論　文

Learning and Complex Adaptive Systems

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要　旨

本論文は，複雑性と複雑適応系の科学，およびそのような科学が人間の学習についての理解にもたらし得る知見について論じる。人間の思考を複雑適応系と見なす可能性について検討するとともに，そこから学校教育の学習環境の設計に対して得られる含意を提示する。筆者は，生徒が事故の学習地平を形成するべく積極的な行動をとることができるよう，「車輪の再発明」を行わせることの重要性について論じる。

Keywords: learning theory（学習理論）, education（教育）, complex adaptive systems（複雑適応系）, autopoiesis（オートポイエーシス）, learning landscape（学習景観 / 学習環境）

Abstract

This paper discusses the science of complexity and complex adaptive systems and how such science might inform the understanding of human learning. The possibility of viewing human thinking as a complex adaptive system is explored and implications for designing formal learning environments are suggested. The author argues for the importance of allowing students to "reinvent the wheel" in order to take an active part in sculpting their individual learning landscapes.

Learning and Complex Adaptive Systems

Part 1: Complex Adaptive Systems

Introduction to Complex Adaptive Systems

The science of complexity and complex adaptive systems has engendered a view of the beauty of self-organization which arises as a result of continual transformation, via nonlinear interactions, within and between co-creating systems. Through this lens, learning is seen as a continuous dynamic, the inevitable actualization of an innate biological potential. When the human individual is viewed as a complex adaptive system and learning is seen as an essential dynamic on which the system depends for survival, conscious learning is recognized as the tip of the learning iceberg. Still, might the concepts that drive complex adaptive systems be productively applied to formal learning situations?

This paper describes the basic characteristics of complex adaptive systems, contrasting complex systems with chaotic ones. A fundamental understanding of the characteristics of complex adaptive systems raises questions about whether these characteristics exist in conscious learning and asks, if they do, what the implications might be for designing effective learning environments and experiences. The exploration begins with an examination of the literature of complex adaptive systems, particularly the work of Kauffman, Holland, and Gell-Mann.

Before we begin, a caveat. The author is trained neither as a scientist nor as a mathematician. Therefore, the understanding expressed of these deep concepts may be limited. The utmost scrutiny is invited. In the overall conversation about the potential of complex science to lend insights into our world, this contribution may be one of many possible branches that, according to Kauffman, characterize responses to innovation, (1995, pp. 14, 202). This is submitted, then, in the spirit and enthusiasm of the evolution of ideas that are the hallmarks of human endeavor.

A New Science

It is important to keep in mind that the field of complexity and complex systems is fairly new and there is certainly not consensus among researchers as to which models are the most successful and which must be modified or abandoned altogether. This is part of the appeal – researchers are in the midst of a lively exploration into questions for which, in the past, it seemed it would never be possible to find answers. Thus, debate about what properties are exhibited by complex systems, how such systems self-organize, and how self-organizing complex systems have come to exist in such great numbers, is in itself intriguing.

Another aspect of the creative confusion involved in studying complex systems is that the researchers studying them come from a variety of disciplines. Complexity can be found at the level of cellular systems, ecosystems, and social systems, and its effects can be seen in the global economy and the spread of disease. Thus, researchers are drawn to these ideas from widely diverse backgrounds and are working on a variety of problems. There is not a linear development of ideas involved; the researchers tend to focus on particular aspects of problems that pertain to their fields of interest. As a result, there is a profusion of terminology and there are sometimes different terms for the same or quite similar concepts.

Complexity and Chaos

In common usage, a distinction is seldom made between the terms complex and complicated. In fact, Webster's New World Dictionary lists *complicated* as the second definition of the word *complex*. However, in the science of complex adaptive systems, there is a significant difference between the two (Waldrop, 1992, pp. 11-12). Something that is complicated is intricate, but essentially static. In contrast, to say that a system is complex is to imply that it is involved in a dynamic process of interactions, a continual state of change. The interactions, more than the structure, distinguish a system as complex.

A complex system is said to exist on the border between order and chaos(Kauffman, 1995, pp. 26-29; Waldrop, 1992, p. 12). However, such an image can be misleading, suggesting that there is a discrete boundary between static order and chaotic disorder, and that complexity stands there at a particular location. Rather than a particular place, though, complexity is a state of dynamic balance between the extremes of rigid order and chaotic disorder. As Waldrop explains, "…complex, self-organizing, adaptive systems possess a kind of dynamism that makes them qualitatively different from static objects such as computer chips or snowflakes, which are merely complicated” (1992, pp. 11-12).

In some systems, the condition between order and chaos is called a *phase transition* (Johnson, 2001, pp. 111-112; Barabasi, 2002, pp. 74-75). A phase transition is a critical point at which a system suddenly changes from one defined state to another. A common example of a phase transition occurs in the magnetization of ferromagnetic metal. In a state of disorder, each agent of the system (in this example, each atom) behaves individually. After the phase transition, all the atoms behave in precisely the same way, in unison. The system locks into stasis, the metal becomes magnetized. Near the critical juncture, the phase transition, the system vacillates between order and disorder; some agents of the system act independently while others join together to act in unison. The closer to the phase transition, the more ordered the system becomes, that is, the more agents join together behaviorally to act in unison.

Although complex adaptive systems and complex networks are not on their way to becoming entirely ordered and static, they exhibit many of the behaviors of systems that do undergo phase transitions. In particular, complex systems move between order and disorder, mixing elements of both in a dynamic process of adaptation. Knowledge of phase transitions has prompted Kauffman to describe complex systems as existing on the edge of chaos (1995, pp. 26-29). A phase transition is a state of dynamic disequilibrium, and such disequilibrium is a hallmark of self-organizing complex systems. As Kelso explains, "Just as Galileo used an inclined plane (which he could manipulate) to understand the free fall of objects (which he could not), so this phase transition situation allows us to understand how coordinated actions are self-organized" (Dynamic Patterns: The Self-Organization of Brain and Behavior 53). Kelso examines the physiological mapping of physical coordination in the brain, but his comment can be said to apply to a variety of complex systems. Rigid order is fairly easy to understand. In contrast, the term chaos can be misleading. Like complex, chaos has a different meaning scientifically than its everyday usage suggests. While in ordinary conversation we refer to something as chaotic when we mean it is randomly disordered, scientifically speaking, chaotic disorder actually follows particular rules.

Characteristically, the slightest change in a chaotic system becomes magnified as the system moves forward in time, making it predictable in the short term, but impossible to predict in the long term. This is called "sensitive dependence on initial conditions" (Gleick, 1987, p. 8). Typical examples of chaotic systems include cloud shapes and galactic clustering (Gleick, 1987, p. 4). Another characteristic of chaotic systems is that "every point is a point of instability" (Strogatz, Sync: The Emerging Science of Spontaneous Order, 2003, p. 189), which means that any particular point in the system is vulnerable to a system-changing alteration. This instability combined with the exponential increase in slight changes over time results in a system which lacks resilience. In a chaotic system, the details are of the utmost importance.

There are other kinds of systems in which slight changes are not so significant. Although an ant colony may live for 15 years (Johnson, 2001, pp. 80-83), a single male ant lives only for one day, while a female ant lives for a maximum of one year. Not only that, but the colony itself matures, that is, an older colony behaves differently than a younger one. How can it be that, although the colony as a system matures, the components of the colony last only a fraction of the system's life span? This is not so different from the human body. You as an entity persist in spite of the fact that your cells are continually dying by the billions. Here, then, is a significant difference between complex systems and chaotic ones. As Johnson says, "The persistence of the whole over time – the global behavior that outlasts any of its component parts – is one of the defining characteristics of complex systems" (2001, p. 82).

Complex Adaptive Systems

A complex adaptive system is a system which persists in spite of changes in the diverse individual components of which it is comprised, in which the interactions between those components are responsible for the persistence of the system, and in which the system itself engages in adaptation or learning (Holland, 1995, p. 4). To say that a system is complex is to say that it vacillates between states of order and disorder, without succumbing to either state. To say that such a system adapts is to say that it responds to information by changing.

Such systems abound. Not only the ant colony and the human body as a whole, but various systems within the body such as the central nervous system and the immune system fall into this category. These are systems that persist in spite of the continual changes of individual components, maintaining coherence and adapting in response to a phenomenal amount of information throughout the lifetime of the organism in which they function(Holland, 1995, pp. 2-3).

Adaptation and Finding Excellent Solutions

Holland argues that adaptation itself builds complexity. Kauffman agrees, saying, "A living system must first be able to strike an internal compromise between malleability and stability. To survive in a variable environment, it must be stable, to be sure, but not so stable that it remains forever static" (Kauffman, 1995, p. 73). Thus, these systems survive and thrive in an evolutionary, or more accurately, a co-evolutionary context.

Kauffman makes a case for the importance of the co-evolution of agents and their environments. As an agent changes, so does the environment, including other agents, and vice versa. Thus, agent and environment act as partners in the dance of evolution. This is easy to visualize when one thinks of the interrelationships in an ecosystem. But how does a particular agent "read" an environment of which it can only "see" a small part?

Kauffman argues that in a system in which there are many underlying conflicting constraints and interconnected variables, there exists an optimum size and number of "patches" or nonoverlapping domains which, acting locally by interacting only with the nearest neighbors, maintain the system in a state of maximum fitness with regard to evolution(Kauffman, 1995, pp. 256-257). Each agent in the system Kauffman models has access only to information in the local vicinity. (The reality is likely more complicated than this as, at the very least, many complex systems will be seen to be small-world networks. See Strogatz, *Exploring Complex Networks*, and Watts for more about this.) At the same time, each agent may be said to have a particular evolutionary goal of which it is unaware, but for which it is suited by its evolutionary history. The ultimate goal, of course, is survival. In having achieved survival up to the present moment, the agent as a system and the larger system(s) of which the agent is a part have engaged in a particular kind of learning that is inherent in adaptation. This learning involves maximizing the system's fitness with regard to the larger environment. Complex adaptive systems exist at a wide range of scales, from neurons to social systems. Therefore, the environment in which an agent acts may be incredibly tiny or it may be vast, from the human perspective. However, it seems likely that the larger system in which an agent participates is always beyond the comprehension of the individual agent within it. According to the theory of complex adaptive systems, the scale of complex systems is of little importance, except, perhaps, in relation to the time involved in the interactions or in the life of the system as a whole (see Gell-Mann 51-52).

Here the idea of maximum fitness means to be able to find excellent solutions to difficult problems rather than being able to find the best solutions (Kauffman, 1995, pp. 247-264). Generally speaking, finding the best solution may be impossible due to the multitude of possible solutions and the limited amount of time available for exploring them. Thus, Kauffman argues, it makes more evolutionary sense to devise strategies for finding excellent solutions at the possible expense of not finding the best or perfect ones.

Holland has worked extensively on this problem as well. He is well-known for having devised the genetic algorithm and the ECHO software for computer simulation of complex adaptive systems. The agents in Holland's computer simulations behave in much the same way that Kauffman describes, finding excellent solutions in the course of interacting with other agents and with the environment.

Gell-Mann explains just how these systems are able to evolve such excellent solutions. Gell-Mann's terminology differs from Holland's in that what Holland refers to as an "adaptive agent," within a complex system, Gell-Mann refers to as a complex adaptive system in its own right. Thus, in Gell- Mann's nomenclature, a complex adaptive system may (and often does) exist within another complex adaptive system and/or it may be associated with other complex adaptive systems that aggregate to form a larger complex adaptive system, and so on (2003, p. 51). Gell-Mann's description of the evolution of schemata in a complex adaptive system is elegant.

A complex adaptive system receives a stream of data about itself and its surroundings. In that stream, it identifies particular regularities and compresses them into a concise "schema," one of many possible ones related by mutation or substitution. In the presence of further data from the stream, the schema can supply descriptions of certain aspects of the real world, predictions of events that are to happen in the real world, and prescriptions for behavior of the complex adaptive system in the real world. In all these cases, there are real world consequences: the descriptions can turn out to be more accurate or less accurate, the predictions can turn out to be more reliable or less reliable, and the prescriptions for behavior can turn out to lead to favorable or unfavorable outcomes. All these consequences then feed back to exert "selection pressures" on the competition among various schemata, so that there is a strong tendency for more successful schemata to survive and for less successful ones to disappear or at least to be demoted in some sense(Gell-Mann, 2003, p. 50).

Thus, a complex adaptive system: 1) interacts with the environment, 2) creates schemata, which are compressed and generalized regularities experienced in those interactions, 3) behaves in ways consistent with these schemata, and 4) incorporates feedback from the environment to modify and adapt its schemata for greater success. When Gell-Mann talks about "identifying" and "predicting," he is not necessarily referring to conscious events. For example, in the case of slime mold, which has no brain, the process is a purely biochemical one (Johnson, 2001, pp. 11-17).

Self-Organization in Complex Systems

The process by which a complex system achieves maximum fitness results in self-organization by the system, that is, agents acting locally, unaware of the extent of the larger system of which they are a part, generate larger patterns which result in the organization of the system as a whole. This concept can be seen at work in ant and termite colonies, beehives, market economies, and can even be modeled on one's home computer using free software such as StarLogo (Starlogo) or NetLogo (Wilensky). The idea that an ant colony is a system that organizes itself without any leader is intriguing. Each individual ant, acting with limited information, contributes to the emergence of an organized whole. “The movement from low-level rules to higher-level sophistication is what we call emergence" (Johnson, 2001, p. 18). This new way of looking at organization as an emergent property of complex systems calls into question some fundamental assumptions about organization in general, and about learning in particular.

Not every system is a complex adaptive system; certain conditions must be met in order for a system to self-organize. First of all, the system must include a large number of agents. Constructing a simple model in StarLogo and adjusting the number of agents involved will readily demonstrate this principle. In addition, the agents must interact in a nonlinear fashion. As Kelso explains:

> If there are not enough components or they are prevented from interacting, you will not see patterns emerge or evolve. The nature of the interactions must be nonlinear. This constitutes a major break with Sir Isaac Newton, who said in Definitions II of the Principia: "The motion of the whole is the sum of the motion of all the parts." For us, the motion of the whole is not only greater than, but different than the sum of the motions of the parts, due to nonlinear interactions among the parts or between the parts and the environment. (Dynamic Patterns: The Self-Organization of Brain and Behavior 16)

Complex Adaptive Systems Summarized

From the discussion so far, the following characteristics of complex adaptive systems can be extracted:

1. Complex adaptive systems involve agents whose local, non-linear interactions result in self-organization by the system as a whole.
2. Complex adaptive systems exist in a mixed condition between order and chaos which enables them to achieve stability and flexibility simultaneously.
3. The agents in a complex adaptive system thrive by devising excellent solutions to difficult problems, rather than by finding best or perfect solutions.
4. Complex adaptive systems find excellent solutions by creating schemata based on regularities identified as successful, behaving in ways consistent with these schemata, and incorporating feedback to adapt the schemata for greater success.

The idea of self-organizing complex systems is a powerful one, with implications for a wide variety of hard sciences. Are there implications for education and human development as well? There are many who believe so. Lewis writes

> The turbulence in dynamic systems thinking is . . . a creative one, . . . and it promises to resolve to a coherent account of the developmental process itself. (2000, p. 42)

Learning and Schemata

It is no accident that the language for describing the behavior of complex adaptive systems includes the terms *learning* and *schemata*. These were consciously chosen by researchers to link familiar ideas with new descriptions of biological and evolutionary behaviors of systems, as well as the behaviors of computer programs such as Holland's ECHO that simulate those systems. Gell-Mann admitted that his use of "the term 'schema' is taken from psychology, where it refers to a pattern used by the mind to grasp an aspect of reality" (2003, p. 51).

Acknowledging that these terms were borrowed in this way raises the question of whether it is legitimate to assume that the terms have the same meaning in the contexts of complex adaptive systems, psychology and education. The answer is both 'yes' and 'no'. If the discussion is about conscious processes, then naturally the answer is 'no' since, to the best of our knowledge, neither slime mold nor computer systems exhibit consciousness. To avoid a lengthy philosophical argument which is not germane to the question of human learning, let us limit this discussion to systems of *living* agents and say that, for this examination at least, the computer simulations of complex adaptive systems cannot be said to learn in the same sense that the term is used in these other contexts, although they can simulate living systems that learn and, in some instances, generate original solutions.[1] Even a focus on living systems does not answer the question in its entirety, however, because there is still the matter of the slime mold, the ant colony, the immune system, and the myriad other complex adaptive systems composed of living agents but without consciousness to consider. Can a system composed of living agents but without consciousness be said to learn?

Yes, it can. To define learning as primarily a conscious human activity and judge other systems based on this view does not make good scientific sense. It makes a great deal more

1 Hall, in chapter 2 of *Beyond Culture*, would argue that confusing the simulation of a system with the system itself is a classic case of extension transference.

sense to take the longer and wider view that is supported by biology and evolutionary studies. From this perspective, a complex adaptive system *must learn in order to survive*. To learn in this sense means to successfully adapt to change. Seen in this light, the conscious human experience of learning is only a tiny fraction of all the learning taking place in an individual human at any moment. Learning does not necessarily involve understanding or meaning. All complex adaptive systems can be said to learn in this fundamental sense of the term.

The use of the term *schema* must be taken more figuratively. Because Gell-Mann has borrowed the term from psychology, the term suggests a human experience involving meaning. The schemata of complex adaptive systems to which Gell-Mann refers are simply compressed regularities of patterns. Pattern recognition in itself does not constitute meaning in the sense of interpretation, although such recognition is a prerequisite for the construction of such meaning. Thus, to use the term "schema" [and Gell-Mann does put quotation marks around it (2003, p. 50)] is to set up an analogy to a conscious human experience. More recently the term schema has been adopted by computer programmers, but again, this use of the term does not involve meaning in the interpretive, psychological sense. Kelso uses the expression "informationally meaningful" (Dynamic Patterns: The Self-Organization of Brain and Behavior 70) to describe patterns involved in the coupling of biological systems, for example. Conscious awareness of this kind of coupling is entirely unnecessary, as such coupling occurs in all manner of complex systems, the majority of which lack consciousness. For the purposes of this paper, *meaning* will be used to denote a conscious experience, although not necessarily a linguistic one.

Thus, it can be said that, for this discussion, the use of the term *learning* in the definition of complex adaptive systems is a valid one, and the use of *schemata* as compressed regularities of data is valid. The attribution of conscious meaning to the schemata, however, is not necessarily a component of all complex adaptive systems.

Autopoiesis

An understanding of Maturana and Varela's concept of autopoiesis will help to guide the following discussion of the human individual as a complex adaptive system. According to Maturana and Varela:

> That living beings have an organization, of course, is proper not only to them but also to everything we can analyze as a system. What is distinctive about them, however, is

> that their organization is such that their only product is themselves. The being and doing of an autopoietic unity are inseparable, and this is their specific mode of organization. (1998, pp. 48-49)

Luisi, in an article reviewing the history of the concept of autopoiesis and its possible future applications, points out that Varela was reluctant at first to apply these concepts to forms of life beyond the single cell (2003, p. 52). However, Maturana and Varela define a unity in terms of its autonomy and argue that the mechanism they call autopoiesis is the process by which an autonomous unity becomes manifest(1998, pp. 47-48). Luisi argues that humans (and all other forms of life) qualify by Maturana and Varela's definition as autopoietic entities(2003, p. 52). A human is a living being and the being and doing of a human individual are inseparable, a unity.

Autopoiesis can be understood as a dynamic process through which a unity becomes distinct, and at the same time inseparable, from its environment. This is not a linear, but an integrated process. This sounds very much like the previous descriptions of complex adaptive systems in which continual mutual transformation of agents and systems (and systems within systems) results in adaptation and survival. In spite of their similarities, it is important to note the distinction between autopoietic complex adaptive systems and other complex adaptive systems: autopoiesis is particular to living entities; in fact, it is a definition of life.

As Luisi explains

> The emergence of life . . . is a very special novel emergent property: with life, an autopoietic unit acquires the singular property of becoming a biologically autonomous system, namely one that is capable of specifying its own rules of behavior.(2003, p. 52)

He further explains the argument posed by Varela and his colleagues that the integrated process of co-creation described by autopoiesis applies equally to life and cognition, including human cognition and consciousness (2003, p. 55). If this view is correct and cognition is an emergent property of autopoietic systems, and if autopoietic systems are likewise complex adaptive systems, then cognition as a complex adaptive system is a valid concept.

The autopoietic living organism endlessly creates itself. The being of a unity is inseparable from its doing, or action, and exists within the context of itself and its internal and external dynamics. This means that integral to any autopoietic entity and its environment is the history of their interactions. The importance of the dynamics of process and context will be stressed again by Kelso in his work, and is a vital theme in the study of all living complex adaptive systems.

The Human Individual as a Complex Adaptive System

In order to exhibit self-organization, a system as a whole must behave in a way that is not controlled by any particular agent of the system. It is characteristic of complex adaptive systems that the actions of agents acting locally result in system wide organization. Until recently it might have been possible to argue that an individual's genetic code controlled the ultimate organization of an individual human. Now that the human genome has been decoded, it is clear that the system is much more complex than was previously imagined (Watts, 2003, p. 26; Johnson, 2001, pp. 84-86). As it turns out, from the very first cells on to the emergence of the individual human, individual cells determine how to differentiate into the variety ultimately necessary to create all the components of an individual by interpreting DNA in the context of information received from neighboring cells. Thus, individual cells acting locally self-organize into a human being with the genetic code as a sort of guidebook.

But once the central nervous system is well formed, does it "control" the rest of the human and all its systems, including learning? This is a controversial topic, but evidence suggests that such is not the case. Maturana and Varela assert that "the nervous system is an expression of its connectivity or structure of connections and … behavior arises because of the nervous system's *internal* relations of activity" (1998, p. 126). They insist that a great deal of the trouble in understanding cognition is a result of not keeping a "logical accounting in order" (1998, p. 136), by which they mean that it is vital in descriptions to distinguish between what is happening within a system and what an observer outside the system observes. This can become quite confusing when considering the systems within systems that constitute the human individual, and beyond the individual, the social, cultural, physical, economic and technological systems of which that individual is a part.

Although Maturana and Varela do not refer to complex adaptive systems per se, their argument follows the same general ideas. To fully understand how it is that the brain or central nervous system does not control the individual, it will help to understand the concept of *structural coupling*. As they explain:

> In describing autopoietic unity as having a particular structure, it will become clear to us that the interactions (as long as they are recurrent) between unity and environment will consist of reciprocal perturbations. In these interactions, the structure of the environment only *triggers* structural changes in the autopoietic unities (it does not specify or direct them), and vice versa for the environment. The result will be a history of mutual congruent structural changes as long as the autopoietic unity and its containing environment do not disintegrate: there will be a *structural coupling*. (1998, p. 75)

Thus, if one accepts Maturana and Varela's argument, the behavior of an autopoietic unity always exists within a context that consists not only of a physical environment in time, but a history of interactions which results in structural coupling. Kelso makes the additional point that, in order for behavior to be successful in terms of adaptation, the coupling must "reflect functional, not merely mechanical constraints" (Dynamic Patterns: The Self-Organization of Brain and Behavior 70).

Maturana and Varela distinguish between structure and organization in a way that correlates with descriptions of complex adaptive systems, where *organization* is the equivalent of the ongoing identity of the system and *structure* equates to the elements of the system. Seen in this light, structural coupling bears a striking resemblance to the regularities of compressed data that become, for example, DNA sequences or Gell-Mann's schemata.

Given this structural coupling which binds a system to its own history and to its environment, does the central nervous system qualify as a complex adaptive system? If it does, then by definition it must be self-organized. To avoid the trap of circular reasoning, one must look for evidence that such a view of the central nervous system is justified.

If it could be shown that the central nervous system exists in a state of relatively rigid order, then a view of it as a complex adaptive system would be out of the question. However, research suggests that such is not the case. In classic experiments as well as in experiences with victims of brain damage it has been shown repeatedly that within certain parameters, the brain can reorganize to adapt to its changed condition.[2] This plasticity of the brain argues against its having a rigid structure. The familiar illustration of the brain divided into sections, each one labeled with a particular function, turns out to be misleading, at best.

2 For an excellent discussion of this, see Schwartz and Begley.

Maturana and Varela discuss neuroplasticity in terms of structural changes in the connections within the nervous system (1998, pp. 166-167). They argue that the overall structure of connections, which they call “broad lines of connectivity” (1998, p. 167), are generally the same within a species, but that structural changes in the local synaptic interactions cause significant modifications in how the network functions. These changes are the result of interactions with the environment and endow the nervous system with its plasticity.

Kelso's work in the field of neurophysiology examines neuroplasticity in terms of the dynamics of neurological structures and correlated behaviors. Based on more than twenty years of research, he is convinced that the central nervous system is self-organized.

> The brain is fundamentally a pattern forming self-organized system governed by potentially discoverable, nonlinear dynamical laws. More specifically, behaviors such as perceiving, intending, acting, learning, and remembering arise as metastable spatiotemporal patterns of brain activity that are themselves produced by cooperative interactions among neural clusters. Self-organization is the key principle. (Dynamic Patterns: The Self-Organization of Brain and Behavior 257)

A self-organized complex adaptive system does not have an agent that is in control of the system. There is no central locus of control. Thus, if the central nervous system is a complex adaptive system, the next question is whether as such it can control the other systems with which it interacts and together with which the larger system, the individual human, is comprised. If an individual human is a self-organized, complex adaptive system, the answer must be no. If Maturana and Varela are right, then the interactions between systems can trigger changes, but cannot direct them.

The Brain as a Complex Adaptive System

Recent research on the brain has revealed that many of our former notions of brain organization were off the mark. The idea that there exists somewhere in the brain representations of objects or ideas seems highly unlikely in the light of results from researchers like Kelso, Fingelkurts and Fingelkurts, Varela, and many others. Their research suggests that the brain is a self-organized complex adaptive system and that the great plasticity and flexibility of the brain’s functioning is due in large part to its characteristics of metastability and multivariability (Kello, et.al.; Fingelkurts and Fingelkurts). This suggests that it is the interconnectivity of neurons that is important. This interconnectivity supports processes that allow for rapid, flexible, efficient functioning.

At the same time, in spite of the enormous number of neurons in the brain, “full neuron-neuron interconnectedness would lead to brains the size of a bathtub” (Fingelkurts and Fingelkurts 5). The problem is solved by scaling, by increasing the number of synapses per neuron and the number of possible structures to which any particular structure may connect (Fingelkurts and Fingelkurts 5-6). These many possible combinations of brain states result in a high degree of multivariability.

In spite of this great flexibility, the performance of the system is constrained by specialization within particular cortical areas and by the functional connectivity within the system (Fingelkurts and Fingelkurts 8). These constraints result in what is termed metastability(Kello, Beltz, Holden, & Orden, 2007; Fingelkurts; Varela, Lachaux, Rodriguez, & martinerie, 2001; Kelso, Instabilities and Phase Transitions in Human Brain and Behavior, 2010; Wallenstein & J.A. Scott Kelso, 1995).

The model of brain functioning that is being constructed by these researchers proposes a view of the brain and neurological system as a hierarchical, multivariable network of neuronal assemblies, transiently linked, that interacts locally and globally within metastable constraints(Varela, Lachaux, Rodriguez, & martinerie, 2001, p. 229). Essential to this view is the importance of the *process* of interactions, in contrast to other models that emphasize brain structure.

According to this view, the metastability of brain states is achieved by phase synchrony of brain signals. Before the synchronization occurs, however, there is an instability that leads to a phase transition; then the signals synchronize and metastability is achieved. Remember that the metastable state is not locked in; rather it is transient, but more stable (that is, more likely to occur), than other possible states. Kelso hypothesizes that phase transitions serve as switches between metastable brain states (Kelso, Instabilities and Phase Transitions in Human Brain and Behavior, 2010, p. 2).

Arguing for the central nervous system as a complex system, Kelso has shown that there are coordination pattern dynamics that are intrinsically more stable than others. By intrinsic Kelso does not mean innate, but he means "capacities that exist at the time a new task is to be learned" (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 163).

> The initial state of the organism never corresponds to a disordered random network, but is already ordered to some degree. Thus, it is very likely that learning involves the passage from one organized state of the system to another, rather than from disorder to order. (Dynamic Patterns: The Self-Organization of Brain and Behavior 163)

Thus, if this is correct, phase transitions in the brain function slightly differently than those in non-living systems.

In one of Kelso’s experiments, participants were asked to cycle the index fingers of their right and left hands in response to cues from two visual metronomes, one for each hand (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, pp. 164-170). Typically, in-phase cycling (cycling the fingers synchronously) and 180 degree antiphase cycling (regular alternating cycles) constitute basins of attraction for this kind of coordination. This means that these patterns tend to be intrinsically stable. Kelso's earlier studies demonstrated this by showing that when individuals were asked to produce cycles other than these, errors tended to occur in the direction of either in-phase or antiphase cycles, with in-phase cycling being the more stable of the two patterns. This is typical of what are called basins of attraction (Kauffman 78, 83, 102, 110; Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior : The Self-Organization of Brain and Behavior 54, 56, 150, 168, 171)– that is, they tend to attract nearby behaviors in a way analogous to the flow of water in a watershed. One can imagine this like a landscape. Imagine that in the landscape there are two low areas. One of these represents in-phase cycling of the fingers, the other, antiphase cycling. In the case of rain on a landscape, the water in the areas around the low points naturally flows down toward them. In the case of cycling fingers, Kelso found that before learning new patterns, when people tried to cycle their fingers slightly out of phase in comparison with one of these two basins of attraction, they tended to slip into one of these more intrinsic patterns.

Wallenstein’s group (of which Kelso was a part) conducted a similar experiment and observed that, during the syncopated phase of learning, on approaching the phase transition, both the observed behavioral pattern and the brain signals began to destabilize and fluctuate before finally settling into synchrony(1995, p. 633). This disequilibrium before a phase transition seems to be characteristic (Kelso, Instabilities and Phase Transitions in Human Brain and Behavior, 2010, p. 2)—a context we will consider further later in this paper. A significant aspect of this study is that there was a correlation between observed learning behavior and the recorded brain signals, indicating that the same non-linear dynamic processes may operate at different levels of observation(1995, p. 634).

For Kelso's study, the attractor layout for each participant was determined before, during and after the experiment and these results were compared (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior 170-171). The task of each participant was to learn a cycling pattern of 90 degrees—one that is not typically an intrinsically stable pattern. What were the results? Kelso and his group found that

> The entire attractor layout changes with learning, not simply the coordination pattern being learned. …That is, with learning, the relative phase of 90 degrees also becomes attractive for neighboring conditions….Required phasings of less than 90 degrees are overshot, whereas those of greater than 90 degrees are undershot. (Dynamic Patterns: The Self-Organization of Brain and Behavior 171)

As a result of the creation of this new basin of attraction, the neighboring basins (for zero and 180 degrees) necessarily altered such that they became shallower.

In Kelso's study, individuals were seen to come to a learning task with intrinsic or pre-existing tendencies which could be mapped to show basins of attraction for dynamically stable coordination patterns. Through the process of learning a new pattern, the topology of the learner's landscape of changed in such a way that not only was a new basin of attraction created, but the pre-existing basins of attraction also altered—in other words, the entire system changed in response to the learned pattern.

If the Brain is Not in Control, What Is?

The basic problem with the question: If the brain is not in control, what is? is that it assumes that some discrete entity must be in control. As the discussion of complex adaptive systems demonstrates, the problem lies in this assumption. To really grasp the implications of what complex science asserts requires one to relinquish the assumption.

Part of the problem harks back to the point made earlier in reference to Maturana and Varela about logical accounting. Most discussions of learning are held from the point of view of an observer. In the case of human learning, this observer's point of view requires special consideration, which will be given in due course. For the time being however, the point must be made that from within the system, there is no need for an agent of control. The system organizes itself. In the case of an individual human, layer upon layer of systems organize themselves. Furthermore, each system is dynamic—learning, changing, adapting—continually searching for excellent solutions to problems as they are encountered. To use Maturana and Varela's expression, each human as a complex adaptive system is busy "bringing forth a world" (26).

Individual identity may be said to be composed of myriad complex adaptive systems which rely on one another for their existence and persistence. Learning is a component of all the complex adaptive systems which constitute a human individual, and the persistent identity which results from learning at all these levels is a product of more than the sum of these living systems. The author suggests that one cannot discuss human learning as separate from human identity. Kelso explains this beautifully in terms of synergetics(Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 9)[3]. He says that in self-organizing systems there exists a kind of circular causality which is the result of the relationship between the cooperation of the individual agents in the system and the feedback the system receives from its environment. Far from being a linear cause-and-effect type of relationship, however, in complex systems there are so many interconnected variables that a simple, linear approach to understanding is woefully inadequate. Kelso further explains that in these complex systems "there is no reference state with which feedback can be compared and no place where comparison operations are performed. …Hence,... the questions of who sets the reference value, who programs the computer, who programs the programmer, and so on do not even arise"(Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 9).

Varela, et. al., also favor a view of neural dynamics that involves reciprocal information exchange rather than a stimulus-response model. They argue that the brain integrates both endogenous activity (such as attention, preparation, and so on) and sensory information in the phase synchrony that results in large-scale integration (2001, p. 230).

To view learning as a dynamic of the complex adaptive systems which comprise an individual human requires a shift of perspective. One has to relinquish the notion of the outside agent that controls the system in favor of an understanding of the immensely intricate dynamics of interrelations between and within systems from which no agent can be extricated. Every agent is necessarily a part of the system at some level. This is as true of

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3　For more on Synergetics, see H. Haken's *Synergetics: An Introduction; Advanced Synergetics; and Information and Self-Organization*, all published by Springer.

conscious identity of oneself as it is of any other apparent observer.

The metaphor of the mind as a computer that controls the machine of the body does not hold up to scientific scrutiny. This is a crucial point when it comes to understanding the relationship of the nervous system to individual identity and a discussion of human learning. If Kelso is right, this challenges some of our assumptions about who we are as humans, how we learn, and how best to educate ourselves and our children.

Enactive Consciousness

Consciousness cannot be considered as separate from the complex systems of which it is a part, even though the conscious self believes itself to be separate and in charge. Consciousness, and more specifically the expression of consciousness as intention, is of undeniable importance in learning, however, as we shall see. But if our model holds true, the expression of intention is only one element of communication between and within the complex systems that are a human individual.

Thompson and Varela have proposed an approach to the neuroscience of consciousness called enactive cognitive science (2001, p. 418). This approach is grounded in nonlinear dynamical systems theory, research into brain processes involving large-scale integration mediated by synchrony, and the earlier work of Maturana and Varela. Their proposal offers an alternative to the “neural correlates of consciousness” approach that seeks to identify a representational system that under specific circumstances will result in the conscious awareness of content (Thompson & Varela, 2001, p. 418). They argue that the representational approach is one-way, while a dynamical systems view favors consciousness as an emergent process that is the result of “reciprocal relationships between neural events and conscious activity” (Thompson & Varela, 2001, p. 418). A conception of the “brain, body and environment [as] mutually embedded systems” results in a view of consciousness that involves “emergence as upward causation” and “global organism-environment processes, which in turn affect (via downward causation) their constituent elements”(Thompson & Varela, 2001, p. 424). According to this view, consciousness is an integral part of a continuous stream of interactions that are co-creative in the sense of exchanging, adjusting and adapting to information.

Intention and the Attractor Layout

Next, let us consider what is meant by the term intention. There may be a tendency to revert to the idea of the brain as the controller of the system where intention is concerned. However, the view of a programmer, be it the brain or a "genetic program," is called into serious question in light of research on complex adaptive systems and studies of the genome itself. Not only is the genome far too condensed to contain a blueprint for all the behaviors of a living system, but there is evidence that it is also not fixed, but that various components are "transposable" (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 140). One result of the view of biological unities being driven by "programs" of one sort or another is the prevalence of a belief in goal-directedness in biology (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, pp. 138-141).Kelso takes a different point of view, however, and demonstrates through research findings the viability of his approach.

> Rather than playing the role of a program sending instructions, intentionality is viewed as an integral part of the overall orchestration of the organism. Formally, an intention is conceived as specific information acting on the dynamics, attracting the system toward the intended pattern. This means that intentions are an intrinsic aspect of the pattern dynamics, stabilizing or destabilizing the organization that is already there. (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 141)

So, what can it mean to say that intentions are intrinsic to the pattern dynamics of a system? What it means is that intentions are not outside forces acting on the nervous system, but instead are parametric influences contained within and constrained by the nervous system itself. Maturana and Varela (135-137) explain this well when they insist that we keep our logical accounting in order. They point out that what seems to observers to be an influence from outside the system, or an internalizing of such an influence, is logically the result of structural coupling. Because of a tendency to view systems as being controlled by centralized forces rather than being self-organized, the understanding of this requires a conceptual shift. Without such a shift, it is difficult to conceive of intention (which in this discussion is a function of consciousness) as arising from within the central nervous system. It is tempting to attribute intention and other aspects of consciousness to some outside force. "But as we know," Maturana and Varela point out, "to make this description would undermine our logical accounting: as though something useful to us for communication between observers were an operational element of the nervous system" (172).

An important strength of Kelso's approach is that he does keep his logical accounting in order, that is, he defines intention and its effects in terms of one and the same system. In this way he avoids some of the pitfalls of other approaches to studies of the effects of intention. There are logical inconsistencies inherent in, for example, defining intention as a qualitative psychological function, considered as a force outside the central nervous system, and then measuring the effects of intention (often defined in terms of goal-directed behavior) using an experimentally quantitative system. As Kelso also points out, such a mixed approach also avoids the question of to what extent an organism's existing organization constrains its intentions (Kelso, Dynamic Patterns: The Self-Organization of Brain and Behavior, 1995, p. 146). But for the possible educational implications, it is vital to know how an individual's abilities are constrained and how to expand each learner's capabilities. In Kelso's experiments, intention is expressed with regard to a particular motor movement, for example, the cycling of fingers as described previously.

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