Complex Dynamical Systems Theory

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Complexity is a systemic property. Adaptive evolving systems like ethnic cliques or complex social situations such as “knife crimes” are best understood as dynamic networks of interactions and relationships, not mere aggregates of static entities that can by analyzed by separately identifying and enumerating them. By definition, relata do not exist in individual particles, only in their inter-relationships. In short, dynamic relations, not isolated agents, constitute the basis from which complex dynamical systems theory takes its start. Thus, instead of attempting to construct the identity and dynamics of a self-organizing network from the bottom up by identifying separate individuals and only afterwards grouping them into what the investigator hopes is the appropriate aggregate, complex systems theory proceeds by letting the dynamic patterns produced by the flows and processes involved identify the specific architecture in question. Because complex systems are differentiated into interlinked levels of organization – with no preferred level of granularity – the appropriate coarseness on which to ground a model is determined by the functional task of interest.

Whether in the physical or social realms, if individuals are independent or even weakly interdependent no complex physical or social structure will emerge; connectivity and interaction are necessary conditions for the emergence of complexity. No closed system can spontaneously become differentiated and show complex organization, form or structure. Stated differently, complexity is the order that results from the interaction among multiple agents; while particles remain separate from each other, no increase in their number will ever produce organization (Brooks and Wiley 1988). In contrast to collections of isolated elements that generate Gaussian (normal) distributions that can be understood and modeled in the traditional manner, a complex system is identified by the signature “relations among components, whether static or dynamic, that constitute a composite unity as a unity of a particular kind” (Maturana 1980). The rich interactions between real complex adaptive systems and their environment also mean that because a given domain “is connected to other domains in various ways, the effects of those changes might propagate through the system and out into other domains in the world, inducing changes of various degrees on all scales… . Those effects might eventually travel back and lead to the disappearance of the original domain or transform its dynamics” (Chu et al. 2003).

Therefore only complex dynamical systems theory and its related disciplines and tools – network theory, agent-based modeling – provide the appropriate prism through which interdependent systems such as social groups can be understood, and coherent, integrated policy recommended.

Boundaries

A complex dynamical system's internal structure consists in the patterns that result from particular objects and the interactions among them. But unlike those systems characterized by linear processes that can be effectively isolated from environmental influence, the external structure or boundary conditions of complex systems are as much as part of the complex system as the internal structure; the interactions between the components and the environment, that is, "the set of all [interactions not components of the system] that act or are acted on by components of [the system]" (Bunge 1979) provides the system with a causally effective external structure. Although the environment of interest is thus not the total environment but the environment that affects and is affected by the thing in question, the feedback provides complex systems with a contextual embeddedness that makes the boundaries of complex systems typically fuzzy and difficult to demarcate.

From a complexity science point of view, therefore, ethnic cliques and situations such as "knife crime", understood as dynamic "structures of process," are not bounded by physical or geographic boundaries. In the case of ethnicity, for example, the dynamic structure of a group no doubt extends spatially into both the group's diaspora a well as the local communities; insofar as ancient traditions, rites and rituals continue to inform and influence present practices, the dynamical system we identify as an ethnic group also extends back in time to pre-diaspora and tribal culture.

The Causality of Complex Systems

This deep contextual embeddedness of complex systems presents additional difficulties for researchers: feedback and interactions to/from embedding domains can spread causally (not as efficient causes but as context-sensitive constraints), thereby expanding the domain of the system in question and propagating unforeseen side-effects uncontrollably (Chu et al.). Due to the interactions that constitute them, complex adaptive systems show not only nonlinear effects, but also what is often called causal spread (Wheeler and Clark 1999), a form of causality different from that of the more commonly understood efficient causality.

The connectivity and interaction required for complex systems to self-organize, and which provides them with their contextuality and causal efficacy, are best understood in terms of context-sensitive constraints (Juarrero 1999) not classical billiard-ball-like (efficient) causality. First order, context-dependent constraints such as nonlinear interactions like positive feedback loops and catalysts make individuals or particles strongly interdependent by altering their marginal probability. Feedback relations with the environment recalibrate the internal dynamics of complex systems to incoming signals. Doing so embeds the system in its contextual setting by effectively importing the environment into the system's very dynamical structure. Positive feedback is a temporal context-dependent constraint insofar as it incorporates the past into a system's present structure. Because the presence of a catalyst changes the probability of a reaction's occurrence, catalysts also function as contextual constraints insofar as they incorporate the environment into a system's present structure. Thus individuals or organizations who play the role of social catalysts and serve as media for feedback loops are physical embodiments of bottom-up constraints that link other individuals and organizations together and embed -tightly link—their dynamic organization to its environment and its history such that the newly formed global structure is no longer independent of either.

By embodying context-sensitive dependencies, feedback and catalysts are bottom-up constraints that render a system constrained by its own past experience and its environment. Complex dynamical systems thus embody the initial conditions under which they were created; their origin and trajectory constrains their future development and evolution. Because such exquisite sensitivity to initial conditions is one of the hallmarks of complex adaptive systems, these dynamical processes are also essentially historical; in Prigogine's words, "they carry their history on their backs," that is, their internal structure reflects their history. Accordingly, self-organizing networks are "path-dependent." Any methodology that purports to understand a given complex system while at the same time ignoring or not fully understanding either its trajectory or the overall context in which it is embedded is bound to fail. The effects of context-dependent constraints, therefore, are described by conditional, not marginal, probabilities. They are, in other words, functional constraints.

Once closure of first-order context sensitive constraints occurs, the resulting global dynamics presents characteristics that aggregates or sums of individuals do not; in technical terms, context-sensitive constraints are enabling constraints insofar as they precipitate the emergence of a global dynamics with an expanded phase space. The dynamic whole has greater degrees of freedom than its components individually - a narrative can tell you more than a Q&A form can. Self-organizing networks described in stories are thus multi-level dynamical systems with emergent properties that are irreducible to their component particles. These characteristics will be ignored and missed if the analytic focus is limited solely to compartmentalized components studied in isolation from each other.

Qua emergent wholes, complex systems function as the boundary conditions that actively influence the behavior of their components. Insofar as individuals - children or adults - envision themselves as caught up in a particular narrative structure, we will be able to foresee their constrained behavior. Top down, narratives act as limiting constraints that restrict the degrees of freedom of their components. Whereas from a traditional mechanistic, atomistic point of view such influence was impossible, complex dynamical systems theory allows us to understand such interlevel causal relationships - ubiquitous in social systems - in a scientifically respectable way. In complex adaptive systems, interactions among individuals weave together a story; and once a narrative coalesces in the minds of an individual, or a culture in turn, and as a global system, it actively influences the behavior of the components that make it up. Only complexity science theory provides the tools to understand this kind of bottom-up and top-down causation typical of the collective behavior of human organizations. When combined with narratives as Cognitive-Edge's SenseMaker® allows, policy makers acquire an indispensible tool with which to map current social patterns and anticipate future trends. Without an appreciation of such global dynamics it is impossible to fully understand the inter-level organizational dynamics of social groups: interacting individuals create stories which then loop back down and alter the behavior of the very individuals that constitute them.

Power Laws

The relationship between (on the one hand) the context-sensitive constraints that make complex self organization possible, and the power laws that describe such systems on the other has become clearer thanks to the research of e.g. Barabasi (2002, 2003). Since many complex systems give evidence of the same dynamics at work on multiple levels of organization (i.e., they tend to be self-similar across levels), scalability is often a central element of complexity science. Through children's narratives it is therefore possible to capture the dynamics of an overall ethnic or social group. Because power laws are frequently "indicative of correlated, cooperative phenomena between groups of interacting agents" (Cook et al. 2004), students of complex human systems recognize that in lieu of Gaussian statistics, linear regression models, normal distributions, etc., they must model their subject matter using the more unfamiliar tools of organizational dynamics, including Pareto distributions, fractal geometries, and the like. Since extreme cases and situations are much more important than average cases and situations to most students of the human sciences, managers, policy makers, analysts and social scientists ignore power laws (which show fat or long tails, infinite variance, unstable confidence intervals, etc.) at their own peril.

Game Theory

Applying game theory to human complex systems, exploring rational choice strategies over time, and investigating the basis of social cooperation, are just a few examples of the increasing pervasiveness of the complexity approach. In each case, the situation is treated as an evolving dynamical system with global properties that emerge from the local interactions among the participants, and between the participants and the context in which they are embedded. Such simulation modeling can capture otherwise intractable nonlinear effects and thereby reveal global patterns that would have been previously out of reach.

Once the usefulness of simulation models became clear, the Asian Development Bank, for example, dropped its opposition to a centuries-old management practice when Lansing's computer model of the complex Balinese irrigation system showed the functional role of traditional water temples bore a "close resemblance to computer simulations of optimal solutions" (Lansing 2000).

Attractors

Attractors are typical patterns of dynamical, interdependent behaviors of limited dimensionality and carved out from a much larger space of possible patterns and dimensions. These global structural patterns, which emerge from interactions among the system's components through phase space, can be characterized as emergent collectives. Social networks can be characterized and studied as attractors.

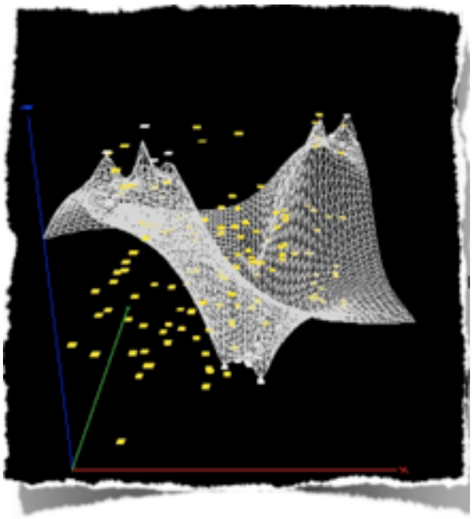
Ergodic behavior patterns describe what are called a system's attractors. Only two attractors were thought to exist: (1) The dynamics of a grandfather clock's pendulum describe a point attractor that draws the bob to a single point in phase space regardless of its original position. Equilibrium models assume that all systems they describe are of this sort; traditional economic models were equilibrium models. Not all processes can be understood as near-equilibrium and drawn into a point attractor; ecological research revealed that predator-prey relationships described a different type of attractor, (2) a periodic attractor. Unlike phenomena characterized by point attractors, predator-prey distribution, for example, typically repeat regularly in a continuous, periodic loop. It was not until the last quarter of the twentieth century that a third type of attractor, so-called strange, chaotic or complex attractors, were discovered: patterns of behavior so convoluted that it is difficult to discern any order at all; complex human systems can often be characterized as complex attractors, of which social networks are one example.

Complex attractors surprised scientists when they discovered that far from being chaotic in the old sense of the word, these complex systems are characterized by a high-dimensional degree of order. Never exactly repeating, the trajectories they trace nevertheless stay within certain bounds. Far from being chaotic in the old sense of the term, these complex behavior patterns provide evidence of highly complex, context-dependent dynamic forms of organization.

Attractor Landscapes

In the 1930s biologist Sewall Wright (1932) developed a model of fitness landscapes intended to capture the processes natural selection by visualizing the “switch and trigger mechanisms” that precipitate a change in a system’s evolutionary trajectory. More recently, thanks to the development of computer simulation models, the dependencies and constraints embodied by attractors can also be visualized as three dimensional adaptive landscapes depicting a series of changes in a system’s relative stability and instability over time. The increased probability that a system will occupy a particular state can be represented visually as a landscape’s wells, dips or valleys that embody attractor states and behaviors; the deeper the valley the greater the propensity of its being visited and the stronger the entrainment its attractor represents. In contrast sharp peaks are saddle points representing states and behaviors from which the system shies away. These landscape features capture the impact of context-sensitive constraints over time. The set of all states that end up in a particular attractor constitutes the attractor basin; different basins are separated from each other by basin boundaries or separatrices. A system’s identity at a particular point in time captures the signature probability distribution of its dynamics – its unique adaptive landscape, so to speak. The most useful image of complex systems is its phase space portrait: its state space carved up into basins of attraction and changing over time.

Since all social phenomena are complex systems it becomes extremely important for makers of social policy to be able to map these convoluted relationships as accurately as possible. Doing so allows policy makers to map a situation’s relative volatility, as well as to explore which changes to which parameters will make the situation more or less stable. Complex dynamical mapping of this sort thus provides an invaluable visual aid in phase shift prediction. Although by their very nature complex systems resist precise predictability, dynamical landscapes and the mathematical software that create these visual aids also show decision-makers the range of "adjacent possible" successor states an unstable situation is likely to tip into.


A fitness landscape

Dynamic landscapes depicting a series of changes of relative stability and instability over time provide a very useful way of visualizing the contextual and historical constraints embodied in the convoluted behavior patterns described by strange attractors. By tweaking the various parameters and filters that produce the landscapes, dynamical mapping with SenseMaker® software can provide decision-makers, for example, with evidence of the presence of "a stable pattern overall, except for those groups that rank high on the combination of two scales, "retributive justice" and "anger." These dynamical landscapes also provide evidence of probable and improbable "successor states" to a given situation, information that can be invaluable, for example, for designing a particular governmental advertisement campaigns on crime prevention etc. Dynamical mapping can prove that the intended network is possible, that it can be built; it can also providing guidance on the most appropriate criteria with which to design the most effective network – or disrupt a noxious one. For example, one city's current landscape might show that it is possible to build a particular network that assists community leaders in precipitating a particular desirable phase change with respect to criminal activity– or, conversely, it can provide decision makers with information that aids and enhances the status quo. Because complex dynamical systems are uniquely individuated, dynamical systems mapping can also provide decision makers with information about whether or not the same advertisement campaign will be as effective in a different city, or a different country.

If a system could access every alternative with the same frequency as every other – that is, randomly – its landscape would be smooth and flat, portraying an object or a situation with no propensities or dispositions, that is, with no attractors. In contrast, the increased probability that a real system will occupy a particular state can be represented as wells – dips or valleys in a landscape – that embody attractor states and behaviors that the system is more likely to occupy. The deeper the valley the greater the propensity of being visited and the stronger the entrainment of its attractor. Dynamic landscapes thus provide governmental leaders with information about how entrenched a set of attitudes or behavior patterns are, and how best to go about preserving or changing them.

Topologically, ridges separating basins of attraction are called separatrices or repellers. Sharp peaks are saddle points representing states and behaviors from which the system shies away and in all likelihood will not access; the probability of their occurrence is low or nonexistent. But if a decision-maker discovers that a system is perched on a saddle point, he can rest assured that it won't remain in that condition very long. The height of the saddle point separating one attractor from another thus also represents the unlikelihood that the system will switch to another attractor given its history, current dynamics, and the environment. Landscape valleys thus provide decision-makers with a very good indication of whether or not a system is locked-in to that particular condition, and what the likely "adjacent possibles" might be. The steeper the attractor's separatrix walls, the greater the improbability of the system's making the transition. On the other hand, the deeper the valley, the stronger the attractor's pull, and so the stronger the perturbation that would be needed to dislodge the system from that behavior pattern. Similarly, the broader the floor of a valley the greater the variability in states and behaviors that the attractor allows under its control; conversely, the narrower the valley the more specific the attractor, that is, the fewer the states and behaviors it countenances.

Complex systems theory tells us that a landscape's valleys and peaks are neither static givens nor external control mechanisms through which we can force change. They are not determinants operating as Newtonian forces. Instead they represent constrained pathways that have been constructed and continue to be modified as a result of persistent interactions between the dynamical system and its environment. Landscapes that incorporate dynamics also provide decision makers with information about the likely direction of change, and of the critical parameters that can influence the direction of that change.

Co-evolution

Predator-prey relationships taught us that the dynamical landscape of a complex system, to continue with the topographical metaphor, is not fixed. A predator will evolve better eyesight to see its prey, but the prey will evolve a disguise, negating the eyesight advantage. Thus "the landscape peak the predator attempted to climb has moved from under its feet, the fitness peak has shifted, the landscape has deformed due to the changes in the prey. This "coevolution" means that the fitness landscape seen by one creature is a dynamic, ever changing map dependent upon the actions of everything else in its surroundings. This is true for occupants of an ecosystem or a social group. It is a highly non-linear, closely coupled system – attractors that vary in both shape and position over time" (Lucas). Co-evolution with their natural and social environment is even more so of human systems than it is of animals. In the case of human beings we are always referring, therefore, to complex adaptive systems.

In other words, since fitness is a relative term (relative to an environmental niche), changes in a (natural, social) niche alter the fitness of the individuals and species within it; in turn, changes in the relative distribution of types of individuals and species within a niche will alter the characteristics of the niche. Thus complex adaptive systems are best characterized as adapting and co-evolving with their environment.

Stability versus Resilience: The Importance of Micro-diversity

Complex dynamical systems theory explains the difference between stability and resilience. A stable system fluctuates minimally outside its stable attractor, to which it quickly returns when perturbed. Stable systems are typically brittle; they disintegrate if highly stressed. Resilient systems, on the other hand, might fluctuate wildly but have the capacity to modify their structure so as to adapt and evolve. Resilient, robust systems are also called meta-stable. Co-evolution selects for resilience, not stability.

Complex adaptive systems are typically resilient. And notoriously robust to random perturbations – but exquisitely vulnerable to targeted interventions, as we will see below.

Understanding what causes resilience or robustness is a central issue for analysts and policy makers. For purposes of Cultural Mapping it is particularly important to understand which specific features of the dynamical relationships that make up the knife crime statistics in the city of XYZ make the situation robust or resilient; it is important, that is, to identify the system's dynamics that allow likely participants to adapt in response to either their own dynamics or perturbations from the outside, and thereby to evolve and persist as a network, despite the removal or incarceration of many of their members. This understanding also points to avenues for intervention by the appropriate authorities. Although still a young science, complex adaptive systems theory has begun to make inroads into understanding (1) the conditions that allow these structures evolve over time in response both to their own internal dynamics and in interaction with the environment; (2) the conditions that facilitate robustness and resilience; and (3) the most effective points of intervention.

Jackson & Watts (2002) note that in a network context, path resistance or network resilience is equivalent to "how many errors or mutations are needed to get from some given network to an improving path leading to another network." Peter Allen defines microdiversity more broadly than simply errors or mutations, as "a measure of the number of qualitatively different types of entity present corresponding to individuals with different attributes." (Garnsey & McGlade 2006, 23). Chu et al. (2003) call such systemic differentiation "inhomogeneity"; they too consider it a hallmark of complexity, as do Carlson & Doyle (2002). In an important article that echoes this general point, the U.S. Naval Academy's Robert Artigiani demonstrates through two military examples that the best way to deal with unpredictable complex systems is by organizing the system so it is maximally adaptive – when leadership cannot solve the problem in advance because no one knows what the problems will be, it is important to build systems that can solve the problem for themselves. Microdiversity in the sense of internal differentiation is one way to do just that.

Allen, who worked extensively with Nobel Laureate Ilya Prigogine in Brussels during the earliest years of this science, has also extensively studied how micro-diversity within a natural or social system drives the qualitative changes that occur in these systems and structures over time. Allen demonstrates that if a particular variation increases an organism's fitness, natural selection will favor that variation; following the landscape metaphor, evolutionary change – i.e., increased adaptation to the environment – is tantamount to hill-climbing.

Allen's early experiments demonstrated that hill-climbing occurs "as a result of processes of 'diffusion' in character space. Using diffusion models, Allen's research also establishes that it is micro-diversity or internal differentiation that confers resilience. Further experiments conducted by Allen and his team at Cranfield University (UK) subsequently confirmed that successful "evolution will be driven by the amount of diversity generation to which it leads. Evolution selects for an appropriate capacity to evolve [more exploration and innovation in novel situations; less exploration in established conditions], and this will be governed by the balance between the costs of experimental 'failures'… and the improved performance capabilities discovered by the exploration." The conclusion Allen draws from the research is that "organizations or individuals that can adapt and transform themselves, do so as a result of the generation of micro-diversity and the interactions with micro-contextualities" (emphasis added). The system's complex regulatory feedback and dynamics also stop cascading failures and enable the system to survive (Carlson & Doyle 2002). Incorporating narrative research into dynamical landscapes is a unique and powerful tool to understand and influence social systems.

Understanding how information and influence disseminate throughout a social group is a key component that cuts across storylines and issues. To the extent that diffusion processes identify a property that is the inverse of robustness (both pertain to the way influence or information disseminates through, or is blocked, within particular communities by components that are different – by social mavericks, in effect), identifying features in a social landscape that promote desirable robustness and resilience is a central task of any decision-maker's mission.

Fail-Safe versus Safe-Fail

Thinkers in the field of public policy have traditionally counseled what might be called a fail-safe strategy. From Plato to Marx, the goal was always to design forms of social organization that, because they were ideal, would remain forever in equilibrium. The traditional goal of public policy makers, in other words, has been stability, the minimization of fluctuations. In stark contrast to this approach, ecologist C. S. Holling argues convincingly that if the notion of resilience applies to society at all, it counsels instead a safe-fail strategy that assumes from the outset that failures will occur despite the best-laid plans. A safe-fail strategy is one "that optimizes a cost of failure and even assures that there are periodic 'minifailures' to prevent evolution of inflexibility" (Holling 1976; Juarrero-Roque 1991). It is clear that Allen's thesis – that evolution evolves to maximize evolvability – is another way of making the same point. Social policy should pursue a goal of resilience, not stability. As this new science develops, valuable lessons are derived from studying dynamical landscapes and the networks described in cluster graphs for the way weak ties, high betweenness links, micro-diversity, and other similar features contribute to the robustness and resilience of complex adaptive networks. In turn, these insights are can inform social organization management.

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