Section on Natural Systems

Date : February 26, 2018

This section is part of a chapter which includes:

- [Overview of Systems Philosophy](#)
- [Section on Natural Systems](#)
- [Overview of Bowen Theory](#)

A natural system is quite simply a system which occurs in nature. Hall and Fagen (1956) write that "The description of these is the task of the astronomer, physicist, chemist, biologist, physiologist, etc., and again the amount one can say about a given natural system depends on the number of essential variables involved" (p. 72). Natural system researchers are typically more interested in direct observation with fewer *a priori* assumptions than Bertalanffy's pure mathematical ideal for GST or Weiner's machine-control philosophy for cybernetics. Though they may use mathematical models to describe the behavior of the system, the models are the result of the inductive process; they are derived from the observations as opposed to explaining the observation from the model. One may think about a naturally occurring system using some of the terms from general systems, but it is the intention of discovering the nature of the system that is not pre-supposed in the human mind that distinguishes natural systems research.

Systems science as the study of complexity is taking root in the study of biological systems (Kitano, 2002). While specialized natural systems research does not bear that name, the multidisciplinary aspect of this class of research falls in line with Von Bertalanffy's (1968/2015) *general systems* vision of uniting the sciences through a common language, most commonly through the use of complex systems methodologies. Concepts such as *hierarchy*, *modularity,* and *connectivity*, *reciprocation*, *autopoiesis*, which focus on relationships instead of essential elements transfer well across natural systems from cellular mitosis to migration of germ cells and wildebeests (Guttal & Couzin, 2011; Meunier, Lambiotte, & Bullmore, 2010). For example, what is it that patterns of change in immunological therapies, addiction withdrawal, and taming a wild stallion, have in common? Could there be an agitated introductory period, followed by a phase of extreme chaotic protest, ending with spindled peaks among a gradual titration of habitual behavior before finally resting in a new equilibrium, as with one of Lorenz's *strange attractors* (Gleick, 2011)? What do these patterns have in common with transitive brain wave frequencies in and out of sleep stages? How might knowledge of these commonalities across these systems allow heterogeneous processes in one area to be transferred to another? These are the types of questions that require the synthesis of data from multiple levels of analysis (i.e. special, temporal, hierarchical, etc.) which is common in complex systems methods (Bassett & Gazzaniga, 2011).

While the study of non-linear patterns in dynamical systems has been part of physics for

some time (Gleick, 2011), it has only recently made its way into the fields of neuroscience (Mattei, 2014; Siegel, 2012). Mattei (2014) writes of the increasingly multidisciplinary nature of neuroscience: "the concept of self-organization has been able to offer a proper account of the phenomenon of evolutionary emergence of new complex cognitive structures from non-deterministic random patterns, similarly to what has been previously observed in nonlinear studies of ?uid dynamics" (p. 1). Models based on complex systems concepts suffer less from this limitation, but may require unlearning old ways of thinking about the brain and the mind in order to grasp the subtle relationship between analysis and synthesis while still remaining within the postpositivist realm (Bowen, 1980). Complex systems possess emergent properties which occur as a function of the relationships among the elements in the system ("the whole is greater than the sum of its parts"), and it is the emergence of higher-level patterned activity in neuronal networks that organizes systems-oriented theories of the brain (Bassett & Gazzaniga, 2011; Sieglemann, 2010; Telesford, Simpson, Burdette, Hayasaka, & Laurienti, 2011).

For example, one way of answering the question of how the concept of *mind* relates to the physical brain is by looking at mind as an emergent property of the complex interactions of the physical components of the brain, body, and environment (Bassett & Gazzaniga, 2011; Duncan, Chylinski, Mitchell, & Bhandari, 2017; Doursat, 2013; Sieglemann, 2010). Seen in this light, the process we call "mind" could possess similar properties as other strange attractors (Gleick, 2011). Those strange attractors could be called "self" from the perspective of human subjectivity. This "self" may possess something akin to the feeling of "personality" in a finicky autopilot on a sailboat or laptop computer which seems to have "a mind of its own", or unforeseen organic-feeling "noise" in an electronic modular synthesizer or guitar distortion pedal which speaks to a "deeper part of us" than a flat, mechanical sounding sine or triangle wave. A relatively reductionistic way to visualize the mechanics of these sorts of strange attractors is using the *double-rod pendulum* , a simple deterministic device which never repeats the same pattern of oscillation twice due to the non-linear effect of two dynamic coefficients (in this case the positions of the two joints) interacting with each other through one simple binomial equation .

All of these examples follow deterministic rules yet exhibit an ordered-disorder in their behavior that makes them appear *alive* due to their reciprocal feedback relationships *(Fleischman, 2012)*. If a property such as strange attraction is *emergent* then there is no evidence of the property derived from properties of individual components alone. Telesford (2011) writes,

> the dynamic nature of a complex system cannot be understood by thinking of the system as comprised of independent elements. This concept also highlights the limits of reductionism; one cannot fully understand a complex system by only understanding its constituent parts (e.g., understanding the brain via knowledge about individual neurons). (p. 295)

Lessons from research in one type of complex system can inform research in other complex systems by virtue of their portability across many classes of natural systems. Bassett (2011) writes,

The concept that emergence of complex behaviors might occur through the interaction of multiple temporal scales is one that, perhaps unsurprisingly, is not confined to neuroscience. Recent work characterizing power structures in animal societies suggests that emergence or the development of aggregates is a direct consequence of temporally dependent system uncertainty which, in social systems can be based on misaligned interests. (p. 9)

Swarming behavior in fish (Tunstrøm, et al., 2013) and locusts (Guttal, Romanczuk, Stephen, Sword, & Couzin, 2012) is predictable at the group level using a few simple variables. However, there is no evidence for this emergent group-level predictability found in the individuals alone. While consistent individual differences (i.e. "animal personalities"; (Jolles, Boogert, Sridhar, Couzin, & Manica, 2017) are found to determine group performance such as the time to find safe areas or areas with food, and factors such as individual tendency toward leadership positions (Couzin, Krause, Franks, & Levin, 2005), the overall emergent patterns of group states such as swarming, milling, and group polarization (Tunstrøm, et al., 2013) remains the same regardless of individual differences (Couzin, et al., 2011; Jolles, Boogert, Sridhar, Couzin, & Manica, 2017; Killen, Marras, Nadler, & Domenici, 2017; Strandburg-Peshkin, Farine, Couzin, & Crofoot, 2015). That is, the program of change in the species appears predictable while the particular pathways chosen within that program are difficult or impossible to predict given the complexity of the related variables. The process is predictable but the content is not.

Research in fish shoaling behaviors has produced theories which show how a few simple variables such as proximity to a neighbor, proximity to a safety gradient, and proximity to a predator, generate a pattern of aversive behavior in a school of fish to a predator which appears to be highly coordinated at the group level, as if each fish had knowledge of the grand plan of changing trajectory and more or less executed the change in direction to suit it (Katz, Tunstrøm, Ioannou, Huepe, & Couzin, 2011; Schaerf, Dillingham, & Ward, 2017; Tunstrøm, et al., 2013). However, individuals are found to have relatively little knowledge of emergent group properties and in fact behave primarily in their own self-interest (Hein, et al., 2015). Each fish will simply move to maintain a comfortable balance of distance and closeness to other fish. Similarly, each fish follows a program to distance from a predator. The approach of the predator initiates the aversive movements in a few fish at the front of the school, which triggers changes in enough other fish to initiate a phase transition where the entire school is moving in the newly emergent trajectory pattern. The speed of the predator may modulate the rate that this programmed aversion response propagates throughout the school of fish.

The area where most of the complex systems research is taking place in humans is in mapping structural and functional modularity and emergent properties of the brain using models based on network graph theory. "Brain networks are increasingly understood as one of a large class of information processing systems that share important organizational principles in common, including the property of a modular community structure" (Meunier, Lambiotte, & Bullmore, 2010,

p. 1). The principles of collective behavior overlap in that they involve the abstract relationships between uninformed parts into wholes which exhibit emergent properties. The brain *as a unit*, in this sense, can be studied somewhat similarly to a school of fish *as a unit*, where what we call "mind" may emerge from the interactions of individual neurons and feedback mechanisms in the rest of the body which are otherwise uninformed of the beautifully coordinated behavior that they are taking part.

Systematic methods of studying natural systems are now emerging as a combination of mathematics and lessons learned through the study of complexity in physics. One method rapidly growing in popularity is *network graph theory*, which "draws from advances in statistical physics, mathematics, computer science and the social sciences to provide a principled framework in which to examine complex systems that are composed of unique components and display nontrivial component-to-component relations" (Bassett & Gazzaniga, 2011, p. 1). Graph theory itself has been around since the time of Euclid (18th century) and organizes processes around a complex unit of nodes (e.g. neurons, organs, or conspecific social individuals) whose relationships are described by edges connecting the nodes (Power, et al., 2011). The focus is not so much what each node is *per se*, but how often one node communicates with each other node, usually limited by some sort of arbitrary salience threshold. "Centrality metrics such as degree, betweenness, closeness, and eigenvector centrality determine critical areas within the network" (Telesford, Simpson, Burdette, Hayasaka, & Laurienti, 2011, p. 295). Mapping at this level of normalization allows for the synthesis (observing overall relationships) of analytical data (reducing the whole into individual parts) at multiple levels (by constructing relationships among hierarchies of *modules*, for example between sub-modules and sub-sub-modules, etc.).

Network graphs are employed to assist in determining the relationship between *structure* and *function* of the brain. The brain may be divided into three dimensional units of brain tissue called *voxels*, where each voxel is a node on the graph. fMRI data would then be analyzed to determine the degree to which each node fires with each other node on the graph, quantifying the strength of their relationships (Bassett & Gazzaniga, 2011). A rectangular matrix called a *dendrogram* could then be used to visualize how each node is connected to each other node (Zemanova, Zhou, & Kurths, 2006). The structure of connections described in the dendrogram is often referred to as a *connectome* (Krakauer, Ghanzanfar, Gomez-Marin, MacIver, & Poeppel, 2017). Connectome matrices show strong relationships down the line from top-left to top-right when the nodes are listed in order of proximity, indicating the *small-world* nature of brain networks, or nodes are typically connected to close-by neighbor nodes for speed of transmission. Groups of nodes may fire so often together that they are designated as *communities*, or groups of nodes, or groups of groups of nodes (Zemanova, Zhou, & Kurths, 2006). Activity in neural communities correlate with specific functions, supporting the notions of functional modules in a network. Modules are organized into hierarchies where modules in similar taxa have stronger relationships, and sub-modules in differing taxa have weaker relationships (Bassett & Gazzaniga, 2011). Network models are usually controlled using a t-statistic by comparing models against synthetic *null models* which express randomized connections between nodes. Randomized relationships in null models are assumed to

illustrate little or no organization (Nelson, Bassett, Chamchong, Bullmore, & Lim, 2017). The use of randomized networks as null models as a sort of white-noise comparator is not ideal but is the best control available as of this writing.

Brian networks can contribute to an understanding of complex pathology in terms of change in the interrelatedness of modules. While studies in schizophrenia in the last 40 years have mostly focused on isolated brain areas or singular genetic causes or predispositions with pharmacological remedies, large-scale network graph research of the brain reveals that schizophrenics may show a breakdown in holistic integration of brain modules at both the structural and functional levels (Nelson, Bassett, Chamchong, Bullmore, & Lim, 2017). Because network approaches normalize data across domains, more holistic connectivity research can integrate analysis from many levels, for example both structural and functional data (Meunier, Lambiotte, & Bullmore, 2010). Unifying neurological data from different levels under a common mathematical framework such as network graphing is a relatively new concept to the field, and shows promise for more integrative methods to come in the future.

Examples of Natural Systems

The similarity of distributed decision-making procedures in social species shares striking similarities across social species and intra-individual organizations such as neural networks in the brain. Contrary to common sense, a single component in a highly integrated system may possess little to no knowledge of the overall patterns emerging at the level of the collective unit. Each component merely acts on the combination of its own internal information state and the information state or states provided by its locality.

For example, a single neuron does not possess knowledge of the process of cognition which only emerges at the level of the whole brain as a property of the coordination of many neurons. Each neuron simply functions upon the combination of its own internal state and the information received from its immediate neighbors. From this view, each neuron is a black box in relation to the totality, and no evidence of the emergence of cognition can be found from merely studying a single neuron in isolation. Indeed, a single neuron cannot function without the relationship context in which it differentiated its own structure (Bassett & Gazzaniga, 2011).

An ant colony will use massively parallel methods of communication similar to the parallel coordination of neurons in the brain (Boi, Couzin, Buono, Franks, & Britton, 1999). Each ant functions like an individual neuron embedded in the larger network by function of mutual excitation. As one ant spontaneously activates, the ants around it may also activate. Many waves of coordinated excitation simultaneously pass through the colony at any given moment. The particular frequency and periodicity may differ from that of neuronal activity in the brain, there may be some overall patterns in the processes at the level of the colony which mimic the level of the brain quite closely. This can also apply to the level of the single ant or neuron. For example, a single ant will activate and then enter a period of rest where the chance of reactivating is less, mirroring the

gradated action potential in a neuron (Couzin, 2009).

Various species employ organizational schemas differently than the highly integrated communication of an ant colony. The bee species *Apis mellifera* relies on the collaboration of parallel efforts of many scouts as it searches for a new nest site. Each scout will begin the search for a single site alone and return to the nest upon finding a suitable candidate. Each scout will then vote on their own site by attempting to recruit another member to follow them to view the site for themselves. This vote is submitted using a *waggle dance* which increases in intensity according to the perceived quality of the site. The scale of intensity appears to adhere to some objective measure which appears to be agreed upon by the group, to some degree. The process repeats as new recruits assess the site and recruit more and more bees using the waggle dance. The hive then migrates to the new site once a quorum is reached at it (Gruner, Fietz, & Jantsch, 2015).

A non-systems perspective would focus on the events described thus far which lead to the selection of the new site. In contrast, a systems perspective would look at the interactions of the various threads of the search carried out by many scouts and how this massively parallel decision-making process increases the overall intelligence of the hive. As such, the non-systems perspective would tend to focus on the parts of the process that pertain to this species while the systems perspective would open the door to examination of the elements of the process which pertain to multiple species and even lower and higher levels of organization such as the single brain or cell, or the interactions of many groups of many species.

Interestingly, the level of ignorance of a single *Apis mellifera* to concurrent search processes is a key element in the selection of a suitable nest. Each scout is only informed of the quality of their own site and the site information transmitted by the individuals around them. This allows each individual to focus on their specified task, a feature which is known to increase the level of intelligence of the collective (Lorenz, Rauhut, Schweitzher, & Helbing, 2011). This counter-intuitive feature of collective intelligence is explained by the tendency for individuals to conform to the opinions of others, but only if they are exposed to them. Conversely, the cognitive power of the collective is dependent on the diversity of opinions (information) among the individuals. When the overall sample provided by individuals is more diverse, there is increased error but also increased accuracy as the variance in the individuals tend to converge around the mean as a function of the *central limit theorem* (Couzin, 2009).

Mann & Helbing (2017) have found that this *herding effect* can be partially mediated by providing incentives to accurate minority predictions. This incentive program would run counter to "market-based" incentives at the collective level which promote herding and conformity (p. 5077). This finding presumably supports individual differences which lead to more accurate information for the overall average. So, if an individual is particularly intuitive, or possesses a superior method of information gathering which is undisclosed to the collective, the incentives would help keep their minority decision in the minority position.

Research in animal decisions shows that accurate minorities increase in value as the group size increases. That is, the larger a group, the greater the chance that an individual minority will persuade ambivalent or naïve individuals (Couzin, Krause, Franks, & Levin, 2005). There are many other factors that influence the speed at which information travels through the group network. More intense responses in an individual can trigger a non-linear increase in the intensity of responses in near neighbors. This gradated response behavior is adaptive in that it optimizes the metabolic effort to the minimum level required to accomplish the required task and expedites certain responses which are time-sensitive.

For example, a school of fish may instantaneously maneuver to evade an attacking predator and will later reconfigure into a slow and stable milling configuration. The basic collective programming for each behavior remains largely the same, but individual differences among the fish make dramatic changes in the character of behavior by virtue of the structure of highly integrated emotional decision networks. Like neurons in the brain, each individual is only aware of the behavior of their neighbor which places the fish on the perimeter in a look-out position and the others in a conservative following position (Strandburg-Peshkin, et al., 2013). A minority of look-outs along the perimeter of the group may notice a predator which triggers a systemic reaction throughout the school fish-by-fish, like multiplexed stack of dominoes. In the slower unperturbed milling configuration, each individual is responding to the cues of its neighbors but perturbations of normal intensity take longer to propagate throughout the group. Similarly, the swarming of crickets and locusts is only motivated and guided by the very real fear of cannibalism, as any cricket that does not fly in line with the swam will literally be eaten by their neighbor (Simpson, Sword, Lorch, & Couzin, 2006). Perhaps humans are lucky that their unique capacity for reflection and self-regulation allows them to stand against the group in longer lasting relationships and without the fear of more primitive regulatory mechanisms like cannibalism.

This highly integrated and reactionary behavior can serve as a weakness when the group is exposed to repeated perturbations which exceed the group's capacity to recover and adapt. The group will continue to increase its integrated reactivity which increases conformity in the group. This is a problem because group conformity can undermine the decision-making power of the group as CI is dependent on high variance in the distribution of individual judgements (Lorenz, Rauhut, Schweitzher, & Helbing, 2011; Mann & Helbing, 2017). The more that individuals can first serve their own function as individuals before contributing to the collective decision, the higher the collective error and the more accurate the collective decision.

Humans and Natural Systems

The above findings using systems models support the importance of the integrative study of natural phenomena as opposed to assuming causal relationships between essential individual differences. But applications of complex systems concepts to research in human behavior have a long way to go before reaching the level of sophistication already found in research on other species. For example, as of this writing there is very little research on human groups which

produce this sort of predictive models. A search on the literature using Google Scholar on July 23rd, 2017 using the keywords "'collective behavior' humans" revealed a striking scarcity of literature on human collective behavior when compared to research on other social swarming species. The results show numerous speculative books on the philosophy of collective behavior in the past 15 years which is sometimes applied to humans, and a single study (Silverberg, Bierbaum, Sethna, & Cohen, 2013), of human swarming behavior. Using video footage of heavy metal concerts, this study observed two stable "gaslike" and "circular vortex" states similar to Tunstrøm's (2013) "swarm" and "milling" states that are similar to swarming behavior in other species.

There is some research on the concept of collective intelligence in humans, a construct based on models of individual general intelligence used to determine differences in group's abilities to solve problems. Collective intelligence, as defined by Wolley et al. (Wolley, Chabris, Pentland, Hashmi, & Malone, 2010) is found to be only moderately correlated with individual intelligence, and more strongly correlated with individual's abilities to determine the emotions of other individuals through visual facial cues. Interestingly, Wolley found that the proportion of women in a particular group was a strong determinant of collective intelligence, probably due to the fact that women score higher on scales which measure ability to determine emotions in others. Where the women score lower on these scales the difference is unnoticeable. Some research reveals the predictability of democratic consensus in animal groups (fish and baboons) based on proportions of informed and uninformed individuals (Couzin, et al., 2011), yet only makes inferences about the outcomes of human decision making. This suggests that we know much less about collective behavior in humans than we do other species.

A rudimentary search through the literature will reveal an increase in non-essentialist models of organization in neuroscience (Bassett & Gazzaniga, 2011). However, branches of neuroscience research tend to apply complex systems methods to social concepts more derived from human subjectivity as opposed to the human individual or social group as a natural system. Though the fields of affective neuroscience and social neuroscience (Barrett, 2013; Jaegher, Paolo, & Adolphs, 2016; Siegel, 2012) generate vital knowledge on the physiological basis for emotion and affect regulation in humans, related hypotheses may suffer the same limitations as the *a priori* psychological assumptions that generate them; namely the assumption that intuited psychological concepts like *anger*, *ego*, *object*, *abandonment, attachment*, *object*, *relational matrix, empathy,* etc. are the primary mode of understanding human behavior (Barrett & Satpute, 2013; Baumeister & Bushman, 2017; Decety & Jackson, 2006; Ibanez, et al., 2016). The fact that these concepts are difficult to define, difficult or impossible to refute, and pertain only to humans may support the possibility these concepts originate more from the subjectivity of the human observer as opposed to direct observations of humans as a natural phenomenon. Thus, the inductive potential of these social domains are limited and are more difficult to transfer without translation to research in other biological realms such as ecology, microbiology, entomology, collective behavior, etc., and non-biological realms such as physics, meteorology, paleontology, astronomy, etc. While social neuroscientists benefit from the application of complex systems research methods derived in other domains, the level of compartmentalization from the natural sciences will remain dependent

on the how much the constructs are derived from human subjectivity as opposed to direct observations of human beings and groups as a natural system.

The described research in non-human species as well as early pioneering natural systems-based research on human behavior (Bowen, 1978; Bowen, 2015) suggest that many properties of individual behavior are not evidenced at the level of the individual but at the level of some emergent property in the collective. Yet, the dominant paradigm for the study of the human behavior remains focused exclusively on the individual. Perhaps this points to a particular feature of the value system of social psychologists and medical researchers which focuses on the relationship of pathology to psychological or physiological variables found only in the individual. Research on reciprocal influence of individual and group behavior is already well underway in other species (Guttal & Couzin, 2011) but is almost non-existent for humans. Future research on human behavior may look into the impact that group variables have on individual behavior and the relationship of these group variables to the enormous canon accumulated on individual differences. Further, this type of research could explore relationships of group variables not just to normal behavior but also to pathological behavior, and possibly even medical symptoms.

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