Chapter 4
Complex Systems and Social Behavior: Bridging Social Networks and Behavior Analysis

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Introduction: Complexity and Behavior Analysis—A Joint Scientific Enterprise?

Complexity is an interdisciplinary approach in science that draws from the recognition of networks of interactions from which new patterns of behavior may emerge. It would be beyond the scope of this chapter to fully describe how complexity is approached in various areas such as computer science, management, and evolutionary biology (e.g., see Mobus & Kalton, 2015). However, there is a common understanding of complex systems as sets of interactions among agents (Axelrod & Cohen, 2001). These interactions comprise the arrangement of contingencies of reinforcement and may be explored through a functional analysis of social phenomena. Hence, complexity science and behavior analysis (BA) are concerned with similar objects of analysis, although they are based on different premises. The purpose of this work is to explore the differences between BA and social network analysis (SNA) and suggest a space for communication between them.

The branch of complexity sciences that studies the structure of interactions in complex systems is called network science. In 2005, the researcher Albert-László Barabási observed an increasing interest in the science of networks. However, he also claimed that much needed to be done in order to develop an interdisciplinary approach toward complexity. As different attempts to bridge different areas of knowledge have brought promising contributions, the relation between network theory and complexity formulated by Barabási (2005) is still valid:

> As it stands, network theory is not a proxy for theory of complexity—it only addresses the emergence and structural evolution of the skeleton of a complex system. The overall behavior of a complex system, which we ultimately need to understand and quantify, is as much

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> rooted in its architecture as it is in the nature of the dynamical processes taking place on these networks. (p. 70)

Complex systems have an emergent character that is often difficult to predict. SNA focuses on emergent phenomena that belong to the past or that have already happened as compared to the time of observation (i.e., a posteriori). Conversely, experimental and applied BA rely on rigorous control and are concerned with the prediction of behavior (i.e., a priori), relying on established methods. The central argument developed throughout this chapter is that there is valuable space for communication between BA and SNA.

There are different attempts to bring a system perspective to BA. Behavioral systems analysis represents the subdiscipline of applied BA informed by systems theory and concerned with the maintenance and improvement of processes and interactions of a system (Brethower, 2004). For example, specific applications include emphasizing the role of selection in organizational change Sandaker (2009); the interaction and evolution among systems of genes, immunology, and behavior (Hull, Langman, & Glenn, 2001), and the analysis and maintenance of cultural phenomena (e.g., Glenn & Malott, 2004). The relational perspective that permeates complexity science and its applications to the study of systems of human organizations, such as organizations or societies, raises questions that are relevant for the analysis of behavior. For instance, one may investigate how behavior spreads in social groups or how the position of individuals in a certain network may explain behavior. Human behavior usually takes place in the context of dynamic processes of interactions that need be seen from a time perspective. This has been highlighted by Skinner (1953) in the following terms:

> Behavior is a difficult matter, not because it is inaccessible, but because it is extremely complex. Since it is a process, rather than a thing, it cannot easily be held still for observation. It is changing, fluid and evanescent, and for this reason it makes great technical demands upon the ingenuity and energy of the scientist. But there is nothing essentially insoluble about the problems, which arise from this fact. (p. 15)

The *Ratio* of a Mutually Informed Framework

The main assumption that permeates the analysis herein put forward is that social structures *matter* when we aim at explaining behavior (Sandaker, Couto, & de Carvalho, 2019). Thus, behavior analysts may enrich their approaches by understanding the main developments in SNA. Conversely, recent work in network analysis highlights the importance of *social reinforcement* in the processes of how behavior and complex information spreads (Centola, 2018). According to SNA, social reinforcement is defined as "the situation in which an individual requires multiple prompts from neighbors before adopting an opinion or behavior" (Zheng, Lü, & Zhao, 2013, p. 2). From a behavioral standpoint, we define social reinforcement as an increase in the likelihood of future behavior as a function of the interaction with other individuals or groups. For example, we may observe the effects of social reinforcement as the conversation between two agents develops: the verbal behavior emitted by one may be reinforcing for the other to continue conversing. However, social reinforcement need not necessarily correspond to verbal behavior. For example, in a classic study analyzing stress and relationships, Birchler, Weiss, and Vincent (1975) distinguished between positive social reinforcement (SR+) and negative social reinforcement (SR−). Positive social reinforcement includes verbal (e.g., agreement, approval) and nonverbal (e.g., assent, smile) behavior; similarly, negative social reinforcement also includes verbal (e.g., complain, interrupt) and nonverbal (e.g., no-response turn off) behavior. Nevertheless, their reinforcing (or punishing) effect is variable over time, environment, deprivation, and experience.

The social aspect highlighted here refers to behaviors taking place in the context of interactions. Hence, network analysis can in turn be informed by BA. Figure 4.1 summarizes the rationale of the chapter by illustrating the space for communication between the two disciplines.

Network theory and network analysis are used to study the interactions in complex systems to help understand, change, or disseminate cultural practices. We explore some of the frequently used concepts and give examples of how network analysis may add value to a behavioral perspective on cultural change and vice-versa. Moreover, we provide examples of how the growing body of scientific knowledge of networks may add value to understanding cultural systems. The discussion concerns bridging SNA and BA in explaining behavior change in social settings. More than promoting an integration between the two perspectives, we shed light on how SNA and BA may enhance their contributions by acknowledging and reinterpreting their respective central concepts. We illustrate how some characteristics of a

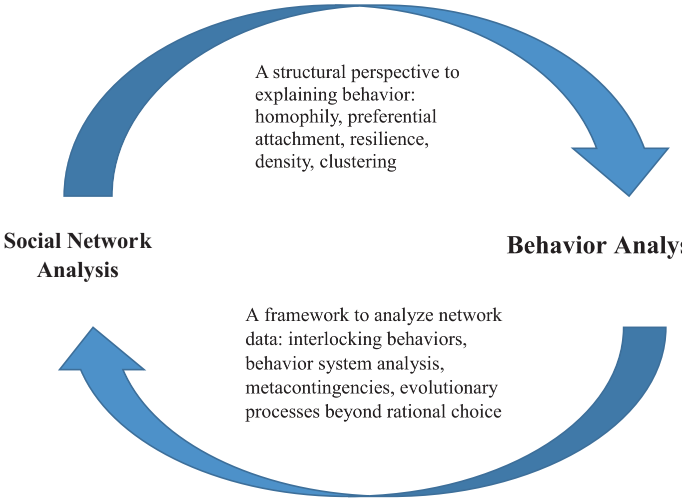

Fig. 4.1 A space for mutual communication between social network analysis and behavior analysis

network, elective homophily and preferential attachment, are susceptible to explanatory forces of BA.

In the first part of this chapter, we discuss the relational perspective in BA. In the second part, we start from some historical remarks on network analysis and describe possible conceptual frameworks commonly applied to analyze network data and possible limitations. Furthermore, we explore the distinction between Being and Becoming, and how these may be representative of instances of network theory and BA, respectively. Lastly, we turn our attention to the behavior analytic efforts to understanding systems and present real-life examples of social contagion.

A Relational Perspective in Behavior Analysis

In BA, the relation between individual behavior and the frequency, magnitude, and immediacy of reinforcement is at the core of understanding behavioral processes. When focusing on the interaction between two or more individuals, it seems appropriate to address this as interlocking behavioral contingencies (IBCs) of social behavior. Skinner (1953) defined social behavior as "the behavior of two or more people with respect to one another or in concert with respect to a common environment" (p. 297). This concept was adopted and further elaborated by Sigrid Glenn (2004) and others (Houmanfar & Rodrigues, 2006) and is a component of the conceptual tool (Todorov, 2006) called *metacontingency*, which plays an important role in the analysis of cultural phenomena. Thus, IBCs refer to the interdependent social contingencies between organisms (de Carvalho & Sandaker, 2016), and comprise the fundamental blocks of any cultural practice (Glenn, 1988). In logic terms, IBCs comprise a necessary but insufficient element of a metacontingency, which describes the functional relationship between the product of IBCs (i.e., the aggregate product) and its receiving environment (Glenn et al., 2016). The elements making up the metacontingnecy are iterative. IBCs are the result of previous events and processes, such as two cooks' interrelated (operant) behavior resulting in a meal that neither of them could have produced by themselves (Glenn, 2004). Table 4.1 includes a definition of terms pertaining to this unit of analysis.

IBCs and behavioral systems analysis describe cohesive sets of operant contingencies wherein the behavior of two or more individuals function as environmental events for the behavior of other individuals (Glenn, 2004; see also Houmanfar, Rodrigues, & Smith, 2009). Hence, IBCs resonate with the relational perspective toward social phenomena that permeates SNA. Understanding this perspective involves an analysis of relational responding in terms of discriminating important data to which to attend. Thus, interlocking relationships between agents involve bidirectional linear relationships in dyads, which comprise the smallest unit of analysis. Here, "each organism's behavior serves as stimulus for the behavior of others" (de Carvalho & Sandaker, 2016, p. 19). As a result of scaling up the number of relationships to the agents in a system, behavioral processes are not only interlocking but interdependent. For example, agents and nodes are the units of

Table 4.1 Central concepts of behavior analysis to be further explored from a social networks perspective

Concept	Definition
Behavior Systems Analysis	"[B]ased on general system theory, organizations are behavioral systems formed by individuals' interactions (IBCs) toward a common goal" (Houmanfar et al., 2009, p. 258).
Metacontingency	"A contingent relation between (1) recurring interlocking behavioral contingencies having an aggregate product and (2) selecting environmental events or conditions" (Glenn et al., 2016, p. 13).
Interlocking behaviors	"The behavior and behavioral products of each participant function as environmental events with which the behavior of other individuals interacts. This is the behavioral view of a cultural practice" (Glenn, 1988, p. 167).
Social reinforcement	The increase in the likelihood of future behavior, as a function of the interaction with other individuals or groups, or, according to social network analysis, "the situation in which an individual requires multiple prompts from neighbors before adopting an opinion or behavior" (Zheng et al., 2013, p. 2).

interdependency respectively in BA and SNA. In the first case, they may elicit or strengthen (or weaken) mutual exchanges; in the second, they serve as emitters and receivers of communication signals. In both cases, they are influenced by feedback loops that receive or select the product or outcome of their interdependency. Thus, the concept of *interlocking*, is herein interpreted as a description of social antecedent contingencies (i.e., interlocking as interdependency). As is the case in complex systems, the metaphor of the living system is an illustrative one. Rather than a mechanical fit, however, the relations in a system are captured by the term interdependency between actors and the complexity that arises organically from these interactions.

Although behavior analysts have had an increasing interest in cultural phenomena and large scale behaviors (e.g., Zilio, 2019), the tradition to a great extent has been based on experiments and practices derived from single subject cases. When approaching a system's behavior, both scale and scope change. The phenomenon of interest is, however, still behavior. It is important to recognize that the very idea there is behavior at the systems level can be a matter of dispute in complex sciences. For instance, Stacey (2009) claims that while we can observe learning in processes of interdependence, it may be misleading to assume that a system *behaves*. Notwithstanding, research in network analysis has shown how networks' structures change in adaptive ways, either facilitating or restricting information flow (Centola, 2018; Naug, 2009). From this perspective, we can observe behavior at a systems level. This also highlights the need to recognize that not every behavior change is related to changes in network structures. Furthermore, complex systems have emergent properties, meaning the whole is not simply a sum of its parts, but arises from processes of interactions. We do not understand a complex system by only looking at its parts in isolation. It is important to look at behavior at different levels of organized complexity. When studying complex challenges like climate change, sustainable behavior, obesity, juvenile delinquency, or drop out from school, solutions call for multidisciplinary approaches.

The structure matters; it may either facilitate or restrain the spread of new cultural practices. However, it is interesting to notice that the recognition of the relation between cultural analysis and behavioral systems has not always been a straightforward one. In *Selection by Consequences*, Skinner (1981) assumed a critical perspective toward structuralism by stating that principles of organization do not determine behavior. Conversely, the effects of principles of organization may be tracked down to their respective contingencies of selection. In a later moment, he addressed the "problem of structure" by stating that although structures may have several properties, these are "simply networks of contingencies. Structure, therefore, cannot have a role in behavior separate from that of contingencies" (Catania & Harnad, 1988, p. 481).

A possible alternative is to adopt a structural perspective to explaining behavioral phenomena. Here we acknowledge the importance of structures comprising behaviors at different levels. The structure evolves to a certain extent together with the function of an organ, an individual, and a group.

The idea of systems is not as developed in behavioral sciences, as it is in systems science. For example, Mobus and Kalton (2015) analyzed the principles of a science of complex systems in depth, specifically pertaining to function, structure, and modeling. On their third principle of systems science, the authors maintained that "systems are themselves and can be represented abstractly as networks of relations. In order to understand the nature of systems in terms of structure, organization, and function (dynamics), we need to understand networks" (Mobus & Kalton, 2015, p. 137). Conversely, systems are described and analyzed in rather metaphorical terms in BA and this represents the topic of the next section.

Behavior Analysis as a Matter of Complexity: The Space for Interdisciplinary Communication

One problem addressed by biologist Edward Wilson (1998), is that social sciences, such as sociology, political science, social anthropology, and psychology, do not share a common conceptual framework based on a cumulative research tradition. Unlike natural sciences, the different social science disciplines represent all different languages, based on different research methods and often represented in antagonistic terms. Conversely, behavior analysts have typically presented behavior science as a natural science (e.g., Johnston & Pennypacker, 1993), thus as free as possible from internal teleological and terminological inconsistencies. As chemistry, physics, and biology may represent complementary perspectives, the social sciences seem not only to represent different conceptual frameworks, but even different dialects within the same discipline that may be in opposition to each other (Sandaker, 2006). Wilson blames the lack of applied societal success for these disciplines to the antagonistic approaches and thus the lack of consilience. Consilience, as Wilson describes it, is the ultimate criterion that separates pseudoscience from science. A prerequisite for consilience, or the unity of knowledge, is a common shared scientific basis that enables disciplines to communicate and hence enables scientists to share challenges and efforts to meet them.

The complexity perspective represents an approach with much in common with BA:

1. It is a generic conceptual framework, based on an empirical approach. However, both complexity sciences and BA recognize the importance of contexts.
2. Both approaches are basically evolutionary and represent a selectionist perspective. As in BA, the complexity approach is concerned with the units of establishing, maintaining, changing, and extinguishing behavioral phenomena.
3. Skinner (1953) describes "the self as an organized system of responses" (p. 285). The self is maintained by its functional relation to the environment and shaped by its consequences. The organization is, however, context-dependent. A system is maintained by its functional relation to the environment and shaped by its consequences. The organization, or the structure of the interactions, is of great interest in systems thinking.

Complexity and Network Structure

Networks are the underlying structure of what we call complex systems (Caldarelli & Catanzaro, 2012; Zweg, 2016). Figure 4.2 illustrates an example of a formal organizational chart and a graphic representation of the actual web of interactions in the same company. Although dependent on the purpose, size, and other characteristics typical of each organization, it may help map how the communication flow and chains of command are intended. It does not necessarily indicate how they manifest themselves, as formal and observed structures of communication need not necessarily concur.

However, complex systems need be understood beyond their underlying structures, specifically in relation to their functions and processes (Sandaker, 2009). The need to grasp the temporal dimension of processes and the self-organizing nature of complex systems highlights the current limitations of network analysis in explaining change. Concepts such as *homophily* and *preferential attachment* have enlightened processes of network growth (Caldarelli & Catanzaro, 2012). Homophily indicates that nodes tend to connect with similar ones. Preferential attachment is a mechanism of network growth that indicates that new nodes tend to connect with old ones that already have a high number of connections (Caldarelli & Catanzaro, 2012).

Beyond understanding network structure, it is important to look at the content of the information flow in networks. Rather than only simple information, the flow often consists of complex information in the form of shared norms and beliefs. For

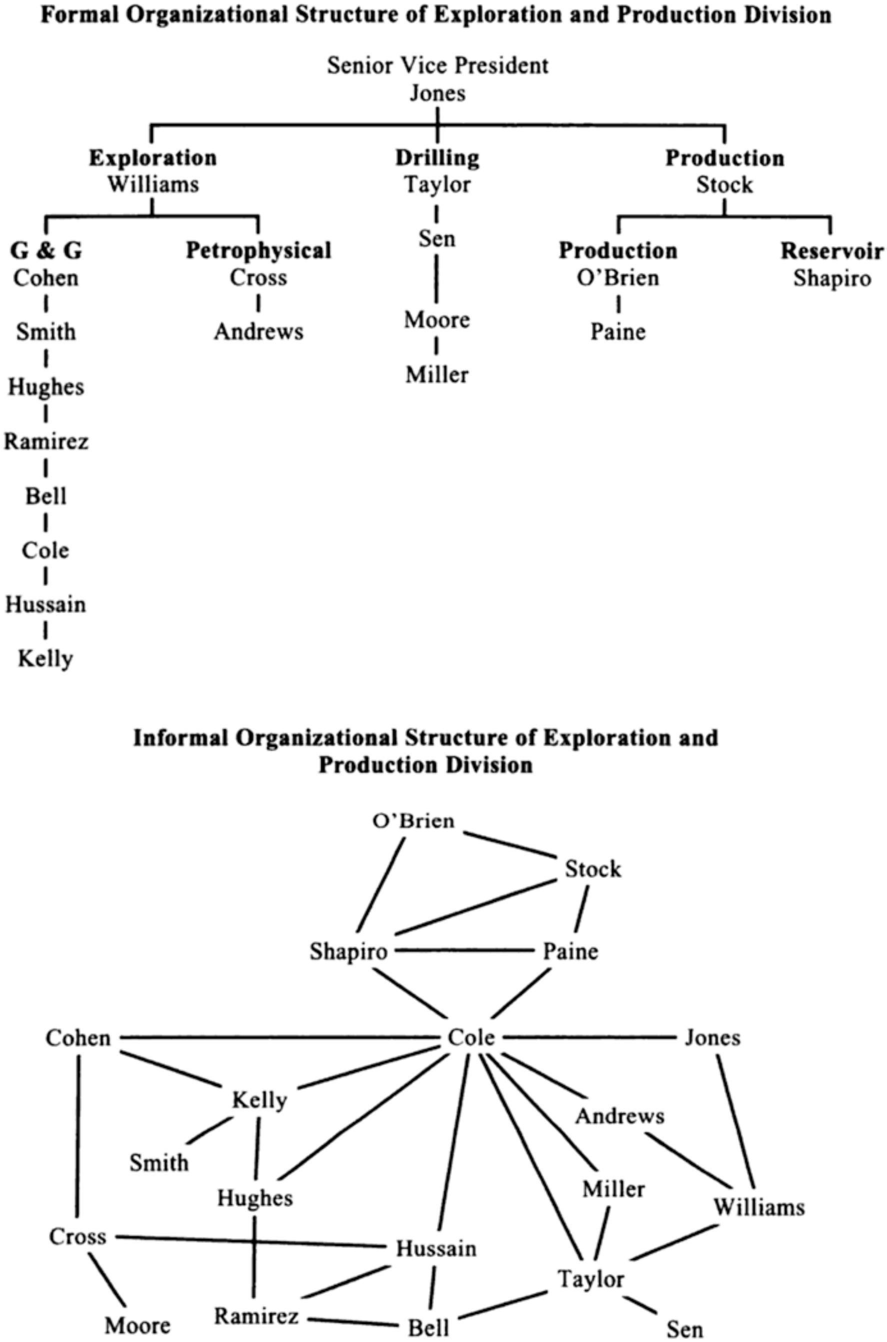

Fig. 4.2 "Formal versus informal structure in a petroleum organization. Note. Names have been disguised at the request of the company" (Reprinted with permission from Cross, Parker, and Sasson (2003), p. 6)

instance, network analysis has been applied to map the context of innovation and cultural change (Parise, 2007). Studies of metacontingencies may therefore be enlightened by concepts of network analysis to discuss changes in organizational culture. Attributed to Peter Drucker, an often-cited phrase is, that "culture eats strategy for breakfast." This implies that even a strongly elaborated strategy may fail to be implemented if it is not in accordance with the organizational culture. Behavior change based on good intentions represents a clear parallel, insofar as the contingencies of reinforcement are not arranged in accordance with the probability of behavioral change. Sandaker (2009) defines a culture as a complex adaptive system with certain observable characteristics selected by the environment. According to Sandaker (2009), a system is relatively stable even though the agents in the system may be changed over time. To implement a strategy or to change a culture we need to understand how the interaction among people or members of the system or organization respectively supports or contrasts the intended changes. The interaction is expressed not only by intentions, but rather by a functional analysis of actual contingencies.

Network Analysis and Theory: The State of the Art

SNA derives from initial developments in structural investigations in the 1930s using the metaphors of the web of social life that permeates efforts to understand social relations (Scott, 2013). SNA evolved from rather nontechnical structural concerns with network structures and has developed mathematical tools used to model relations between different agents (Scott, 2011, 2013). Graphs are constructed using sets of lines to trace the connections that provide the visual representation of a network. The network is then analyzed with mathematical formulations that explain the patterns of interconnections (Scott, 2013). Different network measures, such as clustering and density give important indications of information flow, communication bottlenecks, degree of collaboration, and knowledge distribution in groups (Parise, 2007). Table 4.2 presents concepts deriving from network analysis that may be of interest to BAs researching behavioral systems.

The most common criticism toward SNA is the claim that it provides little in terms of theoretical foundations, and is therefore regarded as purely descriptive (Borgatti, Brass, & Halgin, 2014). Byrne and Callaghan (2014) express the same argument, claiming that tools and representations of network analysis have important potential in generating useful descriptions of connections, but offer little in terms of predictive potential. Therefore, most recent studies have combined SNA with concepts originating from other areas. For instance, sociological concepts such as social capital and communities of practice have been linked to SNA. We argue here that such concepts may bring important descriptive contributions, but have limits in terms of providing a predictive potential. Thus, a framework that is able to bridge network analysis with BA may provide interesting directions

Table 4.2 Central concepts of network analysis to be further explored from a behavior analytic perspective

Concept	Definition
Homophily	"Network researchers frequently investigate selection process such as homophily where actors form a tie because they share one or more individual attributes (sometimes described by the old adage 'birds of a feather flock together')" (Robins, 2015, p. 33).
Preferential Attachment	"Popular actors often tend to become more popular because they have high visibility to begin with. In other words, the rich get richer. So degree distributions are often positively skewed. With a small number of actors with very high degree, and many actors with lower degrees" (Robins, 2015, p. 28).
Resilience	"A system is resilient if it can adapt to internal and external errors by changing its mode of operation, without losing its ability to function. Hence, resilience is dynamical property that requires a shift in the system's core activities" (Barabási, 2016, p. 303).
Density	"Density is the most basic network measure. It is simply the number of ties in the network as a proportion of the total number of possible ties" (Robins, 2015, p. 23)
Clustering	"A common property of social networks is that cliques form, representing circles of friends or acquaintances in which every member knows every other member" (Albert & Barabási, 2002, p. 3).

Transactional Approach, Social Capital, and Communities of Practice: Frameworks of Being

As Scott (2013) points out, initial attempts to understand network data were based upon different forms of what he called a *transactional approach*. This approach is based on the assumption that social ties emerge and disappear due to the rational decisions by agents according to their own self-interest. Although this approach may enlighten some processes of resource exchange, it oversimplifies social relations in many ways. Humans do not always behave rationally and even if and when they do, it is often not in the form of self-interest. For instance, a transactional approach would not be able to explain the formation of different forms of cooperation. In organizational settings, many applications of SNA focus on identifying and nurturing communities of practice that are defined as groups of people who share a craft or profession and learn in processes of interdependence (Cross, Laseter, Parker, & Velasquez, 2006; Wenger, McDermott, & Snyder, 2002). These are densely connected webs of dyadic interactions that often transcend formal organizational charts.

The concept of communities of practice emerged in the early 1990s as a social theory of learning in practical contexts. However, the most commonly used framework to analyze network data is the social capital theory, which was systematically presented by Putnam (2002). According to Lin (2017), the networks that individuals possess are a form of social capital that gives access to different kinds of resources. When the concept is applied at the group level, it refers to factors facilitating a successful flow of resources such as shared norms, trust, and reciprocity (Putnam, 2002). The potential of the network structure in either restricting or facilitating the flow of resources is analyzed in terms of collective social capital.

It would be beyond the scope of this chapter to present a thorough discussion of the strengths and weaknesses of these sociological concepts when applied to analyze network data. However, as we understand such important concepts of SNA, they seem to be based on an assumption of system stability; therefore, they are not theories of adaptation. For instance, it is fair to assume that communities of practice have emergent and adaptive properties in a temporal perspective. However, applications of the concept of communities of practice toward interpreting network data have often missed this temporal dimension.

Network Adaptation and Diffusing: The Importance of Social Reinforcements

The definition of network resilience implies a temporal dimension and a focus on Becoming rather than Being. As defined by Barabási (2016), a resilient system "can adapt to internal and external errors by changing its mode of operation without losing its ability to function. Hence, resilience is a dynamic property that requires a shift in the system's core activities" (p. 330). Resilience is a concept that derives from the study of socio-ecological systems and is commonly regarded as a central property of systems that successfully interact with ever-changing environments. We do not have at this point one particular measure of network resilience, but most studies assume that the adaptive capacity of a system is highly dependent on its capacity to generate and disseminate new knowledge in response to internal failures or environmental changes. Mobus and Kalton (2015) defined resilience as "the capacity for an active system to rebound to normal function after a disturbance or, if need be, to adapt to a modified function should the disturbance prove to be long-lived. […] Capacity for such resilience and complexity go hand in hand" (p. 244). The authors provide pedagogically sound examples of resilience in a manufacturing system, illustrated as the capacity to continue to function after disturbance. For example, when analyzing performance and fitness of athletes, there is a difference between endurance and resilience. While endurance is measured by for how long an athlete can continue an exercise, resilience is measured by the length of the interval between fatigue and recovery.

Building resilience at the system level grants the possibility of establishing new behavior on an intermittent schedule, and, thus, more adaptive. This is different from establishing behavior on a continuous schedule, for example as in systems characterized by robustness. Research on socio-ecological systems describes how networks demonstrate resilience by opening and maintaining channels of communication. For instance, ant colonies exhibit resilience as remaining nodes spontaneously create new social relations when another node dies (Naug, 2009). In this example, network resilience is related to an increase in connectivity in response to an internal failure. We need to define resilience as an interesting variable for behavior; this is something that has already been attempted in the domain of performance management (e.g., Cooper, Liu, & Tarba, 2014).

In respect to system resilience, the work of Centola (2018) on social contagion provides interesting directions and indicates areas in which a behavior analytic approach can give important contributions. His main message is that complex information and behavior do not spread in the same ways as simple information or viruses do. In the case of the diffusion of simple information, the existence of relatively weak ties may be enough. Weak ties refer to connections between nodes that do not possess other common acquaintances. They often perform structural roles as bridges across independent networks. However, the spread of complex information is related to the existence of both wide network bridges and local processes of social reinforcement. Centola's comparison of three organizational network models with varying degrees of connections shows that a highly connected network with little clustering facilitates the spread of simple information. However, it misses the local mechanism of social reinforcement, which stems from the variability that has evolved in the behavior of complex organisms (Skinner, 1953). For example, innovative ideas may emerge and possibly evolve as a measure or product of this mechanism. A network that is highly divided in clusters with few connections among each other may have the local reinforcement processes but miss the wide bridges through which complex information spreads. Thus, an adaptive organization network has a balanced character: it has both clusters with overlapping patterns of spatial interaction, and wide bridges through which new ideas are disseminated. Before widespread integration occurs, local integration needs to take place: "while the viral model suggests that radiating networks of weak ties would lead to successful dissemination, it was instead overlapping patterns of spatial interaction that were the key to widespread adoption" (Centola, 2018, p. 2). Although the importance of social reinforcement is highlighted by Centola, it is not further articulated in network analysis.

There are many implications of network models of social contagion that either resonate with or may be further explored from a behavior analytic perspective. The adoption of new behavior in such models is explained by the position of individuals in their network structures rather than their personal characteristics. The adoption and spread of behavior do not involve rational and conscious choices; rather, they involve normative and informational signals from social reinforcement. Furthermore, interventions deriving from network analysis do not necessarily involve coercion or peer sanctioning. Instead, they involve altering the network structure to facilitate communication and the spread of innovative ideas. As Centola (2018) points out, there is a parallel here with interventions derived from behavioral economics aimed at changing the architecture of individual choices (e.g., Benartzi, Peleg, & Thaler, 2013). However, in network analysis there is a need for a better understanding of the social reinforcement and motivative events not usually considered in SNA: pairing the environmental stimuli serving as behavioral prompts (i.e., the antecedents in a three-term contingency), with social and shared consequences following the target behavior. For example, in the spread of prophylactic measures for HIV included in the study of Centola, measures preceding risk behavior may include information campaigns, education, timely messages and availability of countermeasures, verbal prompts and reminders by family members and health care professionals, and many others. The understanding of the individual's network is key to optimize efficacy of the intervention, retaining precision, and containing costs. Social reinforcement is able to upscale the prophylaxis to an enduring social and cultural practice. It sustains the behavior thanks to the positive consequences delivered by others in the milieu, contingent on safe behavior (e.g., public approval, private praise, community recognition, etc.).

Networks: From Being to Becoming

A sociogram is a "frozen picture" of an interaction system, and it is unable to capture its plasticity unless plotted on a timescale. The sociogram represented in Fig. 4.3 includes the patterns of interaction in one Norwegian state directorate after formal restructuration processes. The figure represents the state of the network in one point in time (Being), but does not account for its future, with respect to prediction or control (Becoming).

A system of interaction "becomes" when selection mechanisms are perpetuated both internally, among members of the network, and externally, in relation to the receiving environment. For these reasons, this distinction is particularly relevant for network theory. *Being* is explicit to the descriptive character of network analysis,

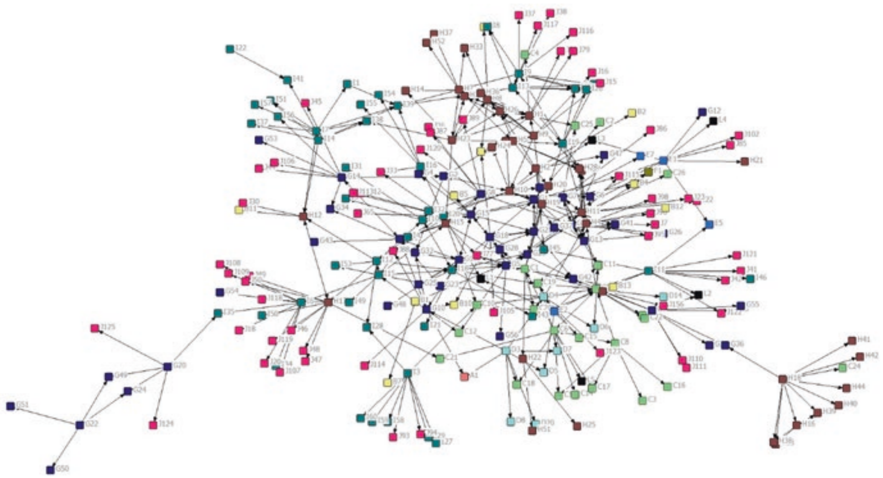

Fig. 4.3 An example of a sociogram depicting interaction channels in one Norwegian public directorate. The lines and arrows represent the direction of communication. The nodes represent people in the system. The colors represent the formal organizational units that they belong to. The letters and numbers are used to code and anonymize participants

whereas *becoming* may be derived and explained by social capital theory (Siisiäinen, 2000).

Prigogine (1980) argued that understanding complex systems demands overcoming what he saw as a dualistic perspective of Being and Becoming. This is particularly challenging for network analysis since its origins in the 1930 were permeated by explicit intention of modeling social systems by identifying physical laws of social gravitation (Scott, 2013). The interest on laws of social gravitation is also embedded by an assumption of system stability as in physical metaphors (Borgatti, Mehra, Brass, & Labianca, 2009). Prior to that, classical writings in social sciences also aimed at founding a new field of social physics, which was aimed at understanding the interaction of atoms in socially structured networks (Borgatti et al., 2009). Table 4.3 summarizes seven main dichotomous characteristics that depict the two disciplines.

The table is not meant to be exhaustive and may represent a categorical oversimplification. Nonetheless, it provides the most relevant characteristics to the contents of this conceptual work, in contrast with one another. We submit to reducing the current distance between the two, starting with their philosophical underpinnings, and finishing with their experimental scope. We use the distinction between Being and Becoming as an illustration for the distinction between structure and process in network analysis. In order to understand changes in network structures, it is important to identify mechanisms of creation and retention of new relationships. Hence, variability represents a dynamic and intrinsic property of both organisms and organizations, and may be depicted and measured through network analysis: in this sense network analysis represents the output of the degree of variation within a specific group or population and represents a requisite for survival.

The mediating role of the environment on the degree of interactions among organizational agents is central, not only according to this approach but in BA altogether. Thus, we suggest a way forward meant to bridge conceptually, and through appropriate tools, the traditionally separate areas of networks and behavioral systems analysis, beyond the original formulation of Brethower (1972). For example, subsequent work includes an integrated approach toward improving employee performance (Abernathy, 2008), conducting performance improvement interventions

Table 4.3 Complimentary characteristics of classification of main characteristics of network theory and behavior analysis

	Network theory	Behavior analysis
Philosophical underpinnings	Being	Becoming
Properties	Robustness	Resilience
Level of analysis	Topography	Function
Survival mechanisms	Exploitation	Exploration
Analytical focus	Structure	Process
Conceptual dimension	Space	Time
Space	Contiguity	Ubiquity
Measure of diversity	Homogeneity, heterogeinity	Variation, variability

in behavioral systems analysis (Diener, McGee, & Miguel, 2009), and on the role of communication networks (Houmanfar et al., 2009).

Whereas networks are traditionally addressed as instances of Being, the selectionist perspective we submit to endorses the evolutionary aspect of Becoming. From a complex system perspective, distinguishing between theories of Being and Becoming opens many questions. For instance, we may look for the network characteristics of systems that have the capacity to change and adapt over time. Adaptation in human networks have emergent properties that cannot be explained by single individual actions or mental processes. Furthermore, it is always important to understand that networks do not have intentions per se. Networks evolve, for good or bad, due to the reinforcing power of (re-)distribution of social and material attractiveness, which is not explained by mental processes, but merely by strengthening (reinforcing) or weakening (extinguishing) loops (Krispin, 2017).

Networks Mechanism of Becoming: Homophily and Preferential Attachment

There are at least two mechanisms of network evolution that can be further explored from a behavior analytic perspective: homophily and preferential attachment. From a behavior analytic perspective, homophily and preferential attachment can be seen as behaviors in themselves, but also as dynamics of consolidation of structural contingencies that can either facilitate or restrain cooperation and the spread of new forms of behavior in social groups. Homophily is defined by Borgatti, Everett, and Johnson (2018) as the tendency of people to establish connections with other individuals with whom they identify similar socially significant attributes. This tendency may be the result of a learning history shaped by the superior availability of reinforcement from peers, rather than more socially or psychologically distant people. In network analytic terms, homophily refers to perceived shared attributes that may facilitate interaction among individuals. If the allocation of reinforcers is distributed unevenly, or if they are distributed under competing and concurrent schedules of reinforcement, the agent must choose with whom it wants to establish or strengthen relations.

The concept of metacontingency (Glenn, 1988, 2004; Glenn et al., 2016; Glenn & Malott, 2004; Houmanfar & Rodrigues, 2006) might be useful toward understanding the retention and maintenance of a cultural practice and cooperation. A metacontingency depicts a relationship between the product of interdependent social behavior (i.e., a culturant) and its environment. Operationally speaking, the behavior of one individual sets the occasion for the behavior of another individual, and "The relations are interlocking because one element of the behavioral contingency of one individual (i.e., antecedent, behavior, or consequence) or its product also constitutes an element of the behavioral contingency or product of another individual" (Malott, 2016, p. 107). This pattern is repeated for as many times as there are individuals contributing to the creation of the group's product, be it an artifact, a service, or a cultural trait. We may say that the metacontingency is a behavioral approach to understanding complex systems. A system always has a function, processes maintaining the function, and a structure. It may be intentionally designed as in man-made systems like businesses or organizations, or the system evolves as a result of both self-organization and interaction with its environment. The environment in the metacontingency is the receiving system. The function parallels the aggregate product. The processes maintaining the function are the interlocking behavioral contingencies. However, the concept of metacontingency does not originally include a parallel to structure. Sandaker et al. (2019) proposed that nested IBCs (nIBSs) be added to the concept of metacontingencies. This indicates that the way in which two or more IBCs are interdependent influences the overall function or the aggregate product of the metacontingency. The tools of network analysis are particularly useful when these interdependencies are analyzed and described. Nevertheless, a functional analysis of both the system's interaction with the environment and the internal practices is necessary to make predictions and possibly influence the coevolving structures, processes, and function.

Networking with someone similar or related to oneself assumes reinforcing value to the extent that it increases the likelihood to engage in more of that behavior. Thus, homophily may be interpreted as a signaled availability of reinforcement due to relational similarities. The "similar" other serves as a discriminative stimulus leading to more interaction and IBCs.

Preferential attachment is a mechanism of social network growth that indicates that new nodes are more likely to connect with old nodes that are highly connected, rather than old nodes that have fewer links (Albert & Barabási, 2002). In other words, the more connected a node is, the more likely it is to receive new connections. Preferential attachment leads to the emergence of scale-free networks characterized by an uneven distribution of connections. This is the case of most, if not all social groups. Networking with someone with more connections is more attractive than networking with someone with fewer connections, due to a higher expected utility in the consequences of the interaction.

Networks may be interpreted as the product of past choice behavior and may evolve over time as an effort of maximizing utility in social transactions. The term *utility* may refer both to the agent's satisfaction (i.e., utilitarianism), and a functional aspect that is consistent with the neoclassical economics of the consumer's choice and preference. The structure of a network may provide cues as to whether and with whom to engage within the system, possibly as a function of (a) the social reinforcement that may be derived from the interaction, and (b) the interdependency within the same organization or social group. For example, according to this perspective, preferential attachment is similar to functional analysis in BA, inasmuch as it represents a structural perspective insofar as freezing the network reveals its underlying structure. However, network structures may facilitate or hinder change at the systems level, which calls for an evolutionary perspective to be interpreted. Thus, this perspective is consistent with a view of Becoming, and may be visually illustrated by an experiment's cumulative record.

BA may help better inform our understanding of preferential attachment by quantifying the relationship between current and potential connections, according to the matching law. According to Herrnstein (1961, 1990), the matching law represents the relationship between relative rate of responses and reinforcement in concurrent schedules. Whereas the basic principles were originally tested in a laboratory setting with pigeons, which displayed linear-like ratios, the matching law needed to be generalized (Baum, 1974) and adjusted to a context of social fitness: the more connections, the higher probability of survival among others. These adjustments include the consideration for rules and verbal behavior. For example, the higher likelihood of reinforcement given the same relative rate of behavior from a multi-connected node as compared to a node with fewer connections may be negatively mediated by prohibitions to interact with a certain part of the network (be it teacher, spiritual community, or in-laws).

However, some limitations of the predictive and descriptive value of the matching law need be acknowledged. In a recent experiment, three predictions concerning the rate of concurrent behavioral responding relative to reinforcement were falsified and comprised further evidence for supporting the alternatively proposed evolutionary theory of behavior dynamics (McDowell, Calvin, Hackett, & Klapes, 2017). Nevertheless, the matching law still remains a reasonable approximation in many applied settings.

The concepts of homophily and preferential attachment play an important role in explaining both the formation of network clusters and the consolidation of bridges among different clusters in a network. They are important in explaining the emergence of spaces of social reinforcement and channels through which behavioral changes may spread. As demonstrated by Centola (2018), clusters are important in providing the local spaces of social reinforcement. This resonates with the classic study by Rogers (2003) that recognized the stronger influence potential of closer relationships as an antecedent for the adoption of new technologies than that of weak network ties. However, it may be argued whether the term *social* refers to being delivered from more than one individual in the network or whether the effects of reinforcement reaches beyond the single individual.

Operants comprise classes of learned responses and reinforcement increases the likelihood that the behavior on which the consequence is contingent increases in frequency. Similarly, *culturants* (Hunter, 2012; see also Glenn et al., 2016) refer to the unit including both IBCs and their aggregate product; social reinforcement increases the likelihood of the agents' interdependency, although a metacontingency is programmed on the selection of the aggregate product of this interdependency.

Magnitude of contingencies of reinforcement, indicating the intensity of behavior in relation to its environment, may help explain preferential attachment and frequency: the more connections, the more frequent is the distribution of reinforcement. This is a display of a lawfulness relation typical of BA. The architecture and the communication of the systems, as well as the relationship with the environment, are fundamental attributes of network theory. These attributes are said to be adaptive, insofar as they interact with the evolutionary logic that seems to be missing in the domain of network analysis.

Social Contagion: Spread of Behavior in Networks

The central idea developed throughout this chapter is that there is an important space for collaboration between SNA and BA. In the remaining part of this chapter, we provide two examples representing a case of emergent changes in the form of the spread of behavior in two different social groups.

The first example is a seminal study by Moreno (1978) about the epidemic of runaways at the Hudson School for Girls in New York. This example comprises one of the first graphical representations of social networks. The school was home for girls between 12 and 16 years old, who were convicted for various forms of juvenile delinquency. In 1932, it recorded 14 cases of student runaways in only 2 weeks' time. Moreno's study demonstrated that this behavior could not be explained by personal attributes or motivations of the girls who ran away from the school but by their positions in their social network. The early SNA conducted by Moreno and Jennings identified channels of influence and information sharing among the girls. Figure 4.4 shows interrelation among the 14 runaway girls identified by initials. The direct and indirect lines show one-way and mutual lines of attraction, respectively.

According to the unit of analysis of social behavior, this example represents a form of social contagion through transmission of a behavioral repertoire; there are not enough interrelated elements to rightfully interpret this scenario as a spreading cultural practice. In fact, even though old members of this organization are eventually replaced by new ones, the example chosen cannot be interpreted detached from its unique point in time and space. This underlines how the structural representation of dynamic processes may hinder more comprehensive analyses. Social pressure and imitation may therefore reinforce the newly established behavior of escaping, as well as facilitating its transmission through nodes in the network of relations. The mutual lines of attraction may be interpreted as rule-governed behavior, modeling, or a form of relational responding, given the girls never experienced the reinforcer before they emitted the behavior. Namely, the escaping behavior of one girl set the occasion for replicating the behavior of another girl, thus serving as a discriminative stimulus, inasmuch as the sociogram was concerned.

Sociometry is "a technique for eliciting and graphically representing individuals' subjective feelings toward one another" (Borgatti et al., 2009, p. 892). Although it stems from different historical and conceptual roots than behavior analysis does, Moreno's (1978) network of runaways presents a functional analysis of the contingencies of reinforcement sustaining escaping behavior, or their verbal description, based on the girls' location in the social network. Tentatively overlooking the claim that the girls may not have been as *conscious* of their behavior as they were about their affection toward one another, the representation of social structures are compatible with the molar view of contingency (e.g., Skinner, 1938), although it is

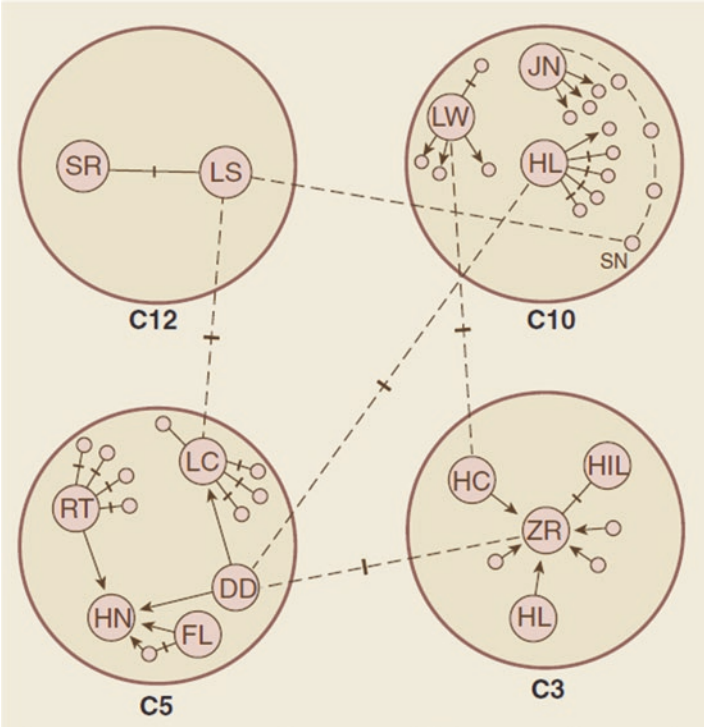

Fig. 4.4 Runaway chain at Hudson School for girls, depicting the force of the structure of relationships among individuals. The larger circles represent the cottages in which the girls lived. The smaller circles contain the initials of each girl. The direct lines represent one-way attraction. The indirect lines show mutual lines of attraction. Reprinted with permission from Borgatti et al. (2009, p. 892) and originally published by Moreno (1978, p. 422). License number 4762990250426, American Association for the Advancement of Science

difficult to empirically separate from the molecular view (Lattal, 1995). This is similar to saying that the social structure of Hudson School for girls' network set the occasion for runaway behavior, but did not cause or elicit it. This structural representation lacks a time frame, and it is not possible to understand who originated the behavioral chain and how it spread from the figure itself. Conversely, according to the unit of analysis of individual contingencies of reinforcement, the focus is on the explanation and description of functional relationships and their properties in the contingency. We submit to a synthesis of both approaches that is able to capture both the Being and the Becoming of the establishment and spread of escaping behavior among the girls. The network analysis could lend itself to prediction of the likelihood of different scenarios of future escape behavior.

Much of the work in network analysis focuses on identifying characteristics of social networks that make them suited for the spread of healthy behavior (Centola, 2018). In this respect, the second chosen example illustrates a contraceptive policy in rural areas in Korea in the 1960s and shows how local webs of interaction may provide channels for behavior change. Most policies aiming at promoting family planning in the same period focused on mass media awareness campaigns focusing on personal accountability. The Korean policy followed a different approach by focusing on the diffusion of the use contraceptive methods through social networks (Kohler, 1997). The government provided information about contraceptive methods to local mothers' clubs and surveyed their implementation in 25 rural areas. The clubs became spaces of peer-to-peer social diffusion successfully increasing the number of adopters (Rogers & Kincaid, 1981). Different contraceptive methods were preferred in different villages, probably indicating the behavior of early adopters. This policy reached better results than other policies in the same historical period by focusing on local social networks as channels for the diffusion of a new social norm.

This example illustrates how cultural practices spread, focusing on the structure as a unit of analysis. In other words, the structure of Being anticipated the Becoming represented by the spread of the contraceptive policy submitted by the government. The study of social norms encompasses the tradition of BA per se and it has been recently addressed to an extensive degree by behavioral insights, among others (e.g., Sunstein, Reisch, & Rauber, 2017). Behavioral insights are concerned with the simplification of decision-making in a given and *better* direction at the policymaking level. In the example above, social norms provide the positive consequence from a meaningful and trustworthy source to engage in the appropriate behavior. Whereas the function of establishing the contraceptive practice needs no further clarification, it should be noted that no interdependency of behavior is strictly necessary for its spread within each given rural area. Each community served as an area of local adaptation.

The relationship resembles a macrocontingency, which identifies a result of the addition of multiple independent behaviors, rather than the product of IBCs depicting a metacontingency. Although the level of complexity may appear higher than illustrated above and the difference may not be immediately evident, representing the differences in the structures of a macrocontingency and a metacontingency may contribute to achieving better clarity. Systemic connections may be found between the government programs setting up informational arrangements and how they are received by each community. If contraceptive choices tended to be different depending on how the communities responded to their exposure (e.g., barrier methods in community A and fertility awareness in community B), it is likely that apparently separate "contraceptive cultures" would emerge in different communities. Furthermore, it may have been possible to upscale these cultures to the village- and region level, thus, reaching (effectively) beyond the contractive choices of each individual within a community. Hence, it is appropriate to invoke the metacontingency concept, insofar as the cultural practice is socially situated as a product of recurrent choice and interaction, and selected, for it emerges and evolves within the encompassing social network. However appropriate for the interpretation of cultural practices, the metacontingnecy tool needs not necessarily be involved nor called for the interpretation of all group and social phenomena. It is worthwhile emphasizing that everything that is not a metacontingency does not necessarily comprise a macrocontingency. Whenever the latter is adopted as the unit of analysis, selection operates on the unit of behavioral contingencies of independent agents who need not necessarily interact (i.e., their behavior is regarded as a *sum*, rather than a *product*).[1]

In the example illustrated above, the main differences may concern the absence of reciprocal relations and a lower level of (interdependent) complexity between community and environment; yet, transmission of the cultural practice in the network and beyond is possible. For behavior analysts, this is an interesting case of behavior transmission that is different from most cases of selection of cultural practices. Although the government diffused information regarding contraception in local communities, there was not any significant process of adaptation to environmental changes that explained the adoption of new behavior but a process of transmission taking place in the context of local interactions in each village.

The two examples discussed here represent classical cases of social contagion. In both cases, mechanisms of homophily and preferential attachment contributed to form network structures that facilitated the spread of complex information and behavior change. In more recent years, SNA has become a broad field of study covering a wide array of topics. In organizational settings, SNA has been applied to map the web of interactions thereby informing practices related to organizational change (Cross, Parise, & Weiss, 2007), knowledge management (Parise, 2007) and employee turnover (Parise, Cross, & Davenport, 2006). Various social phenomena beyond organizational settings are commonly addressed from a network perspective. Some examples include social determinants of depression (Rosenquist, Fowler, & Christakis, 2011), corruption behavior (Ribeiro, Alves, Martins, Lenzi, & Perc, 2018), and the online spread of fake news (Vosoughi, Roy, & Aral, 2018).

The reader may relate to additional and more recent examples, ranging from organizational studies to social phenomena and cultural anthropology. The starting point consists of listing the three main characteristics of a system, in terms of function, process, and structure. The first two are the elective result of a contingency analysis: that is, through environmental contingencies and schedules of reinforcement. In contrast, structures can be inquired through a network analysis. An analysis of cultural evolution and lineages informs the extension from individual to group, and from present to future occurrences.

[1] *Macrobehavior*, as Glenn et al. (2016) used the term, is different from macrocontingency insofar as it results from large-scale individual behavioral change that is the aggregate product and not the sum of behaviors. This may be tangible as in the case of donation to charity or intangible as for political or other preferences. Although it has not been specified what is meant by *large scale*, the main point is that macrobehavior has some societal or cultural consequences.

Conclusion

BA and a complex systems approach share an evolutionary perspective on behavior. While a network, as the architecture of a complex system, gives information of interaction at a given moment in time, BA is able to explain why patterns of behavior emerge and evolve.

Concepts in network theory are generic in the sense that they may be applied whether the context is an ecosystem, dissemination of cultural practices, or spread of diseases. By better understanding system properties like clustering, preferential attachment, and homophily, the joint scientific enterprise between complexity theory, BA, and other behavioral sciences at large can contribute to the development of tools to solve multilevel societal challenges.

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