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Abstract

The diffusion of innovations model (DIM) and complex adaptive systems theory (CAS) can be employed together in the construction of predictive or applied hybrid models of induced change in population behavior. In such interventions, differentiated *heterogeneous zones* may act as catalysts for the adoption of innovation. The present study explores the actual and potential hybridization of these two systems theories, relying on illustrations from historical practical applications of DIM, particularly the STOP AIDS communication campaign in San Francisco.

The resulting co-theoretical model provides an analytical tool for students of innovation, particularly in the public sector, and especially in applications of network analysis predicated on a crucially defining feature of social networks, namely “the strength of weak ties” among their members. In cultivating network ties among heterogeneous groups connected by common aims, it is here argued, the innovator may prompt and, to an extent, guide the complex emergence of innovation adoption in social systems. Commonalities in the concept of heterogeneity in CAS and in DIM is explored in depth, along its many dimensions, including membership and role heterogeneity, with a view to preliminary operationalization of diffusion-management principles.

Keywords: diffusion, innovation, complexity, complex adaptive systems, chaos, AIDS, health, power law, heterogenous, homophily, heterophily, networks, social networks.

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Complex Adaptive Systems, Linearity, and Non-Linearity

The *Complex Adaptive Systems (CAS) Model* was born of the scientific study of complexity. According to James Gleick, the inspiration for complexity science can be traced to John von Neumann's dynamic weather system models of the 1950s at the Institute for Advanced Study in Princeton, New Jersey, an effort that, in turn, goes back to the work of the eighteenth-century philosopher-mathematician Laplace (Gleick, 1987, p. 14). The *diffusion of innovations* model, credited to Everett Rogers, delineates the process by which an innovation spreads via certain communication channels among members of a social system (Rogers, 2003). Diffusion phenomena bear a resemblance to complex adaptive systems. The purpose of the present study is to explore the relationship of the diffusion of innovations model and complex adaptive systems theory, and to consider the potentialities of a hybrid systems approach to managed innovation.

In order to discuss complex adaptive systems, one should first define simple linear systems by way of contrast. "In linear systems the relationship between cause and effect is smooth and proportionate. Linear systems respond to big changes in a big and proportionate manner and linear systems respond to small changes in an equally small and proportionate way" (Kiel, 1995). Most real life situations, on the other hand, are complex. Small changes in initial conditions, and later interventions of whatever size, can result in disproportionately large effects.

A quadratic equation can demonstrate the transition of behavior from simple to complex regimes, and from complex regimes to chaotic ones. The equation is parameterized by $4>a>0$, and $s \in [0,1]$ where "s" is an infinite sequence of binary variables that describe the system—we will examine the quadratic equation $f(s) = as(1-s)$. Simple systems are those systems where $a<1$. In simple systems $s=0$ (Bar-Yam, 1997, pp. 26-33) there is no fluctuation between states, and as a result all changes in the system are simple and occur linearly. However, a complex adaptive system comprises multiple agents dynamically interacting in fluctuating and combinatory ways, following local rules to maximize their own utility while also maximizing individual consistency with influences from network neighbors (Klein, Sayama, Faratin and Bar-Yam, 2002).

Complex systems are about relationships among members of a system, here taken to occur at $1<a<3$. In a complex regime, utility-maximization rules may make for movement from lower to higher levels of group cohesiveness and order. That order is marked by *emergent self-organization*, in relation to complex-network synchronization that is enhanced by heterogeneity (Motter, Zhou and Kurths, 2004). When the resulting system can create emergent behavior capable of response to the environment, it is adaptive (Johnson, 2001). Beyond these parameters chaos begins, such that at $3<a<3.56994567$ "there is a bifurcation cascade with 2-cycles then 4-cycles" (Bar-Yam, 1997, p. 33) and increasing splitting and bifurcations, until at $a=4$ cycles become chaotic (Kiel, 1995). Nonlinearity is a constitutive feature of complex adaptive systems.

The Diffusion of Innovations Model

The diffusion of innovations model (DIM) is concerned with how *innovations*, defined as ideas or practices that are perceived as new, are spread (Rogers, 2003). *Diffusion* is the process through which an innovation spreads via communication channels over time among the members of a social system. This is a social sciences definition of diffusion, one that is not to be confused with the thermodynamic definition of diffusion. Diffusion occurs in complex systems where networks connecting system members are overlapping, multiple, and complex. Diffusion occurs most often in heterogeneous zones, i.e., transitional spaces where sufficient differentiation among network members comes to obtain. Such heterogeneous network connections, which comprise the innovation-diffusion system, occur among innovators and other engaged members of target populations who, in Rogers's original formulation, are called "cosmopolites." Cosmopolites are locally networked system members with heterogeneous weak ties to outside systems.

The first important diffusion studies were conducted some sixty years ago by rural sociologists who investigated the adoption of hybrid seed corn among Iowa farmers. In the ensuing decades, diffusion study has spread to public health, communication, marketing, political science, and most other behavioral and social science disciplines. To date, more than 5,200 diffusion studies have been published (Rogers, 2003). Diffusion investigations have typically focused on the order in which relatively cosmopolite and heterogeneous individuals, organizations, or other units in a networked system adopt an innovation in a synchronous manner. Most of the innovations studied are technological in nature, but some are policy or other social-learning innovations. An example of policy innovation research concerns which of the fifty states in the United States adopt new programs and policies first (and thus are most innovative), which states follow this lead directly, and then which ones follow it indirectly (Walker, 1996). A key finding is that the states with the most heterogeneous or variegated network links to adopter states are the most likely to adopt policy innovations.

Diffusion scholars have also studied why some innovations spread relatively rapidly while other innovations do so relatively slowly. Innovations that are perceived as (a) relatively advantageous (over ideas or practices they supersede), (b) compatible with existing values, beliefs, and experiences, (c) relatively easy to comprehend and adapt, (d) observable or tangible, and (e) divisible (separable) for trial, are adopted more rapidly (Rogers, 2003).

General Comparison of the Two Models

CAS and DIM are similar in several respects, and in a sense coterminous, since they share the ends of adaptation and adoption (emergence). The endpoint for complex adaptive systems is emergence out of disorganization into a more ordered system, with more adaptable patterning and better fit. The usual aim for a managed diffusion-of-innovations program is to effect a faster rate of adoption of a new idea or practice, resulting—it is hoped—in a higher-order, fitter system. It is at the threshold of criticality in both systems models that heterogeneity (adoption, mutation, or change) is rewarded, as members increase both individual utility and interdependency (Klein, Faratin, Sayama and Bar-Yam, 2003). Coalescence occurs at a point where individuals have risen to the group threshold of fitness and adaptation. It is also possible, however, for there to be collapse instead of development into a fitter large-scale system. Collapse often occurs because members were inhibited in their ability to adapt interdependently, failing to rise together to the minimum threshold of fitness required for adaptation or adoption.

Both DIM and CAS models are built on empirical observation of change, both can describe transitions occurring either naturally or as a result of directed change, and both can be statistically analyzed to infer population parameters for processes of change. Diffusion theory is concerned with change occurring among human agents or nodes in an interconnected network of communications, yet it can easily incorporate nonhuman intervention devices such as mass media or electronic technology as reactive agents (with reactivity defined as sensitivity to change). Similarly, complex adaptive systems may consist of human agents or nonhuman factors (such as epidemics, cells, and acts of nature), and even inorganic nodes (ideas, machines, computers, or information webs) in a reactive network. While CAS models originated principally in the physical and biological sciences and DIM in the behavioral and social sciences, they have converged to include or apply to a wide range of human (social) and nonhuman systems.

Comparing the Mathematical Foundations of the Two Models

Working models of either complex adaptive systems or diffusion processes prohibit hand calculations and require computer analysis when scaled to full size. Diffusion of innovation models were originally constructed and plotted in two dimensions (the number of adopters occurring over time) employing multiple-regression techniques and calculus-based rates of change. These early calculations of variables correlated with *innovativeness* (the degree to which a unit in a system is relatively earlier than other units in adopting an innovation or innovations) became cumbersome when a large number of independent variables were included in the analysis. Longitudinal computer simulations of diffusion processes have been conducted, but this approach is yet to make significant contributions to the understanding of innovation diffusion.

It is impossible to calculate the mathematics of a full-scale working model of a complex adaptive system by hand. Stuart Kauffman started designing rudimentary CAS models on paper in 1963 while in medical school, but it was not until he gained access to a computer that he was able to work iterations at scales that would properly test his theoretical model. If his theory had been incorrect, or if his trials had not evidenced self-organization in early iterations—reaching points of criticality in transitional heterogeneous zones—his computer would not have been able to process the possible maximum number of iterations—10 to the 29th power (Waldrop, 1992).

The mathematics necessary to identify a complex adaptive system's *strange attractor* ("strange" because it is orderly when it is expected to be random; attractor because it "attracts" or draws order to itself out of seeming chaos), called *phase-space reconstruction modeling*, requires computer analysis. A strange attractor is a three-dimensional plot of the "thumbprint" of a CAS that is derived from a phase-space reconstruction. In a simple system, a basin of attraction is formed like a depression in a three-dimensional space. The behaviors of individuals in the system gravitate to the basin like water flowing to a valley. In CAS, dynamics "may be described in terms of cycles and attractors" where space-time is found to be insufficient to account for the number of iterations of necessary cycles; thus it is found that part of the strange attractor lies in a fractal dimension (Bar-Yam, 1997, p. 116, and personal communication January 4, 2005).

Reconstruction of a CAS requires a minimum of three differential equations plotting the changing relationships among three variables, and the resulting attractor is plotted in three-dimensional space. Although it partially exists in another fractional dimension, the four dimensions are collapsed into three for purposes of illustration. Strange attractors in CAS will be discussed in this paper in terms of their influence on large-scale behavior, and simultaneously the behavior at the micro and individualized system level that gives rise to large-scale behavior.

An example of phase-space reconstruction in epidemiological modeling was provided by Aron (1990), who demonstrated the effects of introducing a vaccine into a standard, seasonally-forced population composed of what he called susceptibles, latents, infectives, and those who had become immune. As more and more members of the population were immunized, the vaccine inhibited the attractors of the disease (and its ability to self-organize or diffuse). Timing of the introduction of the vaccine was critical—if introduced at the wrong time, for example too late, it would lead to a weak change in the constellation of attractors, and that might still allow the disease to propagate according to its power law. This is because at earlier stages of diffusion, countering the disease requires a smaller number of vaccinations. Introducing a vaccine into the population early, timed to inhibit spread, is equivalent to introducing an innovation early, with diffusion able to perturb the social system and alter the shape of the attraction basin as desired. If vaccinations are introduced late in the spread of disease, after the basin of attraction grows and is strongly reinforced, then inhibition of the disease would require many more vaccinations.

Time Asymmetry and Reversibility in CAS and DIM

One test of a CAS is time asymmetry. Asymmetry in time occurs when a system passes a *bifurcation point*, a pivotal or decisional point where an option is taken over another or others, leading to time irreversibility. Irreversibility means that the system cannot be run backwards—rewound or reversed—so as to reach its exact initial conditions. Systems which, when run in reverse, do not necessarily or typically return to their original state are said to be asymmetric in time (Prigogine, 1997), and asymmetry in time is important in testing for a complex adaptive system. If system-time is symmetric in both directions, then it is reversible, and it is not a CAS but a deterministic system. Complex adaptive systems are asymmetric in time, irreversible and nondeterministic. So, in a CAS one can neither predict nor "retrodict," even with infinite information on initial conditions, because the system "chooses" its forward path. Its "choice" is indeterminate, a function of statistical probability (Prigogine, 1997) rather than certainty.

Diffusion, like CAS, is asymmetric in time, irreversible, and nondeterministic. Time is an essential element in the diffusion process—indeed, the S-shaped adoption curve is graphed as the *rate of adoption over time* (Figure 1), and adopter categories are assigned on the basis of time (Rogers, 2003). At first glance, time might seem reversible in the diffusion process. The growth of an undesirable idea (such as use of a dangerous drug) can be halted or slowed using principles of diffusion theory. Analogously, certain manipulations may retard the complex adaptation, or self-organization, of a system. They do so basically by decreasing system variety and reactivity, building barriers to heterogeneous interaction and removing therefore the prerequisites for complex-adaptive (self-organizing) activity. In neither instance, DIM or CAS, however, is there no true time-asymmetry, or reversibility. Even if there is complete discontinuation of a given practice, one cannot return to the conditions extant before the given innovation was introduced. The drug Thalidomide, for example, was banned once its dangers became apparent, but its social impacts, particularly its effects on mothers and their "thalidomide babies," could not be undone.

Variety, Reactivity, and Heterophily in the Two Models

Variety and *reactivity* are prerequisites of CAS (Waldrop 1992, p. 314). Variety is defined in complexity science as a large enough and diverse enough precondition or population for emergence and adaptation to occur. Variety is found in diffusion theory as *heterophily*, or degree to which individual communicators differ along traits pertinent to predisposition toward adoption. A very high degree of heterophily will likely slow down diffusion, but some degree of heterophily among communicators is nonetheless necessary for an innovation to spread (that is, a source individual must know more, and is assumed to know more. about the innovation than a receiver one). Thus heterogeneous interactions occur in heterogeneous zones—as suggested previously, locations where members, in their variety, can react more sensitively, increase their fitness, and change in a way that enhances chances for survival or forestalls threats of extinction.

Reactivity in CAS entails sensitivity to change, which increases immediately before cascades between steps at system bifurcation points. Cascading mutation/extinction, or changes in individual species, results from reactivity to change and continues in step-like punctuated equilibria that approach the critical point of self-organization (in heterogeneous zones). There is a gap that grows between these avalanches of mutations and step-up plateaus in systemic fitness thresholds. As fitness thresholds or plateaus step higher and higher, the cascades of change (between $1<a<3$ and $3<a<3.56994567$ in the quadratic equation $f(s) = as(1-s)$), with their draw on disposable resources, become larger and larger. Only those species (population categories) with sufficient disposable resources (adaptability to change) can survive at the higher fitness thresholds that occur during change cascades. In this view, only those capable of self-organizing emerge as "select." The cascading continues until the envelope function reaches the critical value f_c of the system (Paczuski, Maslow and Bak, 1996), and it then stabilizes as a complex system.

The power law is discussed in more detail in the next section, *The Movement Toward Criticality.* When nonlinear (complex) values of mutations/extinctions (self-change) are plotted in a quadratic iterative map $s(t) = as(t-1)(1-s(t-1))$, rewritten as $f(s) = as(1-s)$ (Bar-Yam, 1997, p. 26), bifurcation may continue until the system falls into chaos (Bar-Yam, 1997, p. 33). Similarly, in the DIM, innovations diffuse more rapidly and successfully in highly reactant social networks, through relatively heterogeneous *early adopters*, who have the highest level of adaptability to change. They typically have high levels of disposable resources (high socioeconomic status), relatively more exposure to adopters from other social networks, and the inclination to try new ideas (personality values and cosmopolite communication behaviors) (Rogers, 2003, p. 288).

The highest reactivity across all adopter groups is found at the *critical mass inflection point*, point 2 on the S-shaped diffusion curve (figure 1). This is where cascades of change occur. The diffusion curve can be thought of as a smooth curve that passes through the step-up plateaus in systemic fitness thresholds. As the curve rises, certain thresholds are passed for adoption networks. These rising thresholds evoke adaptation (in the case of early adopters) or loss (for laggards). Granovetter (1978) discusses thresholds in terms of eliciting a critical mass of collective behavior. Critical mass is reached at the point where there are enough adopters that further diffusion becomes self-sustaining (Rogers, 2003). At the height of the adoption curve, the fittest members of the social network have self-organized (adapted) to the higher plateau of fitness and adopted the innovation. Bifurcation, or decision, points have been passed on the way at step-like critical-mass thresholds. Unfit adopters, those without sufficient capability or inclination to adopt, have been precluded from participating in the adoption of the innovation.

DIM requires a lower threshold of variety than CAS, yet some variety is necessary in order for information exchange to take place between an innovation sender and an innovation receiver. The functionality of heterophily and variety is consistent with Granovetter's *strength of weak ties* in networks (1973). A related finding of recent diffusion studies is that an innovation has a more rapid rate of adoption when it is easy to "re-invent." *Re-invention* is the degree to which adopters can change a new idea, practice, or technology as it diffuses (Rogers, 2003).

Before a complex system (a social network, a population, or cognition and motivation in an individual) can move into criticality, or complex adaptation, it must have sufficient variety or variability (degrees of freedom or heterogeneity), which can be translated as sufficient resources and inclination toward new ideas and heterophilous interactivity for internal organization (i.e., heterogeneous mutation or adaptation toward self-organization). Similarly, diffusion is more rapid and effective (displays a higher degree of contagion) with a higher frequency of contact (interactivity) among heterophilous units in a system (Rogers, 2003, p. 19), a requirement that corresponds to that of variety in the CAS model (Granovetter, 1973). Both models require prerequisite internal conditions for their most favorable functioning, but diffusion can propagate reliably in low variety and low reactivity one-on-one environments, while a CAS may not. In some idealized hypothetical simulation, a CAS may begin to propagate if it only has one reactive element among a sea of "dead strings," but in other CAS simulations, such as in chemical reactions, there is a threshold floor beneath which propagation of reactivity will not occur.

In DIM, potential adopters, wholly located on the fringe or edge (the highest reactivity, heterogeneous zone) of a system, are seldom certain about whether an innovation is a superior alternative to what they already have or do. Thus, potential adopters are not always able to easily ascertain the benefits of adoption. This imperceptibility or undecidability contributes uncertainty and a lack of guaranteed outcome from the point of view of the potential adopter—uncertainty is the degree to which a number of alternatives are associated with the occurrence of an event but the relative probability of the alternatives is unknown (Rogers, 2003). Uncertainty is a barrier to diffusion, and its antidote is information. A certain degree of uncertainty always characterizes an individual's perceptions of a new idea, practice, or technology, which is one reason why the diffusion process occurs gradually. Uncertainty is also a salient feature of complex adaptive systems, wherein uncertainty is a barrier to reactivity, and thus to emergence and criticality.

The Movement Toward Criticality in CAS and DIM

Criticality is a three-or-more-variable interrelational location toward which complex systems migrate, in reaction to higher fitness requirements in the environment, in order to solve the problems of increasing complexity in increasingly difficult environments. The problem of adapting to increasing complexity is universally recognized as salient in today's world, as system complexity exceeds individual ability to process it sufficiently in real time (Bar-Yam, 1997; Toffler, 1970). The movement toward *cognitive* complexity may not be conscious; it may be an evolutionarily-defined, heuristic if-then rule (Waldrop, 1992, "satisficing" in Simon, 1991).

Rules are structured to identify the direction of system rewards and are important in both models. In DIM, these rules are social *norms*, defined as established behavior patterns and expectations for members of a social system (Rogers, 2003). Rules cannot be violated in either theoretical model with impunity. Expectancy of rewards also prompts agents in a CAS to move towards criticality and to consider heterogeneous ideas despite their uncertainty, or to adapt as a strategy to increase fitness. Agents develop strategies for fitness within boundaries, and "some strategies work better than others" (Waldrop, 1992, p. 310). Similarly, a population involved in innovation diffusion works within rule-sets to shift toward higher adoption rates, as rewards for adoption become widely known (and as uncertainty about such rewards for innovation decrease).

Agents in both models use rules to move toward fitness rewards located at the edge of a heterogeneous zone, where criticality obtains. Changing an agent's strategic fitness has the effect of changing the fitness of adjacent agents: "As each agent develops, it changes the fitness landscape of all the other agents [in its local network]. . . [When] a handful of species manage to find a temporary [local maxima, they are] locked in equilibrium" (Waldrop, 1992, pp. 310-311). Agents move with their neighbors at a pace that varies by degree of proximity (Bar-Yam 1997, 2005), with the closest network neighbors mimicking movement most closely. Similarly, a synapse is part of the fitness landscape of its neighbors and contributes to the fitness of the entire neuronal system. Generally, a localized system exhibiting progressive and interreactive change "strategies" in movement toward maximum fitness will quit moving toward criticality when it reaches a local optimum if it is isolated from the larger population (Waldrop 1992, p. 311).

From the mid-seventies to the mid-nineties, scientists studied and described different phenomena of emergence of CAS out of chaos. Per Bak's sand pile analogies inspired Stephen Jay Gould and Niles Eldridge's ideas of "punctuated equilibria" in evolution. Bak worked with both of these scientists at the Santa Fe Institute in 1989, where he identified punctuated equilibria as indicators of self-organized criticality (Bak 1996, pp. 117-118). Bak also defined the signature *1/f noise parameter* for a self-organizing system: In 1994, Bak, collaborating with Sergei Maslov and Maya Paczuski, discovered the power law: $f(t) = f_c - A\ (\ t/N)^{-1/(y-1)}$ (Bak 1996, p. 169; Paczuski, Maslow and Bak, 1996). This power law describes the delta point for "cascades of change," as in the angle of repose of a sand pile (Gleick, 1987; Waldrop, 1992). By way of illustration and analogy, Figure 4 shows the power law for new HIV infections after the advent of the San Francisco *STOP AIDS* public education and prevention program.

The power law is a tool to identify when criticality is reached in a broad spectrum of systems such as "stock markets, [chemical solutions],… and interdependent webs of technology" (Waldrop, p. 309): "Networks with power-law distributions are often referred to as *scale-free networks*" (Braha and Bar-Yam, 2004, p. 250; Barabasi and Albert, 1999). Maximum fitness, depending upon particular sets of boundaries, occurs "right at phase transition … [and] the edge of chaos is actually where complex systems go in order to solve a complex task" (Waldrop, p. 313). As with CAS's *self-organizing identifiers*, the DIM employs measures of criticality and phase transition. Criticality and phase transition is to CAS as critical mass is to DIM.

Arrival at Self-organized Criticality

Arrival at criticality and phase transition in CAS (critical mass in DIM, as just suggested) can occur relatively fast. It can occur immediately, as in sand piles, or very slowly, as in inter-generational cultural diffusion. In the case of the STOP AIDS program, to be discussed in a section that follows, criticality of new HIV infections occurred between 1978 to 1983, as the HIV virus multiplied exponentially over five years. On the one hand, the virus reached criticality before the STOP AIDS program diffused, and, on the other, the STOP AIDS program reached its own criticality or critical mass due to inoculation-like barriers in the form of safer sex practices.

Per Bak distinguishes between types of self-organizing systems and their differing power-law exponents as classified by speed of formation. "The distribution of avalanche sizes is a power law with exponent 3/2 just like Henrik's random neighbor model …The punctuated equilibrium evolution for a singe species [in the Paezuski-Boettcher model] is …7/4" (Bak, 1996, pp. 166-167). Maximum fitness occurs within particular boundaries "right at phase transition … [and] the edge of chaos is actually where complex systems go in order to solve a complex task" (Waldrop, 1992, p. 313). Waldrop's finding coincides with the present paper's: *Heterogeneous areas are those where emergence is likeliest*. They are located in the CAS epoch, such as between $1<a<3$ and $3<a<3.56994567$ in the quadratic equation $f(s) = as(1-s)$.

Scale is an important consideration in many fields, as the scale may affect the behavior observed, and feedback processes can occur between system levels. Emergence in CAS is a bottom-up rather than a top-down process, i.e., it goes from lower to higher scales. A number of units—cells, people, computer networks, synapses—interact locally, and each unit's actions contribute to the emergence of a global property at a higher level of organization and possibility. The sum of such microbehaviors produces a macrobehavior, and this global-level behavior feeds back to individual units at the lower level (Lewin, 1999). Local interactions are fine-scale-level behaviors, while the emergent level gives rise to global-scale behavior of higher-level fitness.

The observed system behaviors at these different scales are not necessarily the same. It is here where CAS differs from nested or scaled networks. Behavior in CAS is scale-free (scale-free qualities of diffusion are discussed in the "Emergence and Feedback" section below). Macroscale propagation/adoption does not necessarily negate microscale volition (individual choices and propensities toward choice), although group norms from the macro-scale can strongly influence individual behavior through circular causation, feedback, and reinforcement.

Diffusion theory, like CAS, looks at both the fine and global scales of behavior and the relationships between them, and it illustrates emergent behavior and feedback when aggregates of individual behavior scale up to a similar behavior on a system level. Beginning with the level of local interactions, the fine scale, diffusion takes place through a network consisting of individual units (potential adopters). The adopter unit can be an individual or an organization ("individuals" hereafter, for simplicity). Each individual can be self-located in one of the five adopter categories (innovators, early adopters, early majority, late majority, and laggards) and the network provides connections through which an innovation spreads (Rogers, 2003).

As individuals adopt an innovation, their microbehavior contributes to the macrosystem-level scale of behavior. As the rate of adoption of an innovation accelerates and innovation diffusion takes off, emergent adoptive behavior occurs at the system level. As an innovation is adopted by additional individuals in a system, a feedback loop occurs in the diffusion process as observability and other attributes of the innovation process reduce uncertainties associated with the new idea, process, or technology. The progress—initiation and maturation—of adoption is seen in linear relationships between the quality and source of new information and a population's manifest propensity toward an adoption decision. This is an example of a scaled network.

The Micro Scale

Networks are an essential feature of a CAS. Without them, there would be no system. Networks allow the system to solve problems using the large numbers of individual nodes that have local interactions with other nodes. The nodes themselves need not be "aware" they are contributing to this endeavor. They are following their own micromotivated rule-sets and interacting with local network neighbors. Such behavior allows the system to process information, and thus to learn. Moreover, CAS networks maintain their global behavior despite individual turnover (Johnson, p. 2001), even as complex mutual causation occurs at network levels. Diffusion theory is similarly dependent on networks in which individuals interact locally with their neighbors. Individual adopters are not usually cognizant of their contribution to a higher-scale order; rather, they make their decisions about innovations on the basis of their own perceived circumstances. As with CAS, network adoption of innovations is maintained despite population turnover, often for generations, even as different system levels influence one another.

An innovation comes into a system from outside, usually via an innovator or early adopter. Early adopters ("cosmopolites") are typically sufficiently respected in their local communities (relative to innovators and outsiders) that others are willing to follow their lead. They, then, function as role models. An early adopter may also be an opinion leader, and/or well connected, so that s/he has above-average network-connectivity in the system (Rogers, 2003). Early adopters are therefore highly reactive—heterogeneous—and their behavior is conducive to reactivity in others, as they increase perturbation around themselves by virtue of their propensity to innovate. Once brought into the system, innovations diffuse through networks of social ties. These links include relatively strong ties with opinion leaders and weak ties among social subgroups, which bridge sub-networks that would otherwise remain unconnected. Granovetter discusses the importance of these interpersonal and inter-group heterogeneous links in the diffusion process in his "strength of weak ties" theoretical argument (Granovetter, 1973).

A key feature of these links is the degree of *homophily* or *heterophily* between connected units. Homophily is the tendency to selectively interact with and learn from culturally-similar others, so that *degree of homophily* refers to the extent of prior affinity among network actors, including proneness to accept innovation. Greater homophily allows for greater ease of diffusion (although as previously stated, a degree of heterophily regarding an innovation is required for reactivity), while high degrees of heterophily raise barriers to diffusion. At extreme values, high heterophily makes diffusion almost impossible, as several studies illustrate (Rogers, 2003).

In a CAS, as in DIM, the units interacting in a network require a degree of variety—the network cannot link identical units. Heterophily provides variety, and information processing allows even highly heterophilous pairs to interact, albeit indirectly through relatively more homophilous links. The greater the homophily, the less the energy or effort required to transmit information. For instance, individuals in a support group who are homophilous in regard to the group subject (e.g., alcoholism) do not have to expend undue effort explaining their situation; rather they can invest themselves in working directly on their problem. A group of heterophilous individuals (e.g., alcoholics and obsessive gamblers) would not be able to work as efficiently.

An outsider, such as a change agent, needs to expend a large amount of energy or effort when the agent and client are overly different in orientations and attitudes toward the given innovation. In addition to the specific information the change agent must communicate about an innovation, s/he must convey background information about the innovation if it is to make sense to potential adopters. Failure to transmit all such information can result in diffusion failure. An instance is found in the story of a public health worker who attempted to persuade village women in Peru to boil their drinking water (Rogers, 2003). Since the villagers lacked awareness of science, she had to convey not only essential information about germs but also the technological and scientific underpinnings of the proposed intervention in order to justify her call for boiling water for sanitation purposes. Despite two years of intensive effort, the worker failed to prompt water-boiling in the village. The cultural gap was too large for communication, and hence diffusion, to occur. Uncertainty and suspicion served as protective barriers buffering the indigenous system from excessive perturbation, or shock. A social system needs time to absorb new information and integrate change so as to maintain a reasonable internal stability.

The Macro Scale

In both the CAS and diffusion of innovations models, local interactions in networks lead to the emergence of global structures and behaviors at the next-higher level of organization. As individual system units adopt an innovation, the innovation diffuses. Micro-scale behaviors—frequent instances of adoption—create macro-scale phenomena, such as the establishment of a consumer product standard. The often-cited triumph of VHS over Beta is a case in point.

The S-shaped curve represents cumulative adoption over time by members of a system. The two plateau segments (early and late in the adoption process, points 1 and 3) of the S-curve are relatively stable regions where it is difficult to change the system (Figure 1). These segments may be likened to attractors. An example is found in the diffusion of telecommunications innovations. A telephone is obviously useless for the first individual to own it, and even with a few adopters there persists a stable state of "non-telephony." However, telephones did diffuse globally with the rapid adoption of telephone use, whether through ownership or public-access pay phones. Thus, there was a linear stability plateau at low levels of adoption and usage in the early stage (point 1), followed by cascade of change (CAS emergence, point 2), ending in a linear stable stage again (point 3) after the market was saturated.

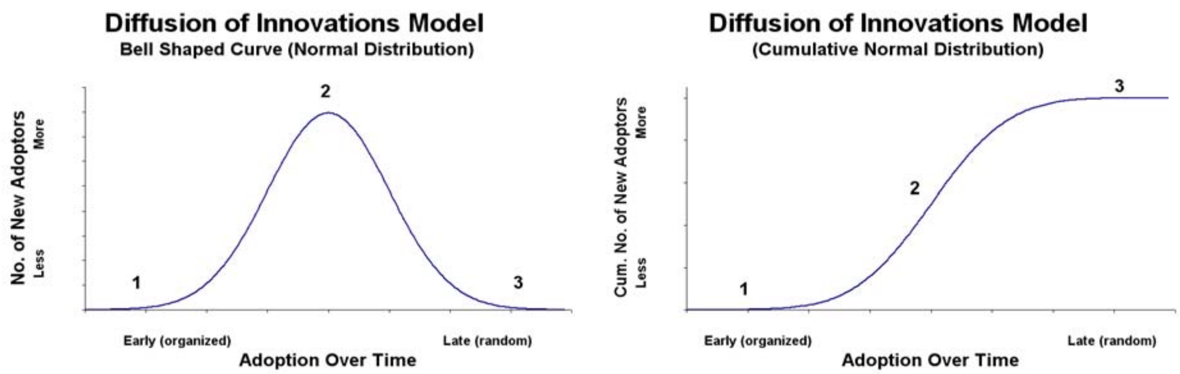

Figure 1: Phase state transition at point two in adoption and cumulative adoption curves compared to points one and three, stable attractor states early and late in the adoption process.

The "biggest bang for the buck" (whether in behavior change or chemical reactions) is found in the heterogeneous and most reactive zone, the phase-state where cascades of change occur at the most rapid rate (point 2). Cascades of change occur as a system processes new information about an innovation, overcomes uncertainty, and in effect, makes a determination that operatively shifts the system from one attractor (point 1) to a new attractor (point 2). The state change could be from non-adoption to adoption of an innovation, or to a defining choice between two competing innovations or behavioral norms. Choice at the bifurcation point leads to adoption and self-reorganization around the adoption, and to arrival at self-organized criticality. Figure 2 compares points 1, 2, and 3 on the distribution curves for the DIM and CAS.

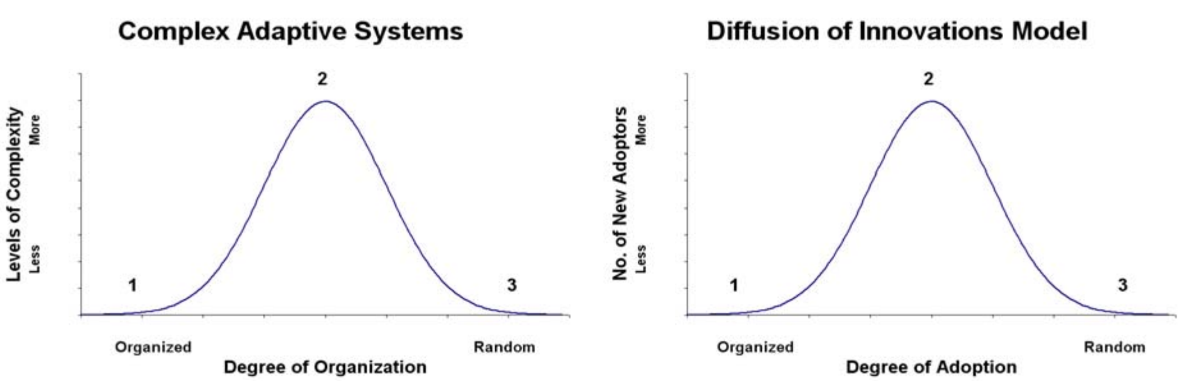

Figure 2: A comparison of distributions for complex adaptive systems and diffusion of innovations models.

When does the system as a whole make an adoption-decision? Where does it switch from one previously stable attractor toward another? The inflection point on the S-curve, about where critical mass occurs (Rogers, 2003), is the key point of interest (Figure 1). A continuing increase in the number of adopters, or synapses, or processing elements, increases the energy being processed in the local system at the inflection point. Until that point of critical mass is reached on the S-curve, the rate of increase in the number of adopters per time unit is nearly linear. Complexity begins at a threshold of nonlinearity (So, Chen and Chen, 2005). In the diffusion system's rate of adoption, this critical threshold has also been called the *tipping point* (Gladwell, 2002), a transitional inflection point associated with higher system reactivity, where system members are sensitive to change. At this conjuncture, the system exhibits the most change ("bang for the buck") for the least increase in energy—corresponding to heightened activity in the heterogeneous zone. Once the rate of adoption in a system reaches critical mass at the inflection point, it is difficult or impossible to stop further phase transition around diffusion (Figure 1). The eventual flattening of the curve owes to a decline in numbers of potential adopters, as the innovation is taken up by more and more adopters, and more easily so.

Emergence and Feedback

The micro and macro scales are connected, as individual actions aggregate to the macro level, also called the large-scale level of a complex adaptive system. Within this system there is a type of feedback (strange attractor) that loops back to influence behavior on the micro or individual level. Feedback is a vital component of CAS—a large part of what makes a complex system adaptive (Johnson, 2001). As each individual unit makes a decision, that decision contributes to the emergence of further decision-action sequences on the macro or global scale. Conversely, the macro or large-scale behavior also influences micro behavior through strange attractors, though the two levels of scale do not necessarily change at the same rate.

Whereas a scaled network produces changes similarly at all system levels, a scale-free network, a complex network, is one where small changes on the individual level can cause large changes on the macro or aggregate level. A scale-free network operates according to the power law. We will offer an example of scale-free network diffusion in the discussion that follows of the STOP AIDS program. In terms of diffusion, individual adoption decisions at the micro level lead to the emergence of innovation adoption by the social system as a whole at the macro level. The S-curve and other aggregate measures are depictions of such macro-level phenomena.

Individual decisions of rejection or discontinuance on the micro level, on the other hand, can grow to a failure of innovation adoption at the system level and thus to a failure of emergence, creating a flattened S-shaped curve (Figure 1). In this context, Rogers spoke of a "KAP-gap" (or "Knowledge-Attitude-Practice" gap), which he conceived of as a relatively homophilous zone where knowledge and attitudes are favorable toward adoption but insufficient for adoption. Rogers emphasized the importance of interviewing nonadopters and discontinuers and asking "why" and "when" and "under what conditions" failure occurred, to ascertain the reasons for failure and generally evaluate the diffusion campaign. Heterophilous members of a target population can be particularly helpful in offering information about determinative attitudes among nonadopters, because heterophilous members offer a dual outsider/insider view. Such interviews often led to a realization that the diffusion campaign targeted the wrong independent variables due to researcher misunderstanding of the culture of the target population—in particular a misunderstanding of that population's unique set of culturally-defined meanings and felt uncertainties. Mistaken attributions on the part of designers of diffusion campaigns are usually the cause of diffusion failure, observed at the macro level as a marked flattening of the S-shaped adoption curve (Medina, personal communication with Rogers, November 17, 2004).

Feedback from the macro level to individual units occurs in complex adaptive systems. In diffusion theory, one route for feedback is observability, as when a potential adopter observes influential people, such as celebrities or recognized experts, using the innovation. As the system adopts, individual adoptions are observable in this manner to an ever-greater degree, making for an increasingly rapid rate of change. The more observable an innovation (for instance, the use of cell phones), the easier it is for feedback to work. Poorly-observable innovations, including many health prevention interventions, offer less noticeable feedback and diffuse more slowly. Trialability, or the opportunity to try a new idea on a small scale or in a short time (with less risk), also allows for feedback. A company may distribute free samples so that an individual consumer can try the new product, obtaining feedback from the trial. Feedback among individuals at the local micro scale is thus important; a primary means of local feedback occurs as adopters (and “rejecters”) share their experiences with an innovation with others in their circle of acquaintances. A potential adopter may see someone else use an innovation (observability), or a tentative adopter may lend it to someone else to try out (trialability). Such feedback reduces uncertainty about the innovation, which may lead to more adoption through reinforcement.

Complexity science helps explain the establishment of order in a population where at first there appears to be none, and where novelty or exception successfully challenges settled rules. The CAS model, like diffusion theory, works well when interrelationships among the members of a system are strong and dense, while allowing for action at the level of individual units (Stacey, Griffin and Shaw, 2000). For both models, prediction is weak when relationships are weak individuals in a system are isolated. CAS models break down or do not work when local units become isolated, or when relationships are broken, are locked into equilibrium, or fade out.

It is argued in this paper that CAS models have the ability to inform diffusion models where diffusion processes are irregular. Furthermore, CAS provides an entirely new toolbox with which to model the diffusion process, essentially giving researchers a new way to look ‘inside the box,’ with a variety of population sizes at the scale of interest. For example, using the hybrid DIM-CAS methodology, one of the authors (Medina) is developing models that mathematically illustrate the process of attaining critical mass within small-group discussions. These models illuminate group norming communication dynamics. Formerly, such a process could only provide descriptive data, so that it was essentially a black box with regard to quantitative modeling and prediction. Likewise, the diffusion of an innovation amongst larger groups can be modeled with a DIM-CAS combined framework in a manner that provides greater insight into the mechanisms of diffusion and adoption. In the following section, a co-theoretical model is more explicitly built around an applied case study, the STOP AIDS experience in San Francisco.

Stop Aids

The STOP AIDS experience in San Francisco from 1984-1987 (Rogers, 2003; Wohfeiler,1998, 2002) and subsequent HIV prevention interventions modeled after it (including *STOP AIDS II*, 1990 to present), in several nations (Singhal and Rogers, 2003) and in certain social networks (Flowers, Hart, Williamson, Frankis and Derr, 2002; Kegeles, Hays and Coates, 1996; Kelly, Heckman, Stevenson, Williams, Ertl, Hays, Leonard, O’Donnell, Terry, Sogolow and Spink Neumann, 2000; Kelly, Murphy, Sikkema, McAuliffe, Roffman, Solomon, Winett and

Kalichman, 1997; Kelly, Sogolow, and Spink Neumann, 2000; Kelly, Somlai, DiFranceisco, Otto-Salaj, McAuliffe, Hackl, Heckman, Holtgrave and Rompa, 2000; Kelly, St. Lawrence, Diaz, Stevenson, Hauth, Brasfield, Kalichman, Smith and Andrew,1991; Kelly, St. Lawrence, Stevenson, Hauth, Kalichman, Diaz, Brasfield, Koob and Morgan, 1992; Miller, Klotz and Eckholdt, 1998; Sikkema, Kelly, Winett, Solomon, Cargill, Rofferman, McAuliffe, Heckman, Anderson, Wagstaff, Norman, Perry, Crumble and Mercer, 2000), have shown that the diffusion of innovations model can be applied effectively in public health and health policy settings.

These studies also suggest that planned diffusion closely parallels emergence in CAS. Diffusion begins in localized areas and spreads throughout a network, increasing in density until adoption spreads. Adoption spreads as more and more members of a social network adopt, meeting an adoption threshold (Valente, 1995). In this manner, adopters influence others to adopt (Rogers, 2003). The STOP AIDS intervention was based on both the diffusion model and on social psychologist Kurt Lewin's strategy of changing behavior in small group networks (Rogers, 1994). STOP AIDS employed outreach workers who were gay, many HIV–positive, to recruit individuals to small group training meetings of from 10 to 12 men (Yorke, 2003).

Meetings were held in homes and apartments along Castro Street and in other neighborhoods where gay men lived in San Francisco. Each meeting, led by a gay man (often one who was HIV–positive), featured explanation of the means of HIV transmission and of the importance of practicing safer sex. Each small group meeting ended with the individuals being asked to raise their hands (1) if they intended to practice safer sex, and (2) if they would agree to organize and lead a future small-group meeting themselves (Singhal and Rogers, 2003). The threshold for individual fitness, and survival, required a change in sex practices. These public displays of support for safer-sex practices created a type of emergent, macro-level normative pattern, a type of strange attractor for behavioral change in the larger community, and a complex adaptive system demonstrating the properties of a scale free network, a complex network.

Planners of the STOP AIDS intervention assumed that if they could reach a critical mass of opinion leaders in the city's gay community, the idea of HIV prevention would then spread spontaneously by interpersonal communication networks to others in the targeted population. Arenas, Danon, Diaz-Guilera, Gleiser, and Guimera (2003) found that community-size social networks exhibit scaling with a power law exponent in the range of -0.5 or –1. This scaling in the STOP AIDS program is illustrated in Figures 3 and 4. Scaling occurred both upwards as the virus spread and downwards as it was denied hosts due to safer-sex practices promoted by the program. Scaling down occurred at the power law exponent of -1.143, with adoption of a *shared commitment to safer sex* as the message reached critical mass in the city's gay community.

This diffusion process can be likened to "the symbolic [cultural] dynamics of a chaotic system [in its ability] to track a prescribed symbol sequence thus allowing the encoding of any desired message" (Yorke, 2003). Figure 4 illustrates log plots of the cumulative diffusion of the STOP AIDS program and its effects of declining rates of HIV infection, showing a power law regime with a fast decaying tail (Braha and Bar-Yam, 2004).

STOP AIDS reached over 30,000 of the total gay population in San Francisco of approximately 142,000. The rate of unprotected anal sex dropped from 71% in 1983 to 27% in 1987. With the decline of this means of transmission, the number of AIDS-related deaths per year dropped from 1,600 in the mid-1980s to only 250 in recent years (Wohfeiler, 1998, 2002). The application of diffusion of innovations theory, combined with networked Lewinian small-group strategies, in effect created strange attractors in large-scale population behavior, i.e., new behavioral norms that attracted and promoted safer-sex behavior. These attractors were evident in the spread of safer sex practices, a development that helped stem the epidemic (Figure 3).

An attitude, defined as a predisposition to action (Rogers, 2003), is, effectively, a reactive agent in the hybrid complexity-diffusion model here proposed. In the STOP AIDS case, the observability of the devastation caused by HIV/AIDS in San Francisco changed attitudes toward safer-sex practices (developed strange attractors within the large-scale that promoted such practices), and these strange attractors sped up the adoption of the innovation. Consequently, gay men became much more willing to use condoms and to otherwise reduce risky behaviors to preserve their health and attractive looks, and to avoid sickness. Attitudes toward safer sex thus became socially embedded in the older gay men's population. Then, as conditions improved and the ravages of HIV/AIDS less visible, there came a new surge in infections in San Francisco. As new cohorts of younger gay men arrived in the city in the early 1990's, they identified the previous HIV/AIDS epidemic with the older gay community, whom they tended to stigmatize. Unwarranted negative word of mouth about the STOP AIDS program among young gays led them to shun adoption, and the adoption threshold therefore rose considerably for them (Erez, Moldovan and Solomon, 2004). Furthermore, in their time, these young gays could not observe the results of unsafe sex behaviors as readily as had their predecessors. The epidemic had been nearly eradicated. Clear-cut benefits to safer-sex adoption were less observable (Rogers, 2003). Hence, the younger gays did not adopt safer-sex practices, and rates of infection once again increased to epidemic level, until the STOP AIDS program was reinstated (Figure 3).

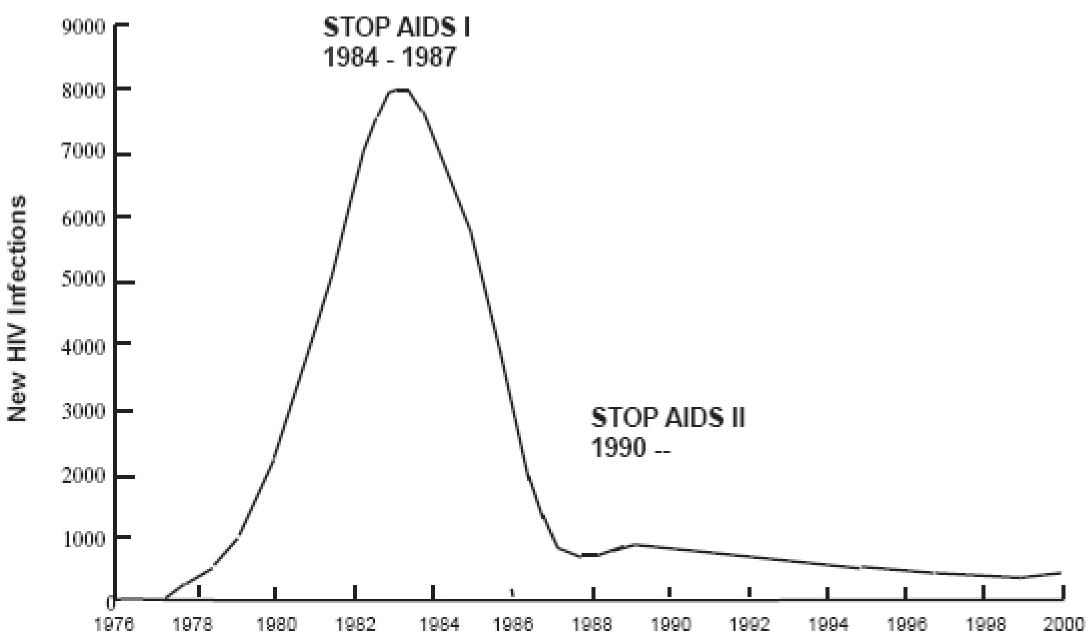

Figure 3: Changes in new HIV infections in San Francisco between 1977 and 2000 showing advent of STOP AIDS coinciding with decrease in new infections.

San Francisco's STOP AIDS intervention of the early 1980s was replicated in several developing countries (Singhal and Rogers, 2003). One program in the United States that was in part inspired by the STOP AIDS model was directed by Jeffrey Kelly and his colleagues (Kelly, Murphy, Sikkema, McAuliffe et al., 1997). In several U.S. cities, opinion leaders were identified and then trained in how to prevent HIV infection among gay men. Again, the objective was to reach a critical mass of at-risk individuals with prevention messages. The opinion-leader strategy is now being implemented and evaluated in at least five developing nations (Rogers, 2003).

Analysis

The foregoing co-theoretical model links DIM to CAS and provides an analytical tool for students of innovation, particularly in the use of public sector collaborative networks. The interdependency of innovation networks and the heterogeneity operative in complex adaptive systems are complementary. This analysis section discusses in detail how the combined model of DIM and CAS offers the possibility of a deeper understanding of diffusion in practice.

The coterminous processes of innovation-diffusion and complex adaptive systems leads, through phase transitions, to a more rapid rate of adoption or emergence, resulting in a higher-order, fitter system. Both models are built on empirical observation of bottom-up change, both can describe transitions occurring either naturally or as a result of directed change, and both can be statistically analyzed to infer population parameters for processes of change. In CAS, the point attractor where organization is 100% and complexity is equal to zero corresponds to the same point in DIM. At this point, an adoption begins to diffuse, organization is at 100 percent (i.e., the original idea is still intact and has not yet been reinvented or reorganized) and the complexity of the social network among adopters is zero (Figure 2). It is here, at the beginning of both systems processes and at the corresponding point on the S-shaped curve, that *the rate of adoption changes little for every additional new adopter*. The rate of change at the beginning is particularly linear, attesting to the given system's status as a simple system (Bar-Yam, 1997). The *rate of adoption* changes less for each new adopter than it will at point two (Figure 1).

In CAS, at point two (Figure 2), the area where strange attractors and complex attractors are found at the most complex points on the curve is also the highest point on the bell-shaped curve. This area corresponds to that in DIM where the adopter network is the most complex, and where strange attractors are stabilized. Here there is the greatest increase in rate of adoption (where the slope is vertical, point two, Figure 1) for the fewest additional cumulative adopters: There is *increased sensitivity to change for the least increase in energy expended toward change*. This is the location of complexity where heterogeneity exists at the border of chaos—that area between simple systems and chaotic systems—the area of scale-free networks.

The disproportionate changes at different system scales or levels identify a scale-free network. The rate of adoption changes more for each new adopter than it did at point one, and the rate of adoption changes more for each new adopter than it will at point three. At point two, the bifurcation threshold has been passed for this population. There is no longer a question of whether diffusion will occur throughout the majority of the population: The population will continue to adopt due to the momentum that has been attained. Point two, the *inflection point* on the curve (Figure 1), is called the point of critical mass because it is where adaptation has met or exceeded the fitness threshold and "further diffusion becomes self sustaining" (Rogers, 2003, p.

343). Point two is another dynamic juncture, a *heterogeneous zone where the rate of change is nonlinear*. At point two, the rate of change is nearly vertical—it approaches closest to infinity.

At point three in CAS (Figure 2), the area where 100 percent randomness and zero percent complexity occur, is the place where infinite attractors are found that cannot be modeled. This area corresponds to the same area in DIM, where an innovation has finished diffusing, and therefore the system is at zero percent complexity—it has returned to a simple system and is again linear. There, perturbations are chiefly associated with resource scarcity or disinclination to new ideas among late adopters. At this place in the bell curve, diffusion as well as CAS cannot be modeled (Figure2). At the correlating point three on the integral S-shaped curve (Figure 1), there is a flattened rate of adoption. That is, late in diffusion the speed of adoption is slowed and there are fewer new adopters. The rate of adoption changes less for each new adopter than it did at point two. The rate of adoption is *stable*, and the rate and quality of change is *rapidly linear*.

It is evident from the foregoing that both the DIM and CAS models can be used to describe behavioral changes in populations as well as other complex systems. The DIM has its strongest utility in the spread of new ideas, products, and practices. CAS may have the strongest value in the real-time monitoring of complex systems and in identifying early stages of phase transition into criticality. As defined previously, criticality or (interchangeably) critical mass is the point at which the random activity of unrelated elements in a system suddenly becomes more complexly structured and ends-oriented, as self-organization takes over. At criticality, a population's actions are no longer random, but rather take on a certain degree of predictability.

That phase transitions into higher levels of order can be anticipated, manipulated, and evaluated holds out significant promise for new applications in the social sciences and in social interventions. Future research might focus on the mathematical definition of zones of heterogeneity at the edge of adopter populations, where both uncertainty and sensitivity (or reactivity) to change are most acute, where the emergence of new attitudes and habits can be identified, and where communicative interventions can therefore be most cost-effective.

The STOP AIDS innovation spread rapidly because it was perceived by the gay community as relatively (a) advantageous over unsafe ideas or practices they superseded, (b) compatible with existing values, norms, beliefs, and life experiences, (c) easy to comprehend and adapt, (d) observable or tangible, and (e) divisible (separable) for trial and adoption (Rogers, 2003). The innovation operated like a vaccine in the CAS model, as more and more members of the gay population participated in the STOP AIDS program and adopted safer-sex practices, at the threshold of criticality (with reference to both DIM and CAS) where heterogeneity (adoption, mutation, change) was rewarded. Adaptation was rewarded as members increased both their individual utility (improved life expectancy, reduced fear and uncertainty) and the constancy and consistency of their interdependence (Klein, Faratin, Sayama and Bar-Yam, 2003).

During this complex transition, the utility-maximizing motivational rules (such as increased life expectancy) prompted individual-scale and group-scale movement from lower occurrence of safer-sex practices to higher levels of cohesiveness and order in group adoption of these practices). This new order was marked by *emergent self-organization.* Group adaptation to safer sex resulted from the increasing numbers and effective communication activities of highly-connected sex health workers in the community. There was complex-network synchronization marked by role heterogeneity (in sustained interaction between health educators and members of the gay community; Motter, Zhou and Kurths, 2004). The resulting heterogeneous system exhibited emergent patterned behavior that enabled the social group to respond more fitly to its environment, as a complex adaptive system (Johnson, 2001). If the social group was in fact a CAS, then a power law analysis should show it to be a scale-free network, one whose activity can be described by the power law. To test for this possibility, power law analysis was conducted by fitting a trend line of the least squares fit through data points (x, y), where x equaled the number of years since initiation of the STOP AIDS program and y equaled the number of new HIV infections. The following equation was applied: $y = cx^{b}$, where c and b are constants. Power law analysis yielded the following equation: $y = 10518x^{-1.143}$, with $R^2 = 0.9039$.

Ninety percent of the variance was accounted for by the equation, showing a power law relationship between the STOP AIDS program and the sharply declining number of new HIV infections. Log plots of the cumulative distribution indicated a power law regime (Braha and Bar-Yam, 2004). The power law relationship between the STOP AIDS program and the decline in number of new HIV infections would indicate that there was a network of short-distance and highly connective iterative relationships between the health workers and members of the gay community (Braha and Bar-Yam, 2004). Qualitative reports on the program tend to validate this assertion (Wohfeiler, 1998). Opinion leaders (highly-connected, influential members of the target social group became health workers and influenced large numbers in the gay community. Members organized in clusters around opinion leaders, and these clusters were highly connected to each other through those leaders. The health communication or diffusion work was iterative, in that it was conducted in virtually identical form in many, and often-repeated, small home gatherings. Pursuant to these conclusions the following graph, figure 4, depicts the power law fit.

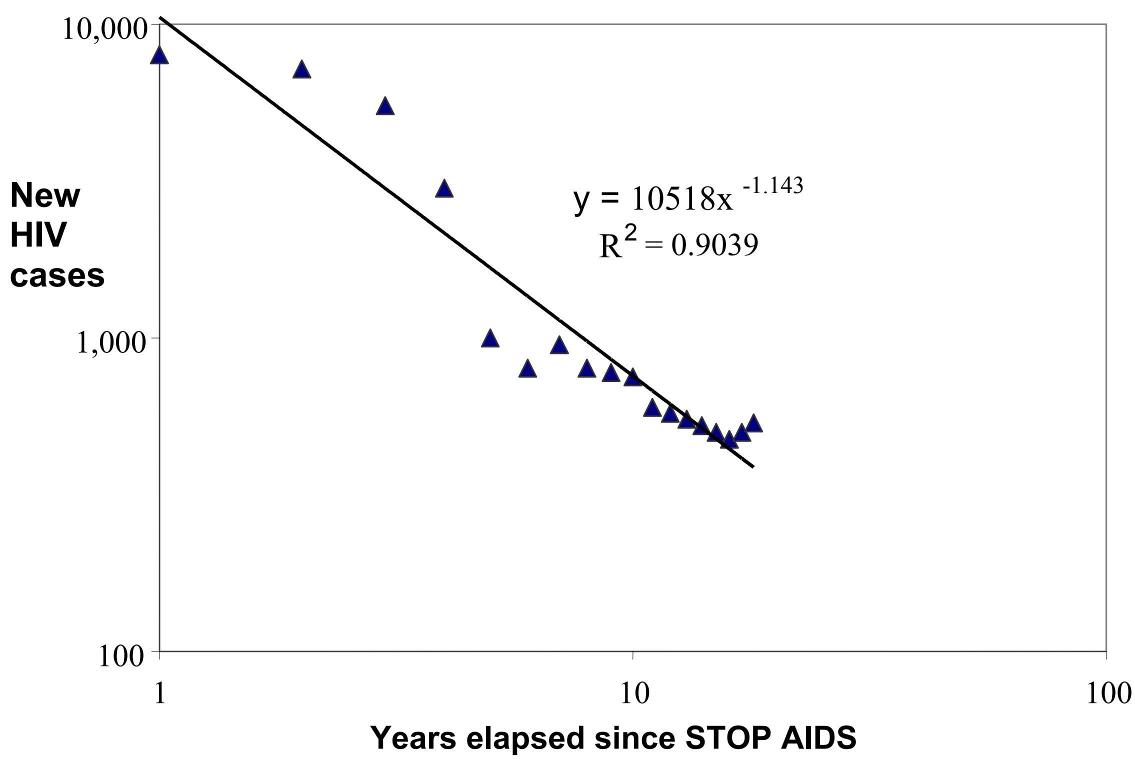

Figure 4: Power law fit between log of new HIV cases and log of time elapsed since STOP AIDS

Conclusion

This conclusion section discusses in widely applicable theoretical terms how the co-theoretical model of DIM and CAS offers a deeper understanding of the theory and practice of diffusion. Recent treatments of STOP AIDS and kindred programs based on diffusion of innovations theory suggest that greater differentiation (heterogeneity)—by way of broader coalitions of activist groups armed with larger arsenals of proven interventions—makes for greater stability, sustainability, and effectiveness (a review of STOP AIDS and related literature is found in Bertrand, 2004; see also Wohfeiler, 1998; Essien, Linares and Osemene, 2000; and Wozniak 2001); broad-based coalition-building is also the organizational and operational premise of the Global AIDS Alliance (Global AIDS Alliance, 2003). This finding, of the need for differentiated advocacy organization in the implementation of research-based interventions, is consistent with the proposition advanced in this paper that heterogeneous, transitional zones of innovation activity in networks can make for sustained efficacy in directed efforts at diffusion.

Bertrand indicates that "the changes in behavior needed to halt the HIV/AIDS epidemic constitute what Rogers has labeled a 'preventive innovation,'" with the catalytic event occurring when "'trend setters' in a social network begin to model a new behavior to others [and therefore] reduced uncertainty and altered the perception of what is normative … (Bertrand, 2004, p. 115). Bertrand adds that as prevention shifts from "predominant focus on individual behavior to recognition of the importance of social norms in defining sexual behavior," innovation diffusion is reasserting itself as a leading theory in the fight against HIV/AIDS (Bertrand, 2004, p. 120).

The increased heterogeneity of AIDS activism is, arguably, a major reason for the normative turn in applied diffusion theory. The greater breadth of membership strengthened the normativity and credibility of AIDS activism, and, in circular causation, greater credibility helps sustain AIDS advocacy. Bernardi (2003) has similarly found that the normative-structural characteristics of diverse social networks working in fertility-choice advocacy, and especially the inclusive quality and connective density of these family-centered networks, account for their effectiveness. Bernardi attributes their effectiveness to social-network synchronization.

In the CAS model DIM practitioners can now recognize the importance of heterogeneity and diversity—in modalities of social action, of ethical and cultural normativity, and of group membership—consistent with *law of requisite variety* (Ashby, 1970), which posits that system variation needs to match the corresponding features of environmental demands if organization and collective action are to be effective. Acknowledging the centrality of heterogeneity is also consistent with Actor-Network Theory, which, along with diffusion of innovations theory, points to the alignment of social and technical systems in *heterogeneous networks*.

Heterogeneous networks encompass interrelated structures of social relations, social values, and behavioral incentives and motivations, creating linkages to multiple chains of influence (Avgerou, 2002, p. 61). Arquilla and Ronfeldt (2001, p. 304) likewise argue that multiplicity or variety of network membership "permits division of labor and adaptation to circumstances . . . The greater the differentiation of groups, the more likely the movement is able to offer something for every sympathizer to do to further the movement's goals."

In social action as in scale-free physical networks, heterogeneity enhances connectivity distribution and network synchronization. With sufficient differentiation, "synchronizability is drastically enhanced and may become positively correlated with heterogeneity," potentially reducing the costs involved in the creation of effective network ties (Motter, Zhou and Kurths, 2005, p. 334). As suggested throughout this paper, in CAS a given system evolves in a non-linear, perturbable pattern of co-evolution among constituent elements.

In a differentiated network, typically marked by "the strength of weak ties," network synchronization is prone to emerge, rendering innovation relatively constant and, in that sense, sufficiently predictable for the purpose of program planning and projection (Cowan, Pines and Metzer, 1995). It is in this sense that Nobel Laureate Murray Gell-Mann (faculty member in Physics at the University of New Mexico and the Santa Fe Institute) writes (Gell-Mann, 1995) of "effective complexity" as a projection of a system's present-level complexity combined with the same system's "potential complexity." With STOP AIDS, effective complexity as a realization of potential complexity was attained when the social actors involved changed prevailing norms to a higher level of fitness, i.e., the social network moved to a safer-sex based normative system.

The foregoing suggests that applications of CAS to innovation diffusion can address not only the rate and sequencing of innovation adoption through the specification of threshold effects and phase transitions but also the acceleration of diffusion. The level of variety or heterogeneity among influentials' interpretations of the value of innovations counters prevailing norms and sensitizes the target population, increasing reactivity and bringing about the *early onset* of innovation adoption. After the stage here characterized as destabilization, the resulting quality and density of communications among all individuals (units of analysis, processing elements) in a given social network becomes more active, draws in more energy, and undergoes perturbation. At this juncture, norms are reorganized (redefined, modified) as new patterns of adoption emerge. In is in this vein that Ortiz-Torres, Serrano-Garcia, and Torres-Burgos (2000, p. 859) argue that working to change "sex-related social norms and normative beliefs" is *subversive*, because "rather than idealizing culture, it promotes changes that respect diversity within the culture and foster participation in the development of new cultural values, beliefs and norms."

What impact might a high level of heterogeneity—or, interchangeably, variety or variance—in the *expected* value of innovation have on diffusion? If expectancies are largely defined by groups and group norms, as Lewin argues, what happens when groups are moved by advocacy campaigns into uncomfortable zones of heterogeneity—for instance, when target populations are deliberately challenged—perturbed—and consequently change behaviors significantly (as did gay men in San Francisco between the eighties and nineties)? Do redefined group interpretations of what constitutes normative behavior lead to individual behavior change? How do perceived changes in the viability and normativity of available options affect the sequencing of choices associated with the adoption of innovations? Does heterogeneity of membership and roles in social networks make for variance of expectations and motivations (consistent with Lewin), as well as for more differentiated normative frames of reference?

Inevitably, the growth and diversification of AIDS advocacy groups and coalitions means that the movement has come to include disparate ethical standpoints and normative belief systems, numerous tested modes of intervention, and a wide array of social and institutional actors which despite their diversity share commitments around AIDS prevention and eradication. It is also the case, often commented, that AIDS is no longer—no longer seen as—strictly a "gay" disease, but rather one that affects the entirety of the population. Differently put, it is seen as differentially but universally affecting the entire population, including, in addition to gay men, heterosexual men, young adults, injection drug users, "sex workers," and other now-standard public-health group categories that, taken together, are virtually all-encompassing.

The preceding discussion suggests that a host of questions remain to be addressed in the innovation-diffusion field. These questions await the application of new mathematical and computational tools, and new theoretical perspectives. As to the first, there are numerous computational tools available, including self-organizing mapping systems, neural network software, and predictive network analysis software. As to the latter, it is suggested here that complex adaptive systems models provide a most promising theoretical and methodological source for innovation research. Under conditions we tentatively specify, the complex adaptive system and diffusion of innovations models are found to be essentially equivalent in important respects. Their synthesis and application could lend impetus to communicative action and advocacy efforts among a wide variety of social groups in varied contexts. It could also make innovation diffusion more predictable, and therefore more subject to planning, implementation, evaluation, and replication measures.

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