foerster [1965] to cognition emphasized the concept of memory without a record. By utilizing functionals to change the functions of state-determined systems, von Foerster formalized the idea that memory can be observed in systems which are able to change their own structure and therefore its dynamics and attractor behavior. Today, we name this kind of memory *distributed*, and refer to the kind of models of memory so attained as connectionist. The categories a distributed memory system classifies are not stored in any particular location, they are nowhere to be found since they are distributed over the entire dynamics established by some network of processes [van Gelder, 1991]. They exist however in the form of attractors which are nonetheless discrete at a higher level of description. Categories are not stored in any particular location of the network, but are identified with particular dynamic attractors, for which we need a new, emergent, level of description. Since classified categories are lumped into the attractor landscape of a dynamical system of many components, they are not merely distributed in the sense of being extended over a number of components, they are in fact superposed in the network of component relationships [van Gelder, 1991]. It is precisely because of this superposition that a new level of description is required, since mere knowledge of component interactions cannot describe the classified categories of a connectionist system. Clark [1993], has discussed in detail how connectionism changed our understanding of cognitive categorization processes. More about cognitive categorization in section 2 of this chapter and chapter 3.

Now, for a self-organizing system to be informationally open, that is, for it to observe emergent classification of its own interaction with an environment, it must be able to change its structure, and subsequently its attractor basins, explicitly or implicitly. Whatever the form of selection, this kind of self-organization must be able to classify its interaction with an environment by utilizing its own distributed memory. For selection to occur we must have some internal vehicle for classification — there must be different alternatives. The attractor landscape, or eigenvalues, offer these vehicles. However, and this is an important point, selection is ultimately not performed on the memory vehicles themselves, but on what they stand for, not on eigenvalues but on eigenbehavior. It is not the pattern of activation of a boolean network which is selected, but its ability to perform a particular task with repercussions on its environment. In other words, it is not the memory which is selected, but the particular repercussions it will lead the self-organizing system to perform in its environment. In terms of the hierarchy of emergence outlined previously, selection takes place on the representational (informational/functional) level (level 3 in figure 2) — a selection of semantics.

⁷ I am thinking more of machine learning here. It can be argued that human learning is based on a more implicit developmental, Piagetian, process [Pask, 1977]. Such a discussion is largely beyond the scope of the present work, but will be given larger attention in section 2 of this chapter.

This form of self-organization can be referred to as *distributed memory selected self-organization*. Its relying on some system-environment coupling of structure has been stressed most notably within second-order cybernetics and systems research. Maturana and Varela [1987] propose structural coupling as the general mechanism for variety increase, Pask [1976] refers to it as conversation in the cognitive realm. Both of these approaches owe a lot to von Foerster's eigenbehavior notions. More recently, in the realm of complex systems and evolutionary systems theory, Kauffman [1993] and others have relied on the notion of autocatalytic sets which are (structurally) mutable, self-replicating, self-organizing systems with distributed memory, evolvable through natural selection. What is yet to be discussed is the potential of this kind of self-organization for efficient, open-ended variety.

1.4.4 Embodiment

So far I have maintained that eigenvalues or attractors represent the building blocks of any system capable of discriminating its environment through some thus embodied construction. However, eigenbehavior (emergent classification) and its variety increase needs a structural coupling of these eigenvalues with some externally selective environment. This kind of selected self-organization obliges us "to understand perception not just as an interactive dynamical structure, but as a process that arises from a more fundamental embodiment that makes it possible for evolution to create structures that are internally assigned interactive roles." [Etxeberria, 1995].

Perhaps the most important characteristic of this distributed memory selected self-organization is the fact that its specific material dynamics both constructs the classification of the environment and ultimately defines selection. That is, distributed memory cannot classify everything, only those aspects of the environment that create internal stabilities. Also, selection eventually acts on the functional characteristics of the dynamics (desired for some task) and not on memory itself. The consequence of this fact for biological systems is that natural selection (acting on this form of self-organization) is not free to evolve any organism, but it is constrained by the dynamic properties of the materiality of the organisms it acts upon — evolution with both a self-organizing and selection component. The consequence for cognitive systems, is that what can be classified is also constrained by the particular materiality of the classifying system at stake — not everything "out there" can be grasped. In other words, the particular self-organizing dynamics of a particular classifying system constrains the universe of its classification. However, we should look into how this process can be made more efficient, and allow for genuine open-ended emergence of variety in classification.

1.5 Descriptions and Symbols

1.5.1 Von Neumann and Description-Based Selection

Von Neumann [1966] defended the idea that a threshold of complexity exists, before which complexity degenerates, and after which complexity can increase in an open-ended fashion. He proposed a self-replicating scheme based on the notion of a memory-stored description $\Phi(A)$ that can be interpreted by a universal constructor A to produce A itself. However, to avoid a logical paradox of self-reference, the description, which cannot describe itself, must be both copied (*uninterpreted* role) and translated (*interpreted* role) into the described automaton. This way, in addition to the universal constructor, an automaton B capable of copying any description, Φ , is included in the self-replication scheme. A third automaton C is also included to effect all the necessary manipulation of descriptions. To sum it up, the self-replicating system

contains the set of automata $(A + B + C)$ and a description $\Phi(A + B + C)$; the description is fed to B which copies it and to A which constructs another automaton $(A + B + C)$; the copy is then handled separately to the new automaton which together with this description is also able to self-reproduce (figure 3).

As Von Neumann [1966] discussed, if the description of the self-reproducing automata is changed (mutated), in a way so as to not affect the basic functioning of $(A + B + C)$ then, the new automaton $(A + B + C)^*$ will be slightly different from its parent. Von Neumann used a new automaton D to be included in the self-replicating organism, whose function does not disturb the basic performance of $(A + B + C)$; if there is a mutation in the D part of the description, say D^* , then the system $(A + B + C + D) + \Phi(A + B + C + D^*)$ will produce $(A + B + C + D^*) + \Phi(A + B + C + D^*)$. Von Neumann [1966, page 86] further proposed that non-trivial self-reproduction should include this “ability to undergo inheritable mutations as well as the ability to make another organism like the original”, to distinguish it from “naive” template-based self-reproduction like growing crystals. Notice that changes in $(A + B + C + D^*)$ are not heritable, only changes in the description, $\Phi(A + B + C + D^*)$ are inherited by the automaton’s offspring and are thus relevant for evolution. This ability to transmit mutations through descriptions cast in separate memories is precisely at the core of the principle of natural selection of modern Darwinism. Through variation (mutation) of memories, populations of different organisms are produced; the statistical bias these mutations impose on reproduction rates of organisms will create survival differentials (fitness) on the population which define natural selection. In principle, if the language of description is rich enough, an endless variety of organisms can be evolved. This is what open-ended emergent evolution means. This point needs to be further elaborated.

1.5.2 Descriptions require a Symbol System

Von Neumann’s model clearly does not rely on a distributed but on a local kind of memory. Descriptions entail a symbol system on which construction commands are cast. These commands are not distributed (superposed) over patterns of activation of the components of a dynamic system, but instead localized on “inert” structures which can be used at any time — a sort of random access memory. By “inert” I mean material structures with many dynamically equivalent states, in other words, the semantic relation, or what the structures are used to refer to, must possess a large degree of arbitrariness so that certain representations are not much more probable than others. In the genetic system, most any sequence of nucleotides is possible, and its informational value is almost completely independent of the particular dynamic behavior of DNA or RNA.

Notice that according to Von Neumann’s own formulation, a symbol system utilized for the construction of self-reproducing systems is not an isolated artifact. Rather, in the context of construction,

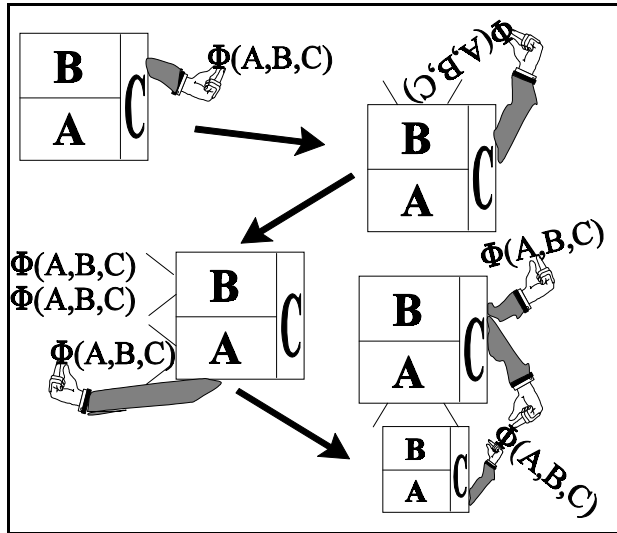


Figure 3: Von Neumann’s self-reproducing automata: Automaton (A, B, C) equipped with a description (Φ) of itself, copies (through B) the description three times. One of these descriptions is fed to the universal constructor A which build another automaton (A, B, C) . C then handles, separately, one of the remaining descriptions to the new automaton which is thus also able to replicate. The third description is kept in order for the process to be repeated.

a symbol system entails a set of available parts. That is, construction blueprints are cast on a symbol system whose primitives are a finite set of parts. In the case of self-reproducing automata, these parts are “and”, “or” and other logical operators, and in the case of the genetic code the parts are the set of aminoacids (the symbols are codons or sets of 3 nucleotides). It is in this sense that open-ended evolution must be understood. A given material symbol system cannot represent everything, only what its primitive parts can construct. Natural selection is open-ended for any form that can be constructed through folding aminoacid chains.

1.5.3 Parts, Symbols, and Embodiment

This parts problem can be rephrased as one of the aspects of embodiment. A particular materiality is tied to specific construction building blocks. The richer the parts, the smaller the required descriptions, but also the smaller the number of classifiable categories or constructed morphologies. For instance, Von Neumann used simple building blocks such as “and” and “or” gates to build his automaton, which in turn required a 29 state cellular automata lattice and very complicated descriptions. Arbib[1966, 1967] was able to simplify von Neumann’s model greatly by utilizing more complicated logical building blocks. Likewise, the genetic system does not need to describe all the chemical/dynamical characteristics of a “desired” protein, it merely needs to specify an aminoacid chain which will itself self-organize (fold) into a functional configuration with some reactive properties. In other words, a given materiality, that is, a given set of parts such as amino acids, provides intrinsic dynamic richness which does not have to be specified by the symbol system on which construction commands are cast [Moreno, et al, 1994] making descriptions much smaller. Embodiment provides this kind of *material information compression*. The other side of Embodiment, is that it also constrains the universe of possible constructions (universe of open-endedness). Living organisms are morphologically restricted to those forms that can be made out of aminoacid chains through the genetic code, while in principle, a formal symbol system, stripped as it is from any materiality, can describe anything whatsoever. Of course, this ‘in principle’ is seriously, and easily, constrained by computational limits, as formal descriptions are much larger than material ones. A complete formal description of a protein would have to include all of its physical characteristics from the atomic to the chemical level, while a gene needs only a description of an aminoacid sequence. In chapter 5 I discuss how to incorporate the notion of embodiment in computational models, in order to obtain some form of descriptonal information compression.

1.5.4 The Symbolic Advantage

Why then is there an advantage of local memory over distributed memory self-replication? Von Neumann’s argument maintains that if we do not have symbolic descriptions directing self-replication, then an organism must replicate through material self-inspection of its parts. In other words, the dynamics must be able to produce copies of itself by template identification of parts existing in its environment. The simplest way would be to have every part of the structure individually heritable. Clearly, as systems grow in complexity, self-inspection becomes more and more difficult [Pattee, 1995a]. The existence of a language, a symbol system, allows a much more sophisticated form of communication. Functional, dynamic structures do not need to replicate themselves, they are simply constructed from physically non-functional (dynamically inert) descriptions. For instance, for an enzyme to replicate itself, it would need to have this intrinsic property of self-replication “by default”, or it would have to be able to assemble itself from a pool of existing parts. But for this, it would have to “unfold” so that its internal parts could be reconstituted for the copy to be produced [Pattee, 1995a]. With the genetic code, however, none of these complicated “gimmicks” are necessary: functional molecules can be simply folded from inert messages. This method is by far more general since any functional molecule can be produced from a description, not merely those that either

happen to be able to self-reproduce, or those that can unfold and fold at will to be reproduced from available parts. The evolution of distributed memory based self-organizing systems is restricted to this type of trivial (in von Neumann's sense) or through self-inspection reproduction [Kampis, 1991].

The symbol system, with its utilization of inert structures, opens up a whole new universe of functionality which is not available for purely dynamical self-replication. In this sense, it can evolve functions in an open-ended fashion. We can refer to this mechanism as *description based evolution*. It is the foundation of the neo-Darwinist position and of all genetic based schemes found in evolutionary computation. Its power is obviously immense. It is however at odds with the notions of self-organization depicted previously. For the purely formal von Neumann scheme, all constructions are possible, that is, in principle, there is nothing a formal symbol system cannot describe in a given set of primitive parts. All classifications, all functions, all morphologies can be attained from a finite set of parts by such a mechanism: open-endedness. In contrast, self-organization tells us that a given autonomous system will be able to classify or morphologically achieve only a (small) subset of all possible system/environment configurations; precisely those for which it can construct dynamic stabilities.

It can always be argued that the random access memory the genetic system establishes, is nothing but complicated dynamics, and the symbolic dimension is just the result of our subjective observation. In other words, again the distinction between the levels of attractor behavior and semantic emergence discussed earlier. But why stop there? The same argument may be applied to the dynamic level itself, since it too is constructed by our subjective observations. The genetic dimension has established a new hierarchical level in evolutionary systems [Laszlo, 1987] which allows a greater level of control of the purely self-organizing dynamics. Failing to recognize this emergent symbolic level, does not allow the distinction between self-organizing systems such as autocatalytic networks [Kauffman, 1993], from living systems whose genetic memory does not require larger and larger autocatalytic networks to develop more and more complicated morphologies. Distributed memory self-organization requires more and more complicated gimmicks to increase the complexity of its organization. There is inherited memory, but it is severely constrained as discussed above.

In evolutionary systems this is at the core of the feud between those who claim that natural selection is the sole explanation for evolution and those who stress that other aspects of evolutionary systems, such as developmental constraints, also play an important role. It is no wonder then that the first group stresses the symbolic description, the gene, as the sole driving force of evolution [Dawkins 1976, Dennett, 1995]. While the second group likes to think of the propensities of matter or historical contingencies as being of at least equal importance in evolution [Gould, 1989, Salthe 1985, 1993, Kauffman 1993]. In pragmatic terms, however, most evolutionary theorists, one way or another, will acknowledge that all these factors play important roles [Eldridge, 1995]. Then, is there some conceptual mechanism that will welcome inclusive approaches to evolutionary systems with both description based selection and self-organizing dimensions? Yes, Pattee's [1982, 1995a] *semantic closure* principle offers such a conceptual avenue. Also, and as we shall see later in chapter 5, in the field of Artificial Life models have been built that incorporate these views with no big fuss.

1.6 Semantic Closure and Open-Endedness

“The symbol vehicle is only a small material structure in a large self-referent organization, but the symbol function is the essential part of the organization's survival and evolution. This autonomous structure-function self-referent organization is what is entailed by my term *semantic closure*” [Pattee, 1995a, page 14]

The notion of description implies a self-referential linguistic mechanism. A description must be cast on some symbol system while it must also be implemented on some physical structure. Since many realizations of the same symbol system are possible, viewing descriptions only as physical systems explains nothing about their symbolic nature in the control of construction. When Von Neumann's universal constructor *A* interprets a description to construct some automaton, a *semantic* code is utilized to map instructions into physical actions to be performed. When the copier *B* copies a description, only its *syntactic* aspects are replicated. Now, the language of this semantic code presupposes a set of material primitives (e.g. parts and processes) for which the instructions are said to "stand for". In other words, descriptions are not universal as they refer to some material constituents which cannot be changed without altering the significance of the descriptions. We can see that a self-reproducing organism following this scheme is an entanglement of *symbolic controls* and *material constraints* which is closed on its semantics, inasmuch as the semantic code it utilizes is defined by the system itself and not from outside, that is, it relies on autonomous coding. Howard Pattee [1982, 1995a] calls such a principle of self-organization *semantic closure*.

A given semantically closed system is based on some sort of coding mechanism between inert and functional structures. However, the code and the associated construction are built on some material substrate constraining the whole semantic closure. I can think of two aspects related to this material dependence that are important: the finite number of available parts, and the dynamic, self-organizing, nature of the coded processes.

1.6.1 Finite Symbol-Part System

The symbolic code is defined by a small, finite, number of symbols (e.g. codons in DNA), which can encode a finite number of primitive parts (e.g. aminoacids). Hence, there is a finite number of functional structures which may be constructed with a given set of parts. This defines the representational power of a given symbol system. In other words, the larger the number of possible equally dynamically inert structures, the larger the universe of functionality that can be represented in them. This implies that systems utilizing Von Neumann's scheme of self-replication (biological organisms in particular) cannot evolve any functional structure whatsoever, since the finite properties of a code constrains the domain of evolvable structures. Nevertheless, the number of possible functional combinations attainable even with a small set of symbols and parts (4 and 20 respectively in the DNA-protein code system⁸) is very large, easily beyond computational limits⁹. In this sense, the emergence of functionality is open-ended though not infinite and universal.

1.6.2 Dynamic Part Compounds

"Organisms have hosts of emergent characteristics. In other words, genes interact in a nonlinear way. It is the interaction that defines the organism, and if those interactions, in a technical sense, are nonadditive – that is, if you can't just say that it's this percent of this gene plus that percent of that gene – then you cannot reduce

⁸ In the genetic system there are 4 nucleotides (adenine, guanine, cytosine, and thymine/uracil), since each aminoacid is coded by 3 nucleotides, codons, there are $4^3 = 64$ possible combinations of these, which makes the genetic code degenerate with only 20 aminoacids.

⁹ To appreciate the dimensions of such a combinatorial universe, consider the often used [Eigen, 1992] sequence space devised by Hamming [1980] for a linear sequence of symbols. A sequence of dimension n , where each position can take 2 values (note that DNA actually has 4 values possible for each position), forms a hypercube of n dimensions where each corner represents a possible sequence. There are 2^n possible sequences.

to the lower-level entities, because the nonadditive features have emerged. These features don't exist until you get into the higher level." [Gould, 1995, page 62]

More important for the constraints applied to a selection mechanism based on a Von Neumann type coding system, are the dynamic characteristics of the coded products. A symbol-part system, even with finite number of symbols and parts, is open-ended in the sense discussed above. That is, from coded messages, a trans-computational number of products can be constructed. However, since the products are dynamic and not symbolic structures, they will have different dynamic characteristics (for which they are ultimately selected). Moreover, the messages encoded stand for some arrangement of parts (strings of aminoacids, phrases in natural language) and not just the parts themselves. An arrangement of dynamic structures, however simple, tends to form a complex dynamic compound which will self-organize according to physical laws. This establishes the sort of network causality described earlier in the discussion of self-organizing systems: e.g. folding of aminoacid chains into proteins in the DNA system.

These self-organized, coded, compounds can interact with one another in many levels of organization which establish the hierarchical nature of evolution [Pattee, 1973; Laszlo, 1987]. Gould [1995], in particular refers to this hierarchy of levels as linked through non-linear relations, meaning that through the network causation of complex dynamic systems we cannot separate individual causes at a lower level from causes at a higher level. This argument is often used to discredit the genetic reductionist stance of Dawkins [1976], as the isolation of genes coding for particular phenotypic traits becomes impossible except for the simplest of cases. Notice that nonlinear behavior is a term often used instead of emergent behavior in complex systems, it is a different way to think about the same phenomenon created by network causality. For instance, the definition of distributed memory as the existence of superposition of representations, as opposed to mere extension of representations across several components, can be rephrased by saying that distributed memory relies on nonlinear representations which are extended across several components of the memory system. If representations were linear, it would mean that, even though extended across components, the percent to which the latter would affect the former would be quantifiable.

In any case, and more relevant here, is to recognize the principle of semantic closure as comprised of symbolic messages that code for self-organizing compounds of material parts. In the computational lingo of Artificial Life, we can say that there is not a linear mapping of coded messages to functional products, rather messages encode dynamic structures which are then left to their own devices as they self-organize. I have referred to this procedure previously as *emergent morphology*. This concept is developed in chapters 4 and 5 in the context of artificial life and evolutionary computation

1.6.3 Development: Constraints on Evolution

The notion of emergent morphology, as implied by semantic closure, has important implications for evolutionary systems and for cognitive systems. This importance lies on the constraints imposed on the evolution of organisms by natural selection, or the environmental classification performed by cognitive systems. As discussed earlier, self-organizing systems cannot classify or construct everything, as they converge to preferred dynamic pathways defined by their attractor landscape. A given dynamic system has in general only a relatively small number of possible final configurations [Kauffman, 1993]. If complex systems are based on the multi-level hierarchies of interacting dynamic systems built out of initially coded dynamic parts discussed above, then the number of possible final configurations (constructed morphologies or constructed representations) is constrained by this whole hierarchy of dynamic network causality. In other words, not everything can be evolved, as the initial encoded arrangement of parts will have to self-organize under the complicated influence of all sorts of levels of dynamic organization.

The process of reaching a multi-level structure through the self-organization of many dynamic parts is known as *development*. This process of hierarchical organization has been studied extensively by many

in the context of evolutionary systems [e.g. Salthe, 1993; Goodwin, 1994; Buss, 1987]. Under semantic closure, development is seen as an orchestration of dynamic material building blocks and contextual environmental factors, under the initial direction of symbolic controls indispensable for the open-endedness of the process of natural selection according to Von Neumann's model. Some aspects of the notion of development are approached computationally in chapter 5.

1.6.4 Selected Self-Organization with Local Memory

We can then think of semantic closure as a conceptual principle that includes both description based evolution and self-organization, in other words, it implies a description based harnessing of self-organizing structures: selected self-organization with local memory. Figure 4 presents a taxonomy of self-

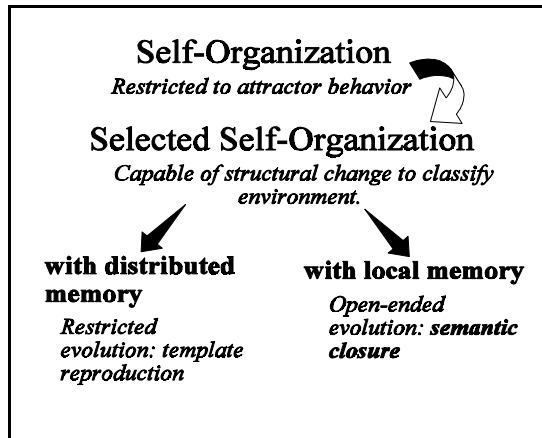


Figure 4: Memory based self-organization

organization dependent on some kind of memory. Notice that distributed memory selected self-organization can achieve plenty of the characteristics of semantic closure I have been discussing, however, without the attributes of local memory, that is, the symbolic dimension of descriptions, we cannot achieve the sort of open-endedness discussed earlier, since construction is not arbitrarily mediated by a code system [Umerez, 1995], but dependent on only those structures that happen to be able to be communicated by template reproduction or self-inspection. This point was discussed in 1.5.

It is here that the emphasis on the symbolic level of open-ended evolutionary systems must be tamed. Strong Darwinism, has emphasized the nature of the symbolic description of living systems. However, semantic closure with its description based selected self-organization is not

reiterating this position. The symbolic component of evolutionary systems is stressed, but the material, dynamic, self-organizing characteristics of matter are equally stressed. It is the ultimate inclusive approach which is neither reductionist nor dualist [Pattee, 1995a]. While it is maintained that a purely physical description of dynamics will not explain symbolic function (as several material systems may implement the same function), it is also maintained that different material structures will not have identical domains of potentially evolvable functions. The important idea is that evolution relies both on self-organization and selection, and only those self-organizing systems able to harness their dynamics to obtain a symbolic dimension can have open-ended evolutionary potential.

1.6.5 The Credit Assignment Problem

To wrap up the concept of selected self-organization let me make a summary of the points expressed earlier:

- a. A self-organizing dynamics cannot escape its attractor behavior unless its structure is changed.
- b. To evolve, a self-organizing dynamics needs to accumulate useful variations of structure. In other words, it needs to classify its interaction with its environment. This amounts to the construction of some sort of memory.
- c. Dynamic systems such as boolean networks have distributed memory, which, from an evolutionary perspective, entails a selected construction, or dynamically constrained

- representation, of their world. Not everything can be classified, only those interactions that lead to dynamically stable behavior and survive in some environment can.
- d. Descriptions (local memory) allow for a more effective form of self-replication based on Von Neumann's scheme.
 - e. Von Neumann's scheme of description based evolution does not include dynamics. It is a purely informational, representational, approach. Everything can be classified.
 - f. Semantic closure offers a hybrid conceptual approach with both description based (symbolic) controls, and dynamic (self-organizing) constraints. Evolution is the symbolic control or harnessing of self-organization.

Following the previous discussion of emergence, we can see that a pure representational approach, that is, Von Neumann's scheme, utilizes only the third level of description portrayed in figure 2. It disregards all sorts of dynamic constraints that a given material substrate imposes on the classifying function. It formalizes the power of natural selection, which is probably the most important engine of evolution, but it fails to recognize its material constraints which many see as an important part of the evolutionary picture [Gould, 1995]. In fact, these constraints may not just limit the scope of representation, but they may also enable important changes in evolutionary trajectories [Salthe, 1993]. Further, some propose that these dynamic constraints obey universal laws or organization [Kauffman, 1993]. These constraints exist at many levels, from the materiality of specific information carriers, to the mechanisms of symbolic expression (e.g. RNA editing, see chapter 4), to ontogenetic developmental constraints, and all the way to social constraints [Wilson and Sober, 1994].

Semantic closure calls for the so-called *credit assignment problem*¹⁰. That is, evolutionary structures are subjected to several different controls and constraints, which must be weighted according to their particular relevance in specific organizations. The problem is posed in trying to establish how much of an evolving complex system can be explained by physical laws, self-organization, development and context, historical contingency, and symbolic driven selection. The inclusive nature of semantic closure implies that models of these systems should include as most of these aspects as possible, and not be committed to one single explanatory mode.

1.7 Evolving Semiotics

“The term ‘semiotic’ goes back to the Greek medical tradition which considered semiotic, embracing diagnosis and prognosis by signs, as one of the three divisions of medicine. The Stoics gave semiotic the dignity of a basic division of philosophy co-ordinate with physics and ethics, and included within it logic and the theory of knowledge. The whole Hellenistic philosophy centered around the semiotic, and in particular the problem of empiricism versus metaphysics was formulated as a problem of the limits of signifying by signs, the Stoics arguing that there were signs (“indicative signs”) which could give necessary knowledge about things beyond the limits of observation; the Epicureans holding that while signs gained their signification through experience, some signs (such as ‘atom’ and ‘void’) could, though only with probability, refer to what was not capable of direct observation; the Sceptics questioned the whole edifice of metaphysics on the ground that signs could refer only to that which was observable, serving to recall (as “commemorative signs”) that which had been observed even though it was not at the moment of reference directly observable.” [Morris, 1946, pp. 285-286]

¹⁰ As introduced by Howard Pattee in the Biological Systems course materials.

Semiotics concerns the study of signs/symbols in three basic dimensions: *syntactics* (rule-based operations between signs within the sign system), *semantics* (relationship between signs and the world external to the sign system), and *pragmatics* (evaluation of the sign system regarding the goals of their users) [Morris, 1946].

“[...] *pragmatics* is that portion of the semiotic which deals with origin, uses, and effects of signs within the behavior in which they occur; *semantics* deals with the signification of signs in all modes of signifying; *syntactics* deals with combinations of signs without regard to their particular significations or their relation to the behavior in which they occur.

When so conceived, pragmatics, semantics, and syntactics, are all interpretable within a behaviorally oriented semiotic, syntactics studying the ways in which signs are combined, semantics studying the signification of signs, and so the interpretant behavior without which there is no signification, pragmatics studying the origin, uses, and effects of signs within the total behavior of the interpretants of signs. The difference does not lie in the presence or absence of behavior but in the sector of behavior under consideration. The full account of signs will involve all three considerations.” [Morris, 1946, page 219]

The importance of this triadic relationship in any sign system has been repeatedly stressed by many in the context of biology and genetics [e.g. Waddington, 1972; Pattee, 1982, 1995a]; in particular, Peter Cariani [1987, 1995] has presented an excellent discussion of the subject. It is a particularly intuitive way of thinking about Selected Self-Organization. Indeed, the three dimensions of semiotics can be mapped to the key aspects of semantic closure. First and foremost, semiotics reminds us that the essential attribute of complex systems with emergent classification is the symbolic, that is, the existence of memory tokens that stand for dynamical configurations. The syntactic dimension can be equated with whatever type of memory tokens¹¹ are utilized to refer to aspects of the complex system’s environment (Level 3 in figure 2). The semantic dimension refers to actual (self-organizing) dynamical configurations and their relation to the memory tokens. The pragmatics dimension refers naturally to the selection of the complex system according to its behavior in an environment. Thus, selected self-organization refers to complex systems that observe an *embodied evolving semiosis* with their environments, which can be open-ended if the natural symbol systems they implement are symbolic and follow von Neumann’s scheme (Pattee’s semantic Closure). Embodied evolving semiosis is the main concept pursued in this dissertation. It takes the form of selected self-organization in biological systems, and evolutionary constructivism in cognitive systems as discussed in the next section. The implications of its application to AI and AL, which is pursued in chapters 3, 4 and 5, is discussed in chapter 6.

2 Evolutionary Constructivism

In section 1 selected self-organization was presented mostly within the context of theoretical biology, particularly in the study of evolutionary systems. In this section, I attempt to pinpoint more explicitly what evolutionary constructivism stands for in cognitive science, by basing it on the understanding of selected self-organization developed in section 1.

¹¹ Memory tokens, as discussed previously, can be either distributed or local. In the local case, they can be referred to as symbols.

2.1 Material Basis: Selected Self-Organization and Constructivism

Selected Self-Organization relies on the following concepts discussed in section 1:

1. Self-Organization
 - a. Embodiment (materiality, dynamics, environmental interaction)
 - b. Classifications as internal stabilities
 - c. Constrained Classification power
2. Hierarchical Development
 - a. Semiotic control
 - b. Contextual Level integration
 - c. Network causality
3. Selection
 - a. Adaptation to an environment
 - b. Pragmatics, fitness, consensus
 - c. Semantics, function

Constructivism, notably in systems research, has emphasized points 1 and 2 above. The idea that classifications are internally constructed and contextually integrated in a hierarchy of development [Piaget, 1971] is its basic starting point. Classifications are not representations of an environment, but *re-presentations* generated by cognitive systems in their embodied interaction with an environment [von Glasersfeld, 1995]. Re-presentations refer to the mechanisms by virtue of which a previously constructed classification is re-presented (replayed, re-constructed) from memory given some sensory interaction with the environment. This is understood precisely in the same way as connectionist machines re-create their classifications from previously learned inputs, not so much a direct link to localized memory banks containing fixed representations of the world, but rather an active, dynamic, re-construction of patterns of activation. In fact, constructivism arises hand in hand with the cybernetic fixation on the connectionist machines of McCulloch and Pitts [1943] and von Foerster [1965]. The ability to increase the variety and creation of new re-presentations relies on psychological development primordially based on physiological primitives [Piaget, 1971; Medina-Martins and Rocha, 1992], which progressively generate hierarchies of re-presentations that can be accessed by the structural coupling of cognitive systems to their environments [Maturana, 1979] or through conversations with other such systems [Pask, 1976]. In other words, cognitive systems start with a variety of sensory primitives that are defined by the systems' physiology. This specific embodiment allows a number of interactions with an environment to create internal stabilities (attractors, eigenvalues) used precisely to classify such interactions. All cognitive capabilities are developed from this ability for emergent classification or eigenbehavior, by virtue of a process of learning that works by associating new classifications with existing re-presentations.

2.1.1 Radical Constructivism

Different breeds of constructivism exist. Traditionally, it has been identified with the radical constructivist position of von Glasersfeld [1995], that many fear much more solipsist than it actually is. Mostly because of the practice of its research program (largely implemented in education science), it has left the impression that radical constructivism stands for the sort of relativism found in the deconstructionist, post-modernist, breed of humanities [Derrida, 1977]: the idea that knowledge is personally or socially constructed, with the conclusion that there is no difference between science and humanities, and we can

never fully understand our environments since everything is a construction anyway. Alas, this is not the case. Even the most radical of constructivists like von Glasersfeld recognize point 3 of the chart above, that is, they recognize that a level of pragmatics exists that leads constructed re-presentations to refer to relevant events in an environment. However, they tend to either consider cognitive development as the key process to achieve this relevance of classifications, or they are simply not concerned with this aspect of cognition, preferring to work on the construction side of cognition which they believe to be much more relevant.

Radical Constructivism asserts that speaking of representations is an illusion [Von Glasersfeld, page 115, based on arguments by Bickhard and Richie, 1983] that cannot be accepted. The argument is based on the notion of representation as an information-theoretic construct. When a semantic code is established, one can only speak of representation and information transfer if not only the signifiers but also the signifieds are accessible. If one cannot explicitly access all the elements of the set of possible items that one wants to symbolize, then an information channel cannot be defined between the world of signifieds and the language of signifiers, and thus no representational relation can be established.

However, by abandoning the notion of representation as a mapping of internal structures to the world outside, constructivism locks itself inside the autonomy of complex systems it so dearly embraces and restricts cognition to internal coherence models. Psychological development is defined as the process of constructing more and more complicated re-presentations from interaction with an environment comprised of other cognitive agents. What is subsumed in development are the mechanisms of selection of re-presentations which by being selected from outside (socially or ecologically) become effective representations (categorizations) of the classifying system's environment. Constructivism has a problem with accepting explicit external selection, thus the resistance to or downplay of natural selection by the theory of autopoiesis, for instance. As soon as one accepts external, explicit, selection, one must accept a relation (or correspondence) between the world and internal re-presentations which become, effectively, representations (intentionality).

Somehow, cognitive systems construct their classifications of an environment, but misclassifications of an environment may result in ecological or social death, and thus have no survival value. An herbivore in the African savannah should not construct a lion as an edible bush. If a lion triggers such a re-representation in the herbivore, chances are that it will not survive long. We can say in this evolutionary, pragmatic, sense, that the herbivore misrepresented its environment, an expression which radical constructivism refuses. Such a notion of representation does not have to be seen as an information-theoretic definition. The herbivore's re-representation of lion, insofar as it allowed the herbivore to survive in the savannah, is effectively a representation of the herbivore's environment where it exists in situated interaction. Such a distinction is possible without explicit access to the environment. A representation is an experiential re-representation with identifiable repercussions in an environment. It is a pragmatically grounded re-representation that can be communicated (internally or externally). Evolutionary Constructivism, as developed in more detail ahead, is precisely interested in the study of how communicable (linguistic) representations can establish a more open-ended system of recontextualization of internally coherent re-presentations, that can model cognitive creativity more efficiently.

2.1.2 Physical Constructivism

Heylighen and Joslyn [1992] have proposed a breed of Constructivism named *Physical Constructivism* which attempts to subsume dynamic, developmental, and evolutionary constraints into a physical dimension. Physicalism tends to reduce the influence of natural selection to laws of dynamics and complexity, stripping it off its pragmatic dimension, and thus preventing any discussion of functionality and representation. If Physical Constructivism merely demands that cognition be understood in terms of the physical processes which manifest cognition, then it is a more reductionist proposal than radical

constructivism as proposed by Maturana [1978] or von Glassersfeld [1995]. There is no room for the notion of representation in such a view of cognition: cognitive categories are nothing but the internal, subsymbolic, stabilities of the brain's dynamics, much like the dynamic attractors of artificial neural networks.

2.1.3 Constructionism

Regardless of the problems with constructivism just discussed, the fact is that it brought to the limelight of science and philosophy issues that were being disregarded. Self-organization, embodiment, contextual dependencies, and hierarchical development have only recently been accepted into the core of scientific research, which has been gradually losing its naive realist stance. Most of the basic tenets of constructivism are found on the *constructionist* theory of learning as proposed by Papert [1991]. It basically asserts two types of construction, an active process in which people actively construct knowledge from their experiences in the world, and it further emphasizes the idea that people construct new knowledge more efficiently when engaged in constructing personally or socially meaningful objects. This approach to education is indeed based on Piaget's ideas, and relies on the basic tenets of constructivism: knowledge is a personal construction of social and ecological interaction. The embodied nature of this interaction is emphasized in the second type of construction used which attempts to maximize learning by physically engaging the participants of a learning experience. Such ideas have been explored by von Glasersfeld and Pask [1976] at least since the 1960's.

2.1.4 Situated Cognition

Similarly, most of the ideas now emerging from embodied artificial intelligence or situated cognition, have strong parallels to constructivist autonomous agents practice [Varela et al, 1992]. Traditionally, AI was concerned essentially with aspects of points 2 and 3 in the chart above. In other words, it relied strongly on models of representation and direct perception of the world. It was mostly preoccupied with functional semantics. The control of its robotic artifacts, for instance, was solely based on the high-level symbol-manipulation of semantic categories.

Artificial Life, mostly through the work of Brooks [1991], whose behavior language replaced the traditional high-level control of robots by a scheme of functional modularization by behavior generating modules, changed all this. Instead of a high-level computation of behavior, the bottom-up (emergentist) self-organization of simpler components produces a variety of behaviors depending on the interaction of a robot with its environment. "Situated" does not mean merely material, but interactive. The material (structural) coupling of the robot with its environment is the source of behavior, and not just the robot control system alone. In other words, the modeling of living and cognitive systems is moved to the dynamics of self-organization of a network of components and its interaction with an environment. Desired behavior is obtained from a hierarchy of simple behavior modules that interact nonlinearly with one another, and through a developmental process of reinforced learning that directs the self-organization of the behavior modules into desired patterns. Mataric [1995] has for instance developed populations of simple social robots that adapt to each other and as a group in this bottom-up fashion.

It can be argued that the behavior modules utilized are still too high level and do not allow the sort of plasticity that living systems observe. Indeed, it is not always obvious how to physically compartmentalize behavior modules: a bird's wing is both an airfoil and engine at the same time [Rosen, 1993]. The sort of behavioral decomposition pursued by Brooks may not offer yet the kind of entailment or network causality found in living organisms [Rosen, 1991; Prem, 1995] which allows for genuine evolution of new behaviors [Cariani, 1992], however, it does mark a very important shift in the practice of AI: the transition from a realist to a constructivist practice of autonomous agents. Cognition is no longer modeled as the creation of

universal classifications of the world, but as the embodied interaction of a self-organizing system with its environment. Whichever way situated robots solve a problem, it is done by the construction of their own classifications, given the set of low level components they have available, as they interact with their environment, and not by externally imposed rules.

Furthermore, recent advances in this field, such as Mark Tilden's¹² research at the Los Alamos National Laboratory, indicate that the descent into simpler material building blocks with rich dynamics, may be able to overcome the criticism that behavioral components are still too high level. Tilden's bots are not programmed with high level behaviors such as the ones traditionally used in situated robotics¹³, in fact they are not programmed at all! They are simply endowed with very dynamically rich components such as legs and antennas, which are nonlinearly connected by a sort of boolean network that converges to limit cycles defining which component is activated and in which sequence. By selecting those that solve intricate tasks by virtue of self-organization alone, Tilden has evolved a very rich fauna of bots capable of the most intricate and interesting behaviors. One shortcoming of his robots, and situated robotics in general, is that they implement solely the dynamic part of selected self-organization, that is, they model self-organization alone. The robots are indeed selected by their behaviors vis a vis a desired task, but for the most part they do not have a mechanism to implement open-ended evolution: the von Neumann scheme. Naturally, this is what situated robotics is trying to move into, though still with many difficulties to solve [Cariani, 1992]. In any case, situated robotics offers an excellent example of constructivist ideas put into practice.

2.2 Realism and Evolutionary Epistemology

As discussed in section 2.1, constructivism is concerned mostly with points 1 and 2 of the selected self-organization bullet chart, that is with Self-Organization and Development. Realism on the other hand is mostly concerned with points 3 and 2: Selection and Development. Selection in the sense that what is important to study is how well a classifying system maps its categories to the real world. In other words, how well it adapts to and performs in its environment, and what is the function and meaning of its categorizations. Realism is concerned with development only to the extent that it facilitates the linear learning of real-world categories, very much like genetic reductionism sees biological development as a cascade of linear transformations under complete genetic control. Realism understands classifications as representations that reflect an external reality.

Very few today pursue a naive realist view of cognition. In fact realism has undergone a series of transformations in order to adapt to systems concepts such self-organization and also to evolutionary thought. Hooker [1995] has reconceptualized realism in terms of Systems Theory and Evolutionary Epistemology sharing many of the motivations pursued by the present work. Being concerned with extreme relativism, Hooker incorporates context sensitivity (social and individual) into the scientific discourse, by regarding cognitive systems (people) as complex adaptive systems, and social processes as the self-organization of many-person systems. Cognitive agency is redefined as the search for increasing performance in a given context (increased fitness). This explicitly allows the introduction of context-dependency. He then views Science as a dynamic self-organizing complex adaptive process, embedded in wider social and biological adaptive systems (society and ecology). Cognition is the process of environmental information collection, given context-specific individual, social, and ecological interactions. Epistemology is thus re-characterized

¹² From unpublished personal communication .

¹³ For instance, "homing", "safe-wondering", "resting" as in Majaric's robots.

as the construction and re-construction of inquiry procedures invariant across systemic contexts¹⁴ [Ibid, page 4].

In other words, this breed of realism assumes contextual, dynamic, systemic categories as the reality from which invariant procedures can be discovered. The reality of the world is no longer things in themselves, but systemic patterns that are observed across contexts. It can be said that in order to achieve a realist, though contextual, correspondence theory of truth, a pragmatic, systemic, metaphysics needs to be introduced, since cognition is defined as fitness in a given self-organizing system which is assumed a priori. It presupposes complex self-organization as the nature of the world. Once we as cognitive agents interact in the multi-level dynamics of the universe, we can act *as if* the invariant processes found across a number of contexts were the reality. In other words, there is a consensual element to reality. Science's role is to explore consensually those invariant procedures across the largest number of contexts (individual, social, and ecological).

Now, either one substitutes naive realism for systemic naive realism, in which we believe that the universe is comprised of a number of forms or propensities waiting to instantiate themselves in different material substrates, or this form of realism is no different than constructivism supplemented with an evolutionary pragmatic dimension. Constructivism has always in practice followed an *as if*, consensual, view of reality [Glanville, 1994]. Given a certain context, for instance the condition of being human which specifies a number of sensory-motor-cognitive primitives, most individual observations in a social environment will be consensually agreed upon by all members of the social group, since, to put it in Hooker's terms, in such a many-person complex system we all share the same evolutionary constraints of fitness and thus our social-ecological reality is essentially the same.

One difference between this approach and the constructivist position is that Hooker seems to take the notions of information and self-organization itself as subject-free observables. He speaks of cognition as environmental information collection to be systematically constructed across contexts, whereas constructivism speaks of information construction as the cognitive primitive. For constructivists, information is by definition always dependent on an observer who constructs it. Evolutionary realism pursues a correspondence theory of truth because it is imbedded in a evolutionary, consensual, systemic, metaphysics. We can speak of truth correspondence between classifications and an environment in the context of natural selection and social-ecological self-organization. As previously stated, this ability to link personal constructed re-presentations to the world was lacking in radical constructivism but can be added by incorporating an evolutionary epistemology dimension. The differences between Hooker's evolutionary realism and the evolutionary constructivist position here pursued are essentially based on that the latter does not require information and systemic constructs as pre-existing realities.

2.3 Critical Realism

“Most scientific discourse is not about the natural world but about representations of selected aspects of that world. Our conceptions of what nature is are mediated by our representations of nature in models, which [...] are subject to certain important constraints. Constraints on our best representations of naturally occurring structures and processes mostly reflect historical conditions for the intelligibility of those representations and the experimental procedures we have devised for manipulating them.” [Aronson, Harré, Way, 1995, page4].

A related avenue to reconceptualize realism in the light of systems concepts has been pursued by Aronson, Harré, and Way [1995] and named Critical Realism. As indicated in the quote above, it is a position

¹⁴ Systemic contexts because all social ecological interactions are defined as self-organizing systems.

that acknowledges our conception of nature as a mental artifact, which is nonetheless historically and experimentally constrained. It shares many of the ideas defended in Hooker's Evolutionary Realism, namely that instead of studying reality as comprised of isolated substances, it is studied as comprised of systemic types, that is, sets of relationships between substances. These relationships specify the kind of constraints imposed on nature which can be observed and are the basis of a new contextual ontology. Dynamic-type hierarchies [Way, 1991] are used to model such constraints. This way, the old-fashioned realist emphasis on propositional truth is substituted by a theory of verisimilitude of models — the degree of match or mismatch between models.

Again, a correspondence theory of truth is maintained by accepting a systemic natural kinds metaphysics and scientific pragmatism. "In other words, ontological atomism is replaced by global-ontological relationalism." [Aronson, Harré, and Way, 1995, page 5]. Pragmatism to the extent that truth is the limit of verisimilitude which is consensually, and pragmatically, worked out as the degree of match and mismatch between models.

Both Evolutionary and Critical Realism share some of the goals of Evolutionary Constructivism though emphasizing different approaches. All accept contextual, embodied cognitive construction. While the new Realism extends Realism with the notion of systemic natural kinds, to be recognized in a contextual ontology, the new Constructivism extends Radical Constructivism with an evolutionary, contextual ontological grounding in an otherwise constructed epistemology. Both approaches are now essentially dual. Critical Realism works with a correspondence theory of truth based on pragmatic, contextual, and consensual verisimilitude, but it requires a systemic natural kinds metaphysics, while Evolutionary Constructivism is based on an internal coherence theory of truth, but it requires an evolutionarily pragmatic correspondence truth metaphysics.

The main difference lies on whether or not one is willing to start with the belief that the world is organized according to systemic natural kinds (based on self-organizing principles) in order to establish a contextual correspondence theory of truth. Realists prefer to ground science this way, while constructivists prefer to start only from the embodied construction of reality, working within an internal coherence theory of truth, which is now supplemented with evolutionary pragmatism to allow a practical belief in a contextual, consensual, *as if*, correspondence theory of truth. That is, Evolutionary Constructivism works to build the largest possible consensus amongst individually constructed epistemologies, which it believes to be selectively grounded in the natural world. Science is the search for those constructions (built with the extended embodiment of measurement devices) which can be consensually agreed by all individually constructing observers.

2.4 Language Theory and Evolutionary Constructivism¹⁵

The increased study of natural language during recent decades is biased toward two schools of thought. On the one hand is a focus on syntax [Chomsky, 1965; Jakobson, 1982], which studies the components of language and their arrangements, and how those arrangements might be determined. More recently evolution, and related biological aspects of language, have been adopted to the Chomskian school [Pinker, 1993]. The second approach, which attempts to describe natural language in purely biological terms, such as Maturana [1979], prefers to see language more as a phenomenon governed by autonomous self-organization (autopoietic) processes, with the relationship of components within a recursive neural network

¹⁵ The material in this subsection reflects work published in [Henry and Rocha, 1996] and [Rocha, 1997a, 1997c]

more a focus than the segregated elements of Chomsky's grammar. Semantics precedes syntax as the more revelatory linguistic feature.

Interestingly, while these methodologies seem opposed in fundamental ways, they each share a commitment to deny symbols and metaphors as proper aspects of theory, arguing for the inappropriateness of these language constructs [Varela et al 1991; Bickerton, 1990] due to the difficulty of objectively describing metaphor and symbolic expression because each requires a high level of subjective interpretive engagement on the part of the observer.

In the following it is argued that any language can be described as possessing four determining aspects:

1. All languages are biologically based on the neurological networks of the brain, thus any language inherits the self-organizing machine of the brain as fundamental to its operations.
2. All languages are a recreated system of structural perturbations.
3. The use of language continually re-contextualizes the epistemology of the individual; the act of recontextualization allows a leap from one dynamic state to another.
4. This recontextualization is inherently symbolic and metaphorical

A language is thus a system of access to the self-organizing machine of the brain, allowing the individual ecology to perturb and reconfigure the existing knowledge states. In other words, it is defended that language, with its symbolic and metaphorical attributes, allows a kind of selection of the dynamic states of the brain ultimately related to a subject's interaction with an environment. In this sense, language liberates the brain from its own, continuous, dynamic behavior and grants it a discontinuous leaping from one dynamic stability to another. This "leaping" opens the door to a much larger universe of meaning, unreachable by pure dynamics alone.

2.4.1 Selected Self-Organization

We know a good deal from ethology, enough to realize that one of the prevalent structuring processes of the animal brain is the propensity to deconstruct observable objects or events and then to respond based upon an assessment of the elemental parts. Lorenz [1981], Tinbergen [1951] and others have painstakingly documented the deconstruction process in bees, birds, and primates. As an example, a goose will 'see' not an egg as it will see elements of an egg such as color, speckled pattern, shape, and size. A goose can be easily fooled into sitting on a nest of wooden eggs with these elements exaggerated (a brighter green, a more perfect ovoid, larger speckles, and the like).

The deconstruction of reality into elements grants obvious and powerful survival potential: an animal will not be focused on one specific egg, but can 'interpret' all eggs within the selected for categorical constraints. The elements can vary — in fact variety of recognizable phenomena is inherent in this process. Events and situations can have different components (a nest in one field will never be identical to a nest in another field years later) but elicit the same survival responses. Categorical flexibility is an optimum trait; responding only to a singular, uniquely 'perfect' egg would lead to extinction.

The self-organizing or connectionist paradigm in systems research and cognitive science, has rightly emphasized these characteristics of mental behavior. A given dynamics, say the neuronal interactions of the brain, will converge to a number of attractor states. Such a dynamic system will then utilize these attractors to categorize its own interactions with an environment. This emphasizes the constructivist position that a cognitive agent is not free to categorize all aspects of its environment but only those for which it can construct internal stabilities according to the dynamic characteristics of its particular embodiment, as previously discussed in this chapter. The ability to relate internal stabilities to environmental interactions has

been referred to as emergent classification in section 1. It has led to the idea of memory without record [von Foerster, 1965] and that symbols are not necessary to explain cognition which is inherently subsymbolic [Varela et al 1991]. In applied domains, we have seen the emphasis turn to connectionist machines which classify their environment by manipulation of a network's attractor landscape.

Clearly, these self-organizing systems, if not chaotic, will classify similar events in their environments to similar attractor points of their dynamics: the categorical flexibility observed above. However, to effectively deal with a changing environment, systems capable of relating internal stabilities to environmental regularities, must be able to change their own dynamics in order to create new basins of attraction for new classifications. In other words, the self-organizing system must be structurally coupled to some external system which acts on the structure of the first inducing some form of explicit or implicit selection of its dynamic representations, this was referred to as selected self-organization in section 1. In the biological realm, this selection is implicitly defined by surviving individuals in varying (genetic) populations, while in the cognitive realm we may have some form of explicit selection referred to as learning. A simple example in an applied domain, would be an external algorithm for selecting the weights (structural perturbation) of a neural network in order to achieve some desired classification.

2.4.2 Improving Structural Perturbation

A relevant question at this point is how effective can this structural perturbation get? Connectionist machines can only classify current inputs, that is, they cannot manipulate their own distributed records. Structural change can alter their classification landscape, but we do not have a process to actually access a particular category at any time, except by re-presenting the inputs that cause it to the network. As discussed in section 1, something similar happens at the biological level. If living systems were purely dynamic, then reproduction would have to rely on components that could replicate themselves in a template fashion, or components that could unfold and fold at will so that copies could be made from available elements. In other words, if life did not have a symbolic dimension in DNA, it would be restricted to those proteins and enzymes that could reproduce in a crystal-like manner, or that could unfold to be reconstructed from available amino acids, and then refold to their original form.

Indeed, DNA introduces a novel dimension to living systems which allows them to construct any protein from a genetic description, and not only those that can self-reproduce in the above described senses. This way, DNA introduces a kind of random access memory so that living systems have access at any time to the blueprints of their own construction. This ability liberates living systems from purely localized interactions; biological reproduction is not restricted to template reproduction as the genetic, localized, descriptions can be communicated much more effectively from generation to generation, as well as to different parts of organisms.

It can always be argued that the random access memory the genetic system establishes, is nothing but complicated dynamics, and the symbolic dimension is just the result of our subjective observation. However, the argument is also extendable to the dynamic level itself, since it too is constructed by our subjective observations. Ultimately, all models are subjective. Having accepted this, we can now go our way trying to establish models and explanations that can be consensually agreed by most. As Pattee [1982, 1995a] points out based upon the work of von Neumann (described in section 1), the genetic dimension has established a new hierarchical level in evolutionary systems which allows a greater level of control of the purely self-organizing dynamics. Failing to recognize this emergent symbolic level, does not allow the distinction between self-organizing systems with some dissipative structure such as autocatalytic networks [Kauffman, 1993] (perhaps even hurricanes), from living systems whose genetic memory does not require larger and larger autocatalytic networks to develop more and more complicated morphologies.

The point here, is that language has likewise opened up a whole new universe of meaning for cognitive systems, as they can access the dynamics of classification beyond local interactions. That is, communication between individuals, as well as internally, is not restricted to only those things we can "show" or otherwise somehow physically mimic: the displacement of local observations. Language may be, as the genetic system, a method to point to and reach a particular dynamics necessary in a particular context. It may allow a (fairly) random access to an otherwise distributed memory, defining a more sophisticated system of structural perturbation.

2.4.3 Metaphor

We can thus say that the existence and use of a language is extraordinarily transformational. The categorical constraints of, purely classifying, instinct-level self-organization can be accessed and recontextualized through the consensual, willful exercise of a system of perturbations. It is the recognition of the access to and limited control over a previously closed, interior ecology of largely self-organizing processes that more than likely gave rise to the myths, prevalent in all ancient cultures, that language was a gift of the gods and made humans god-like in its acquisition [Cassirer, 1946].

Language is thus seen as a systematic influence in the recontextualization of an existing epistemology that allows for the leap from one dynamic state to another. It is also critically important to note that any language, because it resides upon the neurological structure of the brain as its chief biological processor, is necessarily constrained by the self-organizing machine that it so perturbs and disrupts. I believe that the most efficacious means to explore the constraints and at the same time the leap of dynamic states is precisely in symbols and metaphors, which are properties that must occur as products of open-ended dynamic state transition.

Symbols, metaphor, and analogy recapitulate the ontogeny of a dynamic state through contestation with another, resulting in a new synthesis within the epistemological domains of those states that are consequently re-formed. Metaphor, symbol, and analogy all share the key characteristic of synthesis of apparent and, in more advanced utility, non-apparent elements of objects and events. A metaphor is thus a heightened degree of routine association made remarkable because it involves the juxtaposition of apparently dissimilar phenomena. This contributes significantly to our survival, enabling us to transfer solutions across problems with similar goal structures. In the most advanced stages of brain development, we achieve true system mapping [Way, 1991], far surpassing other species in our capability to transcend perceptual similarity. Discerning correspondence in non-similar phenomena is one of our highest achievements [Holyoak and Thagard, 1995; Henry, 1995].

2.4.4 Constraints and Evolutionary Constructivism

Constraints are integral to this selected cognitive strategy. A language is by nature open ended and capable of infinite combinations, but its semantic value would be null if there were no categorical restrictions. The variety and richness of semantics depends on the tension between the language as a means of leaping dynamic states while constrained by the inherited neurological processes upon which those states reside. Meaning, in large part, emerges from this tension, from the continual intersection of an abstracting system of organization that must relate by nature of its associative propensities to the external world.

The metaphoric/symbolic quality of language production is inevitable because meaning must be constructed from the associations of often disparate elements and events. To say language or its component words are purely 'representational' misses a critical point: words cannot represent singular objects or events without recourse to a variety of associations. Essentialism is impossible in linguistic constructs. On the other hand, some cognitive categories must relate to the external world, or an organism would not efficiently

categorize (and thus survive in) its environment, in other words, the construction of categories must be evolutionarily, and consensually, viable.

Evolutionary constructivism calls for an integration of representational, connectionist, and situated, models of cognition, under an evolutionary epistemology framework. Neither open intentionality nor closed construction can alone explain cognition. Representationalism and constructivism must be brought together under an evolutionary model that includes syntax, semantics, and pragmatics. Evolutionary constructivism accepts that cognition is constructed, that is, it is constrained by its own dynamical embodiment and development, but this form of constructivism also acknowledges the pragmatic, functional, necessity of a representational dimension established through environmental selection. In other words, it merely accepts the need for both self-organizing and evolutionary constraints in models of cognitive categories.

Mental categories are certainly constructed by brains, but if the classification power of such categories in a given environment is null, then the biological systems associated with such brains will most probably not survive in the environment they misclassify. This does not mean that cognitive categorization should be seen as open-ended; not at all, a given material system will only be able to classify certain aspects of its environment, those for which it can construct dynamic stabilities. But it must be able to classify well enough in order to survive. An artificial neural network will also not be able to solve any problem, and we will choose different kinds of networks, with different dynamics, to solve different problems. Thus, models of cognitive categorization need to include the contextual influence of dynamic, developmental, and pragmatic (selective) constraints.

Radical constructivism, based as it is on the dynamic and developmental cybernetic explanations of cognition, often seems to either explain away the notion of representation or avoid it altogether. The same trend takes place in connectionist cognitive science. But we also do not have to pursue a naive realist avenue if we wish to study the notion of representation. It does not have to be seen as the syntactic one-to-one mapping of real world categories to brain categories. Quite the contrary, evolutionary constructivism sees representation as emerging from several dimensions that are mutually constraining: dynamics, development, and pragmatics. The representational aspects of categories have to do with the existence of a pragmatic (selective) dimension. But representation is also constrained by the dynamic and developmental dimensions. It is a truly inclusive approach. In Chapter 3, the problem of Cognitive Categorization is approached in this light, and it is modeled by the introduction of a mathematical structure named *Evidence Set*.