Introduction
Complexity Science Applied to Innovation – Theory meets Praxis

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We are caught in an inescapable network of mutuality,

Tied in a single garment of destiny.

Whatever affects one directly affects all indirectly.

- Martin Luther King, Jr.

Introduction

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Introduction: The Rise of Complexity Science in an Interconnected World

At the end of the twentieth century, the preeminent English astrophysicist Stephen Hawking proclaimed that the twentieth-first would be the "century of complexity." Hawking's words were certainly prescient since it is no historical accident that around the globe at this period of time the intensive study of complex systems, an area of research generally known under the appellation of "complexity theory," has become one of the most burgeoning arenas of scientific and practical endeavors. As our world has become increasingly interconnected through vast communication and information networks, so that what happens in one geographical region may go on to have great import for other regions separated by long distances and a huge diversity in cultures, so has complexity science arisen to probe and formulate the nature of interconnectivity and the dynamics of the networks making such interconnectivity possible.

Not only is the scale of this interdependence unprecedented in world history, so is the radical novelty of all those multifarious innovations necessary to support the infrastructure of information technologies as well as organizational transformations which are enabling these networks (Merry and Goldstein, 2003). So again it does not come as a surprise to recognize that complexity theory has ushered in, as one of its main foci of research, the study of radical innovation or what in complexity discourse is termed "emergence" in complex systems, the arising of unforeseen new structures with unexpected new properties (Goldstein, 1999).

Difficulties in Defining "Complexity"

Yet, it is no mean feat to either precisely delineate what constitutes complexity theory or even to define the very term "complexity." These conceptual difficulties result from at least three crucial factors involved in the study of complex systems. The first has to do with an exponential explosion of new findings across a huge number of fields and from a great many countries. Indeed, complexity theory is essentially transdisciplinary in nature, representing the confluence of research from around the world in such ideationally and methodologically varied fields as neuroscience, social psychology, computer science, mathematical graph theory, solid state physics, education, leadership studies, mechanical engineering, and on and on (this list could go on for several pages!). This interdisciplinarity makes it clear that complexity theory is not adequately conceived as merely *one* theory or even *one set* of theories. Rather, complexity science can be compared to the world wide web in terms of its enormous mixture of interests and the diverse knowledge domains involved.

The cross-disciplinary status of complexity science is in fact reflected in several ways in this *Special Issue* of *The Innovation Journal*. First, there are the many and varied fields in which complexity theory is applied: health care, coal mining, leadership studies, library science, crisis management (in face of natural and man-made disasters, e.g., hurricanes and terrorism attacks), organizational change, production processes, the use of simulations for data analysis, collaborative alliances, innovations in public and private organizations and institutions, and the public funding of education. Second, there are the wide-range of countries from which the authors hail - a truly international cast of characters - including Slovenia, Kazakhstan, Canada, the People's Republic of China, Portugal, and the United States. If we include the countries of origin of our authors this list even grows considerably larger. Third, there is a wide variety in the approaches taken in applying complexity science to the specific domains mentioned above. These range from "thick" qualitative descriptions, to case studies, to conceptual analyses, to mathematical methods, to agent-based models, to simulations.

A second factor making complexity theory elusive to pin down has to do with the very nature of what makes a complex system complex. In this regard, due to the radical novelty of the methods and insights making up complexity science, there is a frequent utilization of terminology that is defined in the negative, e.g., *non*-linearity, *un*-predictability, *ir*-reducibility and similar negation prefixed terms. Take the expression "*non*-linearity" which literally refers to the phenomenon of not being able to graphically represent the variables under study with a straight *line* in a Cartesian coordinate system, or in other words, the presence of a disproportionality between causes and effects in complex systems so that a small cause may result in a large effect or a large cause may result in a small effect. Of course, the possibilities for nonlinearity are much more immense than for linearity since nonlinearity comprises the whole plenitude of possible curvilinear representations which obviously greatly exceeds a simple straight line.

But this plenitude in the negative is akin to what the British mathematician Ian Stewart once described as defining all animals that are not elephants as "non-pachyderms." Obviously, the latter definition doesn't yield much information about all these other sorts of animals except for the fact they are not elephants!

Nonlinearity shows up in mathematical representations of feedback loops (positive and negative) and the kind of circular or mutual causality that several of the papers appeal to in discussing the complexity of the various situations they describe, a good example being the paper by Dawoody who points to the kind of "mutual causality" characterizing the interaction of the federal and state governments and local school districts. Nonlinearity can introduce an intractability in solving equations which for the most part doesn't exist in the case of linear math, another indication, therefore, of the confoundedness that comes with a complex system. As one famous complexity-oriented physicist pointed out, when he was in college typical physics textbooks focused on linearizations in mathematical models because the linear equations were mostly solvable whereas he had to turn to the textbooks' appendices to find information about nonlinear systems since the latter were too difficult or even impossible to work with.

The word "complex" is itself defined mostly in the negative as what is *not* simple, as *not* linear, as *not* predictable, as *not* reducible, and so forth. The solid state complexity-based physicist Kurt Richardson (2006) refers to these features of complex systems under the descriptor of the "darkness principle" since complex systems, by their very nature, cannot be known completely. We can see variations of this principle emphasized in the book *The Black Swan* which is reviewed by Gow in this issue. This is a topic that will be returned to in later sections but for now it needs to be stressed that unpredictability as such does not necessarily imply a lack of determinative causes or laws operative in complex systems but rather how the very complexity of such systems hinders attempts to precisely deduce future states.

To be sure, there have many attempts, even valiant ones, to define "complex" or "complexity." One helpful line in this direction is to point out that the "-plex" part has to do with "folds" as in the intricate fold-like structure of the human brain, and the "com-" refers to "with" so that "complex" means "with many folds." What is complex then is usually distinguished from the what is merely "complicated" which, although this term also suggests something not simple such as an entangled fishing line, what is only complicated can become uncomplicated just as a complicatedly entangled fishing line can be disentangled with enough patience. However, a *complex* system refers to systems which are in principle, by their very nature, not capable of being disentangled. Instead, their many folds are what makes them complex and their particular features are the consequences of these many folds that are not amenable to being unfolded since, even if such a thing were possible, that would rob them of what it is that makes them uniquely what they are.

Difficulties in precisely defining "complex" and "complexity" though do not imply that all hope for conceptual clarity is nil. Indeed, even a complex system's unpredictability is yielding to new methods and new models and new conceptions of what is involved in our ability to predict. For instance, the exact state of the weather a year from now, a state indicated by the temperature or barometric pressure, is in principle as well as in practice unpredictable because the weather is a complex system. Indeed, the weather is often used as a prototypical complex system because of the interacting factors involved, but much about the state of the weather is in fact predictable because the climate serves to limit the range of the valuations of the variables of the state of the weather and climate doesn't change with the rapidity with which the state of the weather does.

The Scientific and Mathematical Background of Complexity Science

Even though complexity theory contains a host of new concepts, methods, tools, and insights, for the purpose of this *Special Issue*, it can be helpful to zero-in on four major, interrelated core conceptual underpinnings of complexity theory: networks; differences; emergence; and attractors as indicated by the black underlining in Figure 1 below (for a more extensive explication, see Goldstein, 2007a):

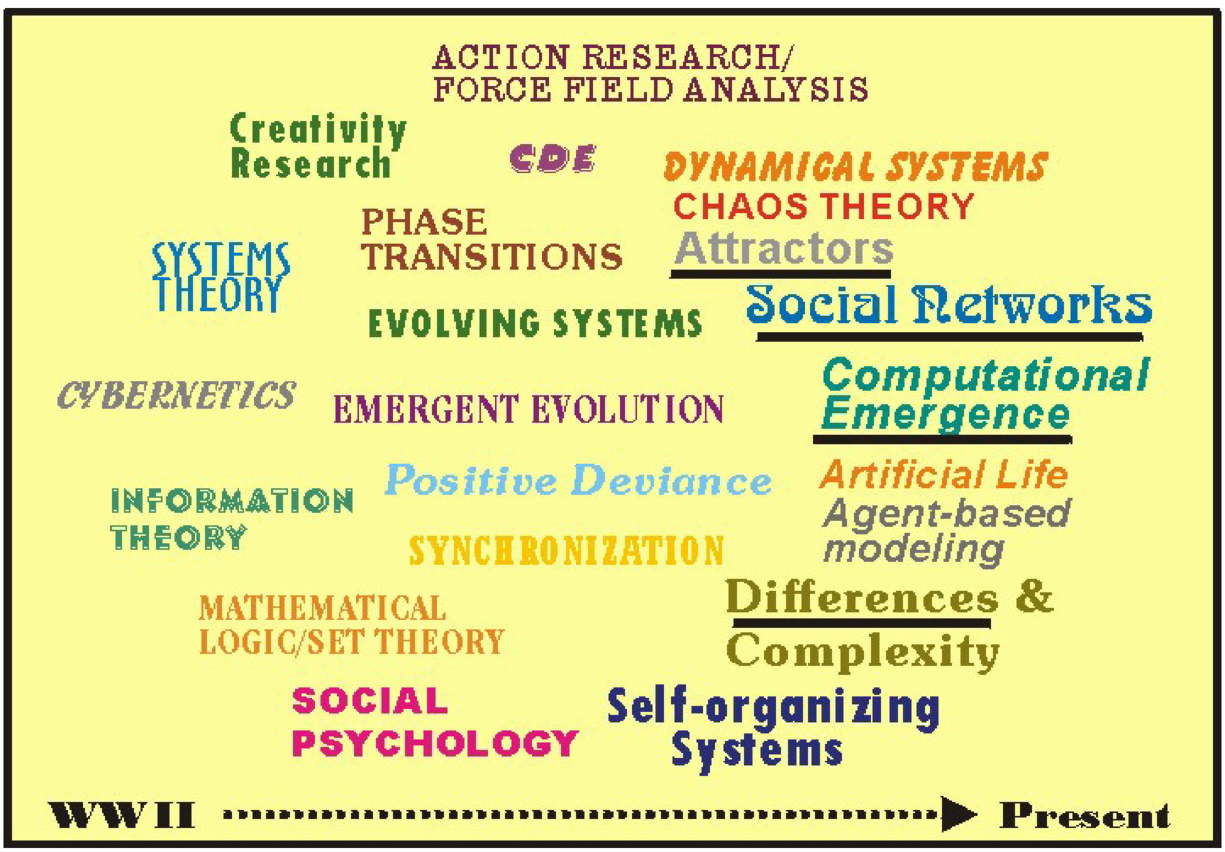

Figure 1: Scientific and Mathematical Sources of Contemporary Complexity Theory (from WWII to the present).

Although the scientific and mathematical disciplines making up contemporary complexity theory formed out of a confluence of variegated sources, many of which can be traced back to the World War II, a description of these four mentioned constructs can give us a sense of what it is that makes up the field of complexity science. Indeed, we shall see that each has close connections with innovation in general. Many complexity principles are described in greater depth in several of the papers of this *Special Issue*, e.g., the papers by Amagoh, Bolton & Stolcis, Johnston, et. al., and Verdon.

Networks

One of the most exciting and more recent developments in complexity science concerns the study of social networks, that is, the way each of us is connected to others through social linkages, whether formally as in an organizational hierarchy or informally as in friendship circles. Social networks, consisting of linkages (or edges) connecting agents (or nodes), come in a variety of types, each with benefits and limitations depending on the purpose of the network. Here, though, we will go over four types of networks for the sake of brevity. The key in understanding the role of networks in complexity theory is their function in connecting parts or agents of a complex system. The connections comprising a network enable the flow of information and other resources within the system and between the system and its various environments. More will be said about what "information" means in the context below in the next section on differences.

One type of network, perhaps the one longest studied since work in the nineteen fifties in the mathematical theory of graphs, is the so-called *random* network, a network in which the nodes and edges are laid down in a random fashion. We can see evidence of random networks in the connections established among people mingling in a large party or the grid of highways in the US linking cities and towns of different sizes (Barabási, 2002). An important feature of random networks is related to the phenomenon of emergence, described in greater depth below, that occurs during phase transitions in a network (Newman, Barabási, & Watts, 2006). A phase transition refers to the usually sudden onset of new properties when a complex system reaches some critical threshold of complexity. An example of a phase transition in a random network is known as the emergence of a "giant cluster" when all the nodes or agents in the system become connected to each other (Barabási, 2002). For instance, a giant cluster can emerge when the host of a party introduces enough single individuals and couples to each other that at some point everyone in the party is connected to everyone else, albeit many are indirect connections through intermediary nodes or agents. One of the features of a random network is a normal distribution (Bell curve) exhibited when the number of nodes with $\boldsymbol{k}$ number of links is plotted in relation to the number of links ($\boldsymbol{k}$). This means that there most nodes or agents have a similar number of links and there are very few highly connected nodes.

In *hub* networks, though, certain nodes or agents possess many links to other nodes or agents, yet many other less connected nodes or agents only connect to other less connected nodes via the more connected hubs. An example can be found in airline traffic routes, e.g., Delta has a hub in Atlanta, US Air in Philadelphia, American in Miami, and so forth. Since in a hub network, smaller cities are connected to larger ones only via the hubs, in order to fly, via Delta Airlines, from Athens, Georgia (where the University of Georgia is located) to New York you would need to first fly from Athens to Atlanta, which is Delta's hub, and then change planes to fly onto New York. Thus, a disadvantage of a hub network is that less connected nodes or agents are only connected to each other through intermediary hubs, a fact exhibited above in the case of air travel. Yet, hub networks obviously offer a number of benefits including, e.g., centralized aircraft maintenance and route efficiencies.

Another type of social network is termed a *small-world* network since it consists of linkages among agents or nodes with as few intermediaries among them as possible, thus making up a “small-world” (Watts, 1999). The small world network achieved some notoriety a few years ago with the so-called phenomenon of “Six Degrees of Separation” (also the name of a Broadway show as well as film) which for some obscure reason focused on the actor Kevin Bacon as being the nodal hub linking across Hollywood film, television, and theater actors, producers, directors, and so forth. The idea was basically that no currently living person on the planet was separated by more than six intermediary persons (agents or nodes). This might seem hard to believe but in many rounds of playing a “small-world” game with friends and colleagues, we managed to find even less than six intermediaries linking a peasant in the middle of China with a politician in South America, two nodes that would otherwise be presumably thought to be vastly separated from each other. As it turned out, studies of actual social networks among actors, etc., demonstrated that it wasn’t Kevin Bacon who was the real hub of Hollywood – instead, it turned out that the actor Rod Steiger played more of a hub role in that Steiger was a greater connecting link among the many people constituting the social network of persons in the entertainment world.

By cutting down on the number of intermediary nodes or agents in the small-world network, the speed of information flowing in the network can increase since there are fewer way stations along the way where the information would have to be received and then retransmitted. On leadership applications of social network theory see the relevant chapters in Hazy, Goldstein, & Lichtenstein (2007) and Marion & Uhl-bien (2007).

Still another type of network, an even more recent subject of research, is known as a *scale-free* network, “scale-free” in the sense that there no one “scale” of connectivity among nodes or agents is more prevalent than another. This means that, unlike the case of the random graph with its normal distribution of nodes with ***k*** number of links in relation to the number of links (***k***), in a scale free network there is instead a so-called *power law* distribution with many nodes having only a few links, a moderate amount of nodes with a moderate amount of links, and a few nodes with many links (Barabási, 2002). A prime example of a scale-free network is the network of linkages making-up the world wide web in which there are many websites with few linkages to other sites while there are a few central hubs with extremely many links such as google, yahoo, or facebook. Scale-free networks tend to consist of densely connected crucial hubs which themselves are multi-connected to outlier agents or nodes on the periphery (Holley, NDa, NDb). In fact, recent ground-breaking research, relying on advanced brain imaging techniques, has demonstrated the existence of mult-hub/periphery - scale-free networks of axons connecting major centers or modules of the brain with more outlying centers of neuronal activity in the human cerebral cortex (Hagmann, et. al., 2008).

One of the disadvantages of scale-free networks can be called the “rich get richer“ syndrome found in developing complex systems: the multi-connected nodes tend to grow even more links while the peripheral, minimally connected nodes or agents remain static in the few number of connections they already have. The social network researcher Gregory Todd Jones (2007) points out that this may translate into a greater marginalization of communities unless a concerted effort is made to connect to the peripherally marginalized (see also Goldstein, Hazy, and Silberstang, 2008).

The idea of rapid information exchange along connected networks is an idea that is central in the papers by Bolton & Stolcis, Lapão, and Verdon.

Differences

It must be recognized that any kind of social (or other type of) network can only carry information from one agent to another when these agents possess significant differences from one another since without these differences all that would be propagated along the network would just be more of the same. The term "difference" as it is being used here was concisely delineated by the British polymath Gregory Bateson (2000), one of the early systems and complexity thinkers emerging after WWII, who defined information as "a difference that makes a difference." Perhaps the clearest and most insightful research on "differences that make a difference" in human systems was conducted by the complexity-oriented economist Scott Page (2007) who demonstrated, through computer simulations, modeling, and actual social experiments, the critical role played by differences in perspectives, differences in interpretations, and differences in conceptual representations on creative idea generation and problem-solving in groups.

Indeed, one of the chief ways of distinguishing a complex from a simple system is the presence in the former of a huge amount of differences distinguishing one agent from another. Of course, the presence of this plenum of differences in a complex system renders such systems difficult to predict and control. At the same time, though, it is the interactions among the differences characterizing the agents, the mixing and recombination of these differences, which gives complex systems their potential for self-organization and emergence into new patterns with new properties, the subject of the next section. Along with the presence of a great deal of differences, complex systems also require means for bridging or exchanging information across these differences plus strong enough boundaries or containers to contain the power of such exchanges (see Eoyang & Olsen, 2001; and Goldstein, 1994).

In biology, evolution depends on difference-generation in genetic material by way of two mechanisms: random mutations which change genetic material into something different than what is inherited; and recombination which also changes inherited genetic material as found, e.g., in sexual reproduction or symbiogenesis (for the latter see Margulis and Sagan, 2002). These difference-generating mechanisms are what lead to the novel traits that may help a species become more adapted to changes in the environment.

Computer simulations known as cellular automata and artificial life, two experimental arenas where emergence is of key importance, utilize similar mechanisms of randomization and recombination in generating differences that eventually show up as new computational emergent patterns (Holland, 1998). Cellular automata and artificial life are the sources of the kind of simulations and agent based models found in several of the papers in this *Special Issue* including the ones by Johnston, et. al. and indirectly in the papers by Sabelli and Thomson.

The idea of difference is also fundamental to the type of gradients resulting in self-organization in physical as well as social systems which will be discussed in greater detail below. Suffice it for now to point out that it is through an impetus in bridging both internal gradients as well as gradients between systems and their environments that complex systems may self-organize into new patterns. That is, the presence of differences and the consequent propensity to overcome them act as both a kind of fuel and a "push" that leads certain complex systems to innovate.

Such experiments in innovation often stem from differences between the peripheries and the more central modules of complex systems, which as will be recalled from the previous section, can be connected by way of networks. Differences in the behavior at the literal geographical periphery as well as the more metaphoric "periphery" in the sense of being outside the normal way of doing business, can be the seed bed of social experiments which try out new social practices possibly containing the seeds of improved adaptability on the part of complex systems.

One of the most exciting social methods for exploiting the role of such differences as the germination for solving what seem to be intractable social problems is that of *Positive Deviance* developed by Jerry Sternin (Bertels & Sternin, 2003). Basically, Positive Deviance is a method for identifying spontaneously occurring experiments in innovative social practices at the "peripheries" and then disseminating these experiments as solutions to social challenges without at the same raising opposing forces that resist or reject the innovations. In this *Special Issue*, the paper by Lapão discusses "risky zones" of experimental innovation in health care organizations, innovations leading to collaboration, even a kind of self-organization of clinical services. In Lapão's paper, it is quite interesting that such experimental dynamics are of help in both finding emerging diagnostic patterns in patients (like fibromyalgia or diabetes, etc.) as well as in re-engineering the clinical service to better adjust to patients' demands. The paper by Hua-ling Song, et. al., also discusses various types of experiments in innovation occurring outside the mainstream norms of the organization.

An important role of the idea of differences also shows up in the various metrics that have been devised to measure the complexity of a complex system. For example, differences are at the heart of the metric of "information entropy" which is used in the mathematical analysis of the Shandong Mining Company in the paper by Hua-ling Song, et. al. In order to grasp the relationship of differences to this kind of complexity metric, a few words are needed about the mathematical field known as information theory developed during and after WWII by Claude Shannon and others. Information, as stated above, assumes difference. Indeed, in information theory there is a close connection to the idea of entropy in physical systems in that, if flow of information in a channel is to be considered *genuine* information and not the mere propagation of redundancy, it must contain inherent differences inside the message. For example, consider sending a message containing the following numerical pattern in sequence: 7 7 7 7 7 7 7 7 7… Each new seven is the same as the preceding one so there is no new real information being sent in the channel and the whole message could have been much more economically sent as "repeat the number 7 ***n*** times". Contrast that message with this one: 7 3 5 8 2 1 9 9 3 7… The latter message contains real information since each new digit is *different* from the preceding one and this difference is, in a sense, unpredictable or a surprise since there is no immediately obvious pattern to the sequence. Hence, in Shannon's formulation of information the key was on indicating uncertainty which arose from unpredictable differences in patterns. That is why using the metric of "information entropy" in analyzing the complexity of a system is akin to knowing how many calculational steps are necessary to make a right guess about what is really going on in a system. That is, the complex system is clouded over by our uncertainty about it (see Williams, 1997). This is related to the point made above that complex systems possess by their very nature an obscuring of our ability to gain knowledge or certainty about them.

Emergence

Emergence refers to the arising of new, unexpected structures, patterns, or processes in a complex system (for a full exposition see Goldstein, 1999). Emergent phenomena are understood as existing on a "macro"-level which is considered a "higher" level in respect to the "lower" or" micro"-level level components from which the emergents emerge. For example, the temperature of a liquid is considered a "higher level" "macro-" phenomenon since it can be observed with a thermometer at the scale of our everyday world whereas temperature is produced by the kinetic energy possessed by the liquid's molecules moving at the "lower" or "micro-" level that is not directly observable to inspection.

Emergent phenomena seem to have "a life of their own" with their own rules, laws, and possibilities which are radically novel with respect to the lower level components. The term "emergent" was first used by the nineteenth century philosopher G.H. Lewes and came into greater currency in the scientific and philosophical movement known as emergent evolutionism in the 1920's and 1930's (Blitz, 1992). In an important respect, the research connected with the Santa Fe Institute and similar complexity centers focuses on emergence observed in such computational simulations as cellular automata and artificial life and thereby represents shifting the study of emergence from armchair philosophical speculations to laboratory conditions.

In organizations, emergent phenomena are happening ubiquitously yet their significance is often downplayed or downright neglected by command and control mechanisms grounded in the officially sanctioned corporate hierarchy. One of the important lessons for leaders coming from complex systems theory is how to facilitate emergent structures and take advantage of the ones that occur spontaneously.

In complexity theory emergence has customarily been coupled with the idea of self-organization or the supposedly spontaneously occurring, bottom-up arising of new order in a system. The idea of self-organization as such turns out not to be a new one since notions of it can be found as far back as in the work of Descartes (Shalizi, 1996) as well as later in the *Naturphilosophie* thinking of Kant and particularly in the Romanticist Idealism of Friedrich Joseph Schelling (Heuser-Kessler, 1986).

The idea of self-organization puts the emphasis on how new emergent structures, patterns, and properties arise without being externally imposed on the system. The "self-" of "self-organization" connotes this lack of external imposition and thus indicates similar properties such as being innate, natural, and spontaneous. Self-organization achieved prominence in studies of emergence in simply physical system whose conditions have been described as "far-from-equilibrium" in the thermodynamics approach founded by the Nobel laureate Ilya Prigogine and his followers (Nicolis, 1989) or in terms of "order parameters" in the approach known as the Synergetics School founded by the German physicist Hermann Haken (1981).

Recently, this author has questioned some of the "folklore" surrounding the idea of self-organization especially the belief that it is a naturally occurring spontaneous phenomena (Goldstein, 2007a). Instead, emergence has been decoupled from self-organization as such since the arising of novel emergent order with novel properties requires the presence of many *constraining* factors with the result that emergence is now thought of as a type of constructional activity in which lower level patterns and properties are transcended.

Emergence in Simulations and Agent-based Models: Emergent phenomena as macro- or collective level dynamics are one of the important elements found in the simulations and agent-based models used in several of the articles in this special issue. An agent-based model refers to a computer simulation in which key factors or variables in the complex system under investigation are represented by agents in interaction with one another, these interactions following certain programmed-in rules of interaction (Axelrod, 1997). In the agent based models, for example, utilized in the paper by Erik Johnston, Ning Nan, Wei Zhong, and Darrin Hicks, game theory simulations are used to research collaborative alliances by examining the emergent phenomena arising during the simulations.

Game theory (for an accessible introduction, see Davis, 1983) consists of two or more persons or agents "playing a game" in which the parties involved negotiate or interact with each other to achieve certain payoffs. Thus, in one of the most famous of such games known as the Prisoner's Dilemma, two suspects of committing a crime together are placed in separate cells. The rule is that each of the suspects may confess or remain silent with each knowing the possible "pay-offs" to each of the actions. One pay-off is that one suspect confesses while the other does not, the one confessing turning state's evidence and going free while the other goes to jail for twenty years. A second possible pay-off is that both suspects confess and they both go to jail for twenty years. A third possible pay-off is that both remain silent with each going to jail for only a year for a lesser charge. The question then is what the prisoners should do to optimize their pay-offs. A game theory simulation of the Prisoner's Dilemma can be repeated many times with emergent dynamics arising out of the agents' learning of the possible pay-offs occurring each time the game is played.

The study of emergence in computer simulations need not be confined to game theoretical situations. Thus, in the article by Thomson, we find a computer simulation of the processes involved in the diffusion of innovation. Simulations can also involve computational graphic displays of calculations involving certain nonlinear dynamical equations like the "bios" equation described in the paper by Sabelli. In computer runs using this particular equation emergent behavior and its properties, e.g., novelty, can be observed as the equation is iterated over time.

Emergence is also of prime important in the collective level phenomena found in market economies described in the paper by Verdon, who expands upon Adam Smith's original postulations about the dynamics of "free" markets in the direction of our networked new world. Indeed, the study of this type of macro-level dynamics was pioneered forty years ago by the economist Thomas Schelling (2006). Again, this collective behavior is found in the game theoretic simulations in the paper by Johnston, et. al. mentioned above, where "decentralized interactions among autonomous actors can lead to system-level regularities."

At the same time, though, that attention to emergence shifts interest toward macro-level dynamics, the micro-level determinants of the macro-level also require investigation. That in fact is the focus of the paper by Silberstang & Hazy who explore the micro-level enactments that go on to make up leadership on a more collective level.

Such a mixture in studying macro- and micro-levels, even simultaneously, follows a methodological suggestion concerning the study of complexity made by the Nobel laureate and trailblazer in the study of complex systems, Herbert Simon (1981: 86): "in the face of complexity, an in-principle reductionist may be at the same time a pragmatic holist."

Attractors

The idea of an attractor is a central conceptual and methodological linchpin of the mathematical field known as *nonlinear dynamical systems theory* (NDS), one of the crucial conceptual and methodological underpinnings of complexity theory in general (along with such other mathematical disciplines such as graph theory which underlies the study of social networks, information theory, and the study of cellular automata which initiated the fascinating study of artificial life at the Santa Fe Institute and other centers of complexity research). NDS arose out of the ground-breaking work of the celebrated French mathematician Henri Poincaré a century ago and then was developed through the work of many esteemed mathematicians including Liapunov, Andronov, Birkhoff, Cartwright, Peixoto, Smale, Arnol'd, May, Feigenbaum, Yorke, Li, and many others (see Abraham & Shaw, 1984; Diacu & Holmes, 1998). The ability to pictorially represent the evolving status of a dynamical system made possible the advent of micro-computers and their amazing graphics capability elevated the study of attractors as well as NDS in general.

The meaning of the "nonlinear" part of NDS was discussed in the introductory section above as a designation for a disproprotionality between cause and effect in complex systems. More particularly, the term refers to the nonlinear type of equations studied by NDS (see Scott, 2005). The "dynamical" part of NDS refers to the way that systems modeled by these nonlinear equations exhibit a kind of evolution or development through a series of different phases, the behavior of each constrained by its "reigning" attractor(s). Such phases and their attractors can be likened (very loosely) to the stages of human development: from infancy through toddlerhood through childhood through adolescence, young adult hood, adulthood, and seniority.

Each or phase stage has its own characteristic set of behaviors, developmental tasks, cognitive patterns, emotional issues, and attitudes (although, of course, there is some variation among different peoples and cultures). The attractors dominating each phase denote the long-term and not the transient behavior happening during that stage. This means that attractors are designations of the stable dynamics of each phase in that if the dynamics is temporarily perturbed it will eventually come back to that behavior consonant with the reigning attractor.

Technically an attractor is a pattern in an abstract mathematical space called a *phase or state space* which is a way of representing the relationship of the key variables to one another that differs from a *time series* of data points. A time series on a Cartesian graph (the typical ***x*** and ***y*** axes) usually displays change in time on the ***x-*** axis and one or more variables on the ***y, z, w***,.. axes. For example, capital markets are customarily depicted with time on the horizontal axis (e.g, 15 minute intervals, days, weeks, years) and prices on the vertical axis. The recent, very dismal charts of the stock prices of Citigroup or General Motors zig zagging downward to the right over the past several months are examples of time series. But so are the more promising zig zagging downward graphs of the price of crude oil!

In a phase or state space diagram, however, there is a simple revision of how to graphically depict and therefore understand the relationship among key system variables. Instead of plotting one or more variables on the ***y***-axis against time on ***x***-axis, phase space simply plots key system variables against each other, e.g., the speed of a pendulum's bob on the horizontal axis with distance from the vertical resting place on the vertical axis. In such a phase space diagram, time is now only implicit. This simple move, though, provides a spatial or geometrical view of the system's dynamics as they change over time. In that way, the "portrait" made in the diagram of the changes in the variables over time supplies a spatial view of temporal dynamics which can provide insights not as easily seen in time series charts (see Abraham & Shaw, 1984, Guastello, 1995, and Winfree, 1987, on how temporal dynamics can be insightfully captured by the spatial patterns of phase portraits). The dimensions of a phase or state space correspond to the number of variables that are considered important to study dynamics of the system.

Typically, attractors come in three varieties: fixed point which refers to a point toward which the trajectories made up of the data points converge; limit cycle or periodic attractors which refers to an oval or circle or set of ovals and circles towards which the trajectories converge; chaotic attractors which are very complicated multi-dimensional phase portraits of systems exhibiting technical "chaos" popularized by so-called "chaos theory."

Chaos is a particular type of system dynamics characterized by being deterministic, that is, unfolding in determined manner from one state to another without any necessary incorporation of randomization yet shows a pattern hardly distinguishable from one generated by a totally random system. Moreover, chaos has the property known as sensitive dependence on initial conditions which in popular parlance goes by the name of the "butterfly effect", that is, the notion that the system is so nonlinear a very small change like the wind produced by the flapping of a butterfly's wings in Brazil may later cause a thunderstorm in Kansas (Lorenz, 1993). Moreover, chaotic attractors may also be "strange" meaning their spatial patterns in phase space have a fractal structure (although technically there is not a complete equivalence between chaotic and strange attractors). The discovery that chaotic attractors could be strange was startling since one area of mathematics know as fractal geometry (Mandelbrot, 1992) was shown to be intimately to another one, i.e., the study of dynamical systems. The way in which two previously separated realms of mathematics are shown to have a close relationship is not uncommon and often signals a leap forward in mathematical understanding. Although the words "chaos" and "complex" are close enough in meaning that they are sometimes used interchangeably in complexity theory, it is important to keep in mind that they in actuality refer to quite different dynamics. Few complex systems can be characterized as chaotic in the technical sense and chaotic systems need not possess the other properties of complex systems as described herein.

Sometimes attractors have been seen as "final causes" of a system, following Aristotle's famous scheme of four essential types of causes: material causation or the "matter" out of which a system is made; formal causation or the pattern or shape to which a system in the long run tends; efficient causality or the immediate precipitating event which initiates new dynamics in a system; and final causation or the purpose or end (the "telos" of "teleology") shown in a system's "design." The association of attractor with final causation comes from the manner in which the very word "attractor" seems to suggest that it is something to which a system is drawn or attracted. However, it should be kept in mind that attractors, as abstract patterns in an abstract mathematical space, are not appropriately thought of as actual causes at all.

Because attractors are *stable* phase space patterns, a system can go through changes while under the sway of the same attractors but these changes will need to conform with what is allowable by the reigning attractors of each phase. This kind of system change could be called "*intra*-attractor." However, sometimes a system may undergo a much more significant type of change, a phase transition into a new phase dominated by different attractors. This kind of system transformation, an "inter-attractor" change, is termed "bifurcation" of which there are various kinds. Bifurcations result when there is a change in certain critical parameter values toward a threshold. Sometimes this kind of criticalization is known as a far-from-equilibrium condition in the study of self-organizing systems which was described above in the section on emergence.

It can be helpful to consider the difference between "intra-attractor" and "inter-attractor" change when thinking about the organizational change and innovation described in the papers by Glor, Amagoh, and Verdon.

The "bios" equation studied in the paper by Sabelli is offered as an alternative to the usual emblematic equations used in NDS and chaos theory in particular. "Bios" provides several intriguing properties such as novelty and diversification not directly found in the usual mathematics of NDS.

Conclusion

In this introduction to the *Special Issue on Complexity Science* of *The Innovation Journal: The Public Sector Innovation Journal* some of the main ideas and methods involved in complexity theory have been described. Of course, the exposition of these central concepts has been greatly condensed for the sake of brevity. The interested reader, though, can follow through on most of these complexity notions by means of the many articles and books referenced and found in this special issue.

Each of the four main complexity constructs discussed above – networks, differences, emergence, and attractors – are intimately related to innovation. Thus, innovation can be said to diffuse via social networks, innovation can be said to come about through the recognition, mixture, and amplification of differences from the norm, innovation can be said to be all about the emergence of new structures with new properties, and innovation can be said to involve both inter- and intra-attractor change, the deeper the innovation the more likely it represents a bifurcation into new attractor regimes.

To be sure, complexity theory is a strange brew of the very technical, even the abstruse, the descriptive and the wildly metaphoric. This combinatory characteristic of complexity science is reflected in the style and content of the papers in this issue. Some of the papers do indeed include some very technical material but the authors were asked to relegate such technicalities mostly to the appendices. Each of the papers speaks for itself which is a major reason why more time was not spent in this editorial introduction describing the content of the papers. Complexity science can indeed be conceptually challenging and that is why it is only through the careful reading and rereading and mulling over of the ideas that their insights can be appreciated.

It might be thought that complexity theory consists of a uni-directionality of influence, that is, that it mainly concerns the application of the so-called “hard” sciences and mathematics in the direction of the “softer” realm of social systems. Yet, this would be a rash judgment since a reverse directionality of influence can be discerned in the most contemporary research into complex systems, e.g., the study of social networks. Even though social network theory utilizes the abstract mathematical theory of graphs (nodes, edges, and so forth), it has been, from a deep investigation of actual networks active in complex human social systems that many advances in complexity theory have proceeded. This directionality of influence from social system back to “hard” science in fact is similar to what took place in the case of statistics in the nineteenth and early twentieth century where the study of human social systems led to the devising of statistical metrics that were then applied to physics, chemistry, and other sciences. Indeed, complex social systems are directly accessible for research without the need for sophisticated technologies such as microscopes or telescopes. No doubt, many more such advances in complexity theory will be forthcoming from the investigation of complex human social systems.

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References

Abraham, R., & Shaw, C. 1984. *Dynamics: The Geometry of Behavior* (4 parts). Santa Cruz, CA: The Visual Mathematics Library/Aerial Press.

Axelrod, R. 1997. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton: Princeton University Press.

Barabási, A. 2002. *Linked: The New Science of Networks,* NY: Perseus.

Bateson, G. 2000. *Steps to an Ecology of Mind: Collected Essays in Anthropology, Psychiatry, Evolution, and Epistemology*. Chicago: University of Chicago Press.

Bertels, T. & Sternin, J. 2003. "Replicating Results and Managing Knowledge," in Rath & Strong Consulting (Eds). Hoboken, New Jersey: John Wiley & Sons, pp. 450-457.

Blitz, D. 1992. *Emergent Evolution: Qualitative Novelty and the Levels of Reality*, Dordrecht: Kluwer Academic Publishers.

Davis, M. 1983. *Game Theory: A Nontechnical Introduction*. Mineola, NY: Dover.

Diacu, F. & Holmes, P. 1996. *Celestial Encounters: The Origins of Chaos and Stability*. Princeton: Princeton University Press.

Eoyang, G. & Olsen, E. 2001. *Facilitating Organizational Change: Lessons from Complexity Science*. Pfeiffer.

Goldstein, J. 1994. *The Unshackled Organization*. Portland, Oregon: Productivity Press.

Goldstein, J. 1999. "Emergence as a Construct: History and Issues, *Emergence: Complexity Issues in Organization and Management*, 1(1): 49-62.

Goldstein, J. 2007a. "A New model for emergence and its leadership implications," in J. Hazy, J. Goldstein, and B. Lichtenstein, (eds.), *Complex Systems Leadership Theory,* Mansfied, MA: ISCE Publishing, pp 61-92.

Goldstein, J. 2007b. "Complexity Science: The Evolution of the Field," In M. Uhl-bien & R. Marion (Eds). *Complexity Leadership: Part 1: Conceptual Foundations*. Charlotte, NC: Information Age Publishing.

Goldstein, J., Hazy, J., & Silberstang, J. 2008. "Complexity and Social Entrepreneurship: A Fortuitous Meeting," *Emergence: Complexity & Organization (Special Issue on Social Entrepreneurship, Systems Thinking and Complexity)*, 10 (4): 9-24.

Guastello, S. 1995. *Chaos, Catastrophe, and Human Affairs: Applications of Nonlinear Dynamics To Work, Organizations, and Social Evolution***.** Mahwah, NJ: Lawrence Erlbaum Associates.

Hagmann, P., Cammoun, L, Gigandet, X., Meuli, R., Honey, C. J., Sporns, O., & Wedeen, V. J. 2008. "Mapping the Structural Core of Human Cerebral Cortex," *PLoS Biology* 6 (7): 1479-1493. Available at
www.plosbiology.org 1479 July 2008 |

Hazy, J., Goldstein, J. & Lichtenstein, B. (Eds.). 2007. *Complex Systems Leadership Theory,* Mansfied, MA: ISCE Publishing.

Haken, H. 1981. *The Science of Structure: Synergetics*, NY: Van Nostrand
Reinhold.

Heuser-Kessler, M. 1986. *Die Produktivität der Natur: Schellings Naturphilosophie und das neue Paradigma der Selbsorganization in den Naturwissenschaften,* Berlin: Duncker & Humblot.

Holland, J. H. 1998. *Emergence: From Chaos to Order*. Reading: Perseus Books

Holley, J. (NDa --no date). "Network Weaver," Available at http://www.networkweaving.com/june.html

Holley, J. (NDb--no date). "Networks and Evaluation," Available at http://www.networkweaving.com/june.html

Jones, G. T. 2007. "A NetLogo model for the study of the evolution of cooperation in social networks," *Conference Proceedings: North American Association for Computational Social and Organizational Science*, Atlanta, GA. Available at http://law.gsu.edu/gjones/publications.htm

Lorenz, E.N. 1993. *The Essence of Chaos*. Seattle: University of Washington Press.

Mandelbrot, B. Mandelbrot, B.B. 1982. *The fractal geometry of nature* (2nd ed.). New York: W.H. Freeman.

Margulis, L. & Sagan, D. 2002. *Acquiring Genomes: A Theory of the Origin of Species*. NY: Basic Books.

Merry, U., and Goldstein, J. 2003. "The Implications of Complexity," In D. Kiel (Ed.), *EOLSS (Encyclopedia of Life Support Systems)* United Nations: UNESCO. Available at: http://www.eolss.net/

Newman, M., Barabási, A., & Watts, D. (Eds). 2006. *The Structure and Dynamics of Networks* (Princeton Studies in Complexity). Princeton: Princeton University Press.

Nicolis, G. 1989. "Physics of Far-from-equilibrium Systems and Self-organisation," in P. Davies (ed.), *The New Physics*, Cambridge: Cambridge University Press, pp. 316–47.

Page, Scott. 2008. The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies. Princeton, NJ: Princeton University Press.

Richardson, K. 2006. "Systems theory and complexity: Parts 1 and 2." In K. Richardson, J. Goldstein, P. Allen & D. Snowden (Eds.), *Emergence: Complexity and organization 2005 Annual*, Volume 6. Mansfield, MA: ISCE, pp. 490-508.

Schelling, T. 2006. *Micromotives and Macrobehavior*. (Revised Edition). NY: W. W. Norton.

Scott, A. 2005. *The Encyclopedia of Nonlinear Science*. NY & London: Routledge.

Shahlizi, C. 1996. "Is the Primordial Soup Done Yet? Available at http:///www/santafe.edu/-shalizi/Self-organization/soup-done/

Uhl-bien, M. & Marion, R. (Eds). 2007. *Complexity Leadership: Part 1: Conceptual Foundations*. Charlotte, NC: Information Age Publishing.

Watts, D. 1999. *Small Worlds: The Dynamics of Networks between Order and Randomness*. Princeton: Princeton University Press.

Williams, G. 1997. *Chaos Theory Tamed*. Washington, DC: Joseph Henry Press.

Winfree, A. 1987. *When Time Breaks Down: The Three-Dimensional Dynamics of Electrochemical Waves and Cardiac Arrhythmias*. Princeton: Princeton Univ. Press.