Networks

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A network is defined as a set of entities connected by one or more relations. A social network refers to a set of entities and relations in a social system. A communication network is one type of social network. The entities in social networks are often referred to as *actors*, and can be individuals or aggregates of individuals such as teams, organizations, or even entire nations. Actors can also be nonhuman entities with which human actors may engage, such as movies, articles, concepts, tasks, or websites. Historically, the relations in a communication network were *messages* – symbolic forms that convey meaning such as images, data, affect, information, and knowledge. Messages are created by, and transmitted among, one or more actors in a network. Today, communication scholars also examine relations that represent the extent to which actors share affect, interpretations, and cognitions. The intellectual premise of studying networks is that the relationships in which we are embedded emerge from, and contribute to, human behavior and attitudes.

Intellectual history of social network scholarship

Graph theory

The study of networks dates back to the early 16th-century city of Königsberg, Prussia (present day Kaliningrad, Russia) and the Swiss mathematician Leonhard Euler. The city of Königsberg was situated on both sides of a river and comprised two islands connected to each other and the mainland by seven bridges. A popular brainteaser proposed by the locals was to offer tourists a large prize if they could traverse all seven bridges while only crossing each bridge once. Euler, a mathematician, wondered if he could determine a priori if this traversal was even possible. In order to address this question, Euler simplified the map of Königsberg by substituting each landmass with a single node (or vertex as they are often referred to in graph theory) and each bridge with an edge.

Euler determined that traversal was only possible if each node had an even number of edges connected to it. That is, traversal across all bridges exactly once was only possible if each landmass had two, four, or any even number of bridges that connected it to other landmasses. This was because in order to complete the task a person who entered a landmass via one bridge needed to exit the landmass via a second bridge. Clearly this was not the case for any of the landmasses in Königsberg. In solving this problem, Leonhard Euler had derived the proof for the first mathematical theorem of a new subdiscipline of

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mathematics called graph theory (Euler, 1736). It took two centuries for these advances to be applied to the study of social networks.

Sociometry

In the 1930s, Jacob Moreno, an Austrian American psychiatrist based in New York, developed the first graphic representation of social networks which he called sociograms. In a *sociogram*, nodes represent individuals and the relationships between them are represented by edges. Moreno highlighted the importance of one's position in a network in his study of runaways at the Hudson School for Girls in upstate New York. Moreno and his assistant Helen Jennings used what he called sociometry, the study of sociograms, to map the networks of 500 girls. Their findings indicated that the runaways from the school were isolated in the social network (Moreno, 1934).

The birth of communication networks

Moreno was interested in studying networks as they occurred naturally, but Alex Bavelas, founder of the Group Networks Laboratory at the Massachusetts Institute of Technology, was one of the first network researchers interested in designing and engineering better, more productive networks. He focused on studying the effectiveness of different patterns of communication in helping small groups of people solve simple tasks. Bavelas (1950) conducted an experiment in which he organized five-person groups into four different configurations. Individuals (denoted by the letters a, b, c, d, and e) were only allowed to communicate with specific other individuals (denoted by a solid line; see Figure 1). He gave the group a simple problem to solve, and gave each individual some of the information required to solve the problem, and tracked how quickly the task was completed, whether or not the task was completed correctly, and the extent to which participants enjoyed the experience. Bavelas discovered that the star configuration, illustrating high localized centrality with an obvious leader, was the most conducive to accomplishing simple tasks in a quick and accurate manner. Morale and satisfaction, however, were found to be the highest in the pentagon configuration,

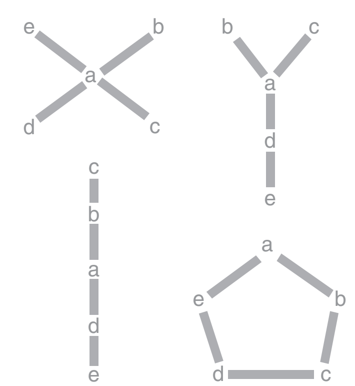

Figure 1 Sample network structure
(Bavelas, 1950, modified with permission from Taylor & Francis)

where there was low centralization and no easily discernible leader. Bavelas's work highlights how different network structures can influence the attainment of different goals, and was among the first that specifically examined communication networks.

Small world networks and the birth of social network research

Bavelas was interested in networks among small bounded groups; but, in 1967, American social psychologist Stanley Milgram devised an experiment to study the patterns of direct and indirect communication networks among seemingly disparate individuals in large unbounded contexts. In the experiment, Milgram (1967) sent packages out to 160 people in Omaha, Nebraska. Participants were asked to forward their packages to Jeffrey Travers, a stockbroker who worked in Boston, Massachusetts, with the primary rule being that they could only mail their package to someone they knew personally who might personally know Travers or someone who might know someone who might know Travers, and so on. This required participants to rely on their network in order to forward their packages to people whom they believed could get the packages to their ultimate destination. Only 44 out of the 160 packages were delivered to Travers, but curiously, those that made it did so in 5.6 steps on average. This experiment was replicated in different contexts and the average number of steps connecting a person to the targeted stranger was always around 6. This led to the concept of *six degrees of separation*, where every person on earth is postulated to be connected to every other person via no more than six steps. Yet another noteworthy discovery in Milgram's small world experiment was that almost half of the Nebraska packages that reached Travers were finally handed off to him by only three people in his network, including a clothing merchant named Mr. Jacobs. Jacobs served as a point of mediation between Travers and the rest of the world – a role that has come to be known in the network literature as a "broker."

At the same time as Milgram was conducting his small world experiments, Harrison White, a professor of sociology at Harvard University, and J. Clyde Mitchell, a social anthropologist at the University of Manchester, were leading a revolution in the way people conceptualized societies. White and Mitchell suggested viewing societies as networks, focusing on the relationships among people instead of their individual attributes and attitudes. White would go on to advise some of the most well-known researchers in the field of networks, including Mark Granovetter, Ron Breiger, and Kathleen Carley. The Mitchell Center for Social Network Analysis at the University of Manchester commemorates the intellectual legacy of Clyde Mitchell.

Strength of weak ties and the rise of communication networks

In 1970, Mark Granovetter, an American sociologist and student of Harrison White, was finishing up his PhD at Harvard University and looking to enter the job market. Knowing that he would be searching for work in a struggling economy, Granovetter became interested in addressing the issue of how people find jobs. For his doctoral dissertation, Granovetter studied the egocentric networks of several hundred workers in Newton, Massachusetts. He discovered that a large number of the workers found their jobs through personal contacts (rather than job ads), and that these contacts were not close friends, but mere acquaintances. These results highlighted a phenomenon that Granovetter coined as the *strength of weak ties*, which refers to the strength of casual "weak" interpersonal relationships in providing rich and novel informational support. The resulting article, aptly titled "The strength of weak ties" (Granovetter, 1973), has become one of the most cited social scientific articles to date.

While scholars such as Granovetter and others had been studying communication networks, the first bona fide network research in the field of communication began in the late 1960s at Michigan State University (for a detailed review, see Susskind et al., 2005). In 1968, Donald Schwartz wrote his dissertation on the organizational networks of faculty and administrators at MSU's College of Education, under the primary guidance of Eugene Jacobson, an organizational behavior scholar in psychology. Schwartz would soon go on to join the communication department at MSU. Around the same time, Everett Rogers, a rural sociologist by training who was already quite well known for his theory on the diffusion of innovations, also joined the communication faculty at MSU and went on to become one of the most influential network researchers in the field of communication. Along with one of his students, Larry Kincaid, Rogers wrote the first book on communication network analysis in 1981 (Rogers & Kincaid, 1981).

Schwartz, Rogers, and Vincent Farace, a professor of organizational communication, are largely credited with introducing networks to the field of organizational communication. Farace and one of his graduate students, Donald McDonald, published the first notable journal article on communication network analysis in 1974. In addition to McDonald, Farace mentored a large number of graduate students. One of those students, Peter Monge, has been the doyen of scholarship on organizational communication networks. Additionally, George Barnett and James Danowski were among the pioneers of studying electronic communication networks.

In 1970, an MSU undergraduate named Bill Richards, a roommate of George Barnett, would begin work on what would become the first network analytic software. After observing the painstaking efforts of Farace and his graduate students in mapping network matrices on large sheets of graph paper, Richards resolved to digitize the process. Under the guidance of Jacobson, Richards devised a procedure that built upon Robert S. Weiss's original network algorithm (Weiss & Jacobson, 1955). Richards continued to refine his software based on additional guidance from Ron Rice, another of Rogers's PhD advisees. In 1975, Richards began publicly distributing his network analytics software, called Negopy, short for "negative entropy" (Richards & Rice, 1981).

In 1977, Barry Wellman, a Canadian American sociologist, formed the first professional organization for the study of social networks, known as the International Network for Social Network Analysis (INSNA). Notable founding members included Everett Rogers, Harrison White, Mark Granovetter, Paul Holland, and Samuel Leinhardt. In 1979 they founded the journal *Social Networks* which continues to be a prestigious outlet for network research. In 1981 INSNA would hold its first official academic conference in Tampa, Florida, appropriately titled "Sunbelt." The conference has grown dramatically in size from around 50 attendees in the early 1980s to around 1000 in 2015.

In summary, communication scholars have played a pivotal role in the study of networks. Rogers was one of the founding members of the premier scholarly association.

Richards developed the first network analysis software and went on to become the President of INSNA until he passed away. George Barnett succeeded Richards as President of INSNA. More recently, Tom Valente, an advisee of Rogers who is currently on the faculty at the University of Southern California, was honored by INSNA with its 2015 Simmel Award for outstanding scholarship.

Social capital and UCINET

Networks as an academic area of inquiry continued gaining traction in the 1980s as James Coleman, an American sociologist at the University of Chicago, began developing the concept of social capital, which is used extensively in the study of communication networks. Ronald Burt, one of Coleman's former students turned colleague, was another prominent researcher of social capital who became well known for his concept of structural holes. Robert Putnam, a political scientist at Harvard University, further popularized social capital with his book *Bowling Alone*, in which he argued that Americans were losing social capital as fewer and fewer people connected socially with each other. Meanwhile, Kathleen Carley, who was trained by White at Harvard, was extending traditional conceptualizations of social networks in two distinct but influential directions. Starting with her dissertation research, Carley demonstrated the power of networks to model the construction of consensus and meaning that laid the foundation for semantic networks and text analytics. Second, Carley was at the forefront of the movement to use computational modeling to simulate dynamics both in the underlying structure of networks and in the flows of information on those networks.

Around the same time, an avid team of network researchers at the University of California, Irvine, led by Linton Freeman, were pushing the envelope in terms of methodological advances as well as developing new software that implemented these methodologies. Freeman and his graduate student, Steve Borgatti, programmed several versions of UCINET (named after their institution, UC Irvine) throughout the 1980s, which would go on to become one of the most widely used pieces of software for social network analysis. Martin Everett, a mathematician from the United Kingdom, later joined Freeman and Borgatti to develop subsequent versions of UCINET. UC Irvine also contributed to advances in social network analysis methodologies by researchers such as Kimball Romney, a colleague of Freeman, and his graduate student Katherine Faust. Faust would go on to coauthor the definitive bible for social network analysts titled *Social Network Analysis: Methods and Applications* with Stanley Wasserman (Wasserman & Faust, 1994). Another prominent UC Irvine alumnus, David Krackhardt, pioneered the concept of cognitive social structures and helped evangelize the theory and practice of network perspectives in organizations.

The World Wide Web and the popularization of networks

During the 1990s and early 2000s, networks metaphors and imagery became part of the mainstream consciousness. This was due, in part, to the creation of the ARPANET back in 1969, a system that the US Department of Defense's Advanced Research Projects

Agency (ARPA) commissioned BBN Technologies to build in order to connect geographically separated computers to a single network. This would allow a greater number of researchers access to more powerful workstations. The original network consisted of only four nodes, at UCLA, UC Santa Barbara, Stanford University, and the University of Utah. Over the next 20 years, ARPANET would morph into the Internet.

The development of the Internet in the early 1990s also enabled Sir Tim Berners-Lee and colleagues to develop the World Wide Web, a globally connected information system that offers individuals the ability to navigate a network of distributed linked digital content. The rise of Google as the premier search engine was in large part based on its use of a page ranking algorithm that ordered search results using a metric that was already well known in the social network research community. Basically, it ranked a webpage higher if it was linked from other pages that were ranked highly. Those pages were ranked highly because they were linked from other pages that were ranked highly. This seemingly circular definition of highly ranked websites relies on a mathematical formulation (eigenvector centrality) that was already well established in the social network research community. The WWW also paved the way for the proliferation of "social networking sites" such as MySpace, Facebook, LinkedIn, and Twitter, further embedding network imagery in the minds of the public.

The 21st-century (re)birth of network science

The emergence of large-scale online email and social networking sites captured the imagination of physicists, mathematicians, biologists, and computer scientists who saw an analogy to the mathematical and computational models they used to investigate a wide range of large-scale physical and biological systems such as electrical power networks, neural networks in living beings, transportation networks, and particle condensation. This interest resulted in the popularization and elaboration of two very specific thrusts: the small world phenomenon and the scale-free networks.

The first thrust, the *small world phenomenon*, revisited Milgram's experiments in the late 1960s. Duncan Watts and his thesis adviser at Cornell, Steve Strogatz, found that "small world" networks exhibited two unique properties. First, actors in small world networks were far more likely to have most of their connections with others who were also connected to each other than one would expect in a purely random network. Second, the average degrees of separation between actors in small world networks would be only slightly different (typically, less) than the degrees of separation in a random network. Watts and Strogatz found that many social networks exhibited small world properties. Prompted by the popularity of the website Oracle of Bacon (a site that shows how Kevin Bacon is directly or indirectly connected to every other actor and actress in Hollywood via co-starring ties), Watts and Strogatz analyzed data from the Internet Movie Database (IMDB). They found that the co-stardom network of movie actors, where links between actors were defined by movies in which they co-appeared, was a small world network. Co-stars of actors in one movie were much more likely to co-star in other movies than one would expect in a random actor network. Furthermore, the degrees of separation between any two movie actors in the co-starring network were almost the same as one would expect in a random network. Contrary to popular belief at the time, Kevin Bacon was not the "center of the Hollywood universe." A recent study shows how Kevin Bacon was not even among the top 100 actors with the shortest average co-starring connection with all other actors. The top honor went to Eric Roberts who was connected to 25% of the 1.91 million actors in the IMDB by two or fewer degrees of separation. Watts and colleagues showed that indeed many other networks, including the power grid network in the United States and the neural network of a roundworm, exhibited small world properties.

The second thrust of network science, *scale-free networks*, built on a well-known social phenomenon first described as the *Pareto principle* (known colloquially as the 80–20 rule). In 1896, Italian economist Vilfredo Pareto showed that 80% of land in Italy was owned by 20% of the population. While the actual percentages vary, the proverbial 80–20 phenomenon has been shown in a wide range of contexts such as linguistics, where 20% of the words in any given language are used 80% of the time, and literature, where 20% of published books account for 80% of all purchases. In 1999, Albert-László Barabási, a physicist at Notre Dame, and his graduate student Réka Albert found that this principle also applied to a wide range of networks. In the parlance of the 80–20 rule, 20% of the actors in a network maintained 80% of the network's connections. That is, a few nodes in the network were hubs or "stars" with a very large number of connections, while the rest of the actors in a network had many fewer network connections. They called networks that exhibited this property "scale-free" networks to underscore the notion that the proportion of nodes with a specified number of ties was independent of the size (or scale) of the network. As was the case for small world networks, Barabási and his colleagues found that there was a wide range of networks that demonstrated scale-free properties: the network of Internet routers, the pages on the WWW, the co-stardom network from IMDB, and the power distribution grid. The widespread prevalence of small world and scale-free networks was popularized by Duncan Watts in a 2003 bestselling book titled *Six Degrees: The Science of a Connected Age* and in a 2002 bestselling book by Barabási titled *Linked: The New Science of Networks*.

Research on small world and scale-free networks at the turn of the 21st century was the harbinger of the (re)birth of scholarship on networks, which came to be called *network science*. The INSNA community of social network researchers, who were primarily from the social sciences with a handful from education and mathematics, were now joined in their intellectual quest by a large and growing community of intellectual luminaries from applied mathematics, computer science, economics, information sciences, information technology, medicine, and physics, to name a few. The broader interest of this larger community led to the convening of the 1st International Workshop and Conference on Network Science (NetSci) in 2006, and was organized by several scholars including Noshir Contractor from organizational communication. The NetSci conference has grown dramatically in the past decade to include a broader community of researchers whose interests go beyond social networks to include contexts such as food webs, protein networks, regulatory networks, metabolic networks, and critical infrastructure networks. Although the number of topics has increased, the community maintains a common interest and commitment to studying network methods. In order to help coalesce this larger community, NetSci members founded the Network Science Society in 2014.

Related to these developments, the influential National Research Council convened a workshop in 2003 and a study group report in 2005, with the goal of examining the potential of social network analysis and modeling including applications for the military. These led to the funding of a 10 year, approximately $125 million Network Science Collaborative Technology Alliance – a partnership of around 30 universities, industry partners, and army research facilities aimed at conducting fundamental research on the critical scientific and technical challenges that emerge from the close interdependence of several genres of networks such as social/cognitive, information, and communications networks. In addition to research, there has been a substantial investment by the National Science Foundation in building an educational infrastructure for network science via major interdisciplinary graduate training programs funded at Carnegie Mellon University, Cornell University, and most recently at the University of California Santa Barbara. In addition, the first interdisciplinary PhD programs in network science at Northeastern University in Boston and Central European University in Budapest is now up and running. The intellectual output of all these activities is well captured in Figure 2, which plots the dramatic growth in publications about social networks, especially since the advent of the 21st century.

Dimensions of networks

With this intellectual history as backdrop, the next sections organize current knowledge about networks in general, and communication networks in particular, along two dimensions: description and explanation. Describing networks is a larger and more complex enterprise than it might appear at first glance and has dominated network scholarship. However, there has been a concerted effort to move beyond description to explanation, especially in the past two decades. The first of the sections on explaining networks reviews a broad spectrum of theoretical mechanisms used to explain the emergence of networks. The second briefly discusses recent methodological advances that are specifically well suited to provide inferential statistical tests of network explanations.

Describing networks

Networks are visually represented by *graphs*, in which each actor is a single *node*. A network that includes two or more types of actors is called a *multimodal network*. A multimodal network that includes individuals and the encyclopedia entries they read would be a *bipartite network*, as it contains two types of nodes. In the same vein, a multimodal network that contains three types of nodes, such as a network of authors, the encyclopedia entries they write, and the keywords they associate with their entries, would be a *tripartite network*. The lines or edges that connect the nodes to each other

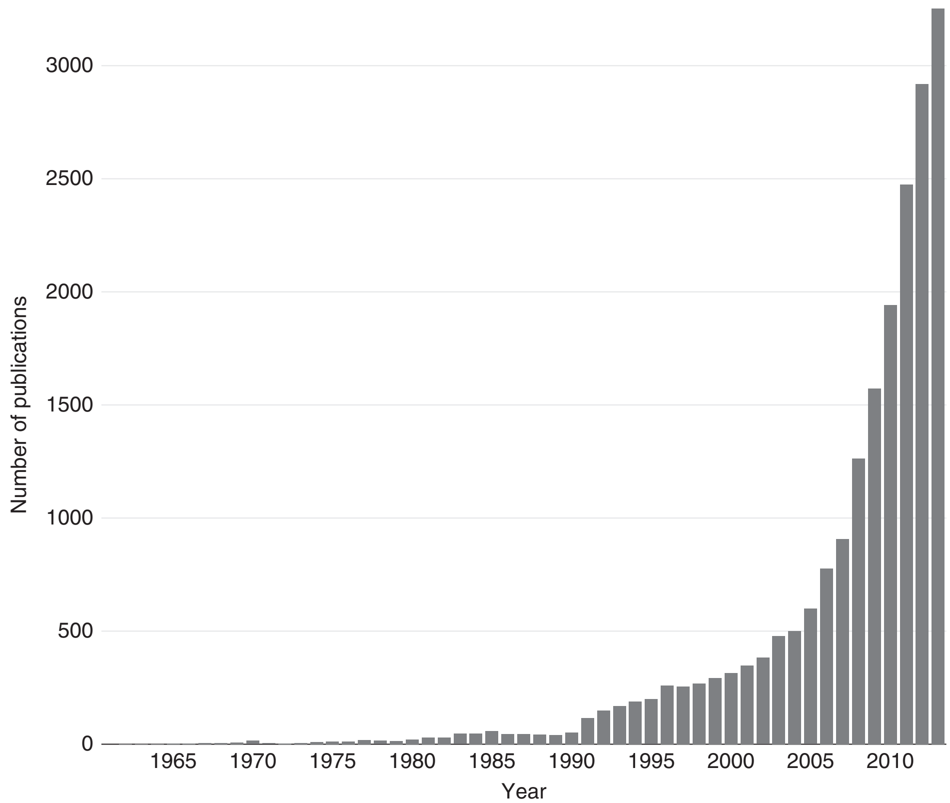

Figure 2 Social networks publications 1961–2013
(data source: Web of Science; data extracted by Drs. Yun Huang and Ryan Whalen)

are called *relations* or *ties*. Some ties, such as who seeks advice from whom, are directional ties. A *directional tie* is denoted by an arrow highlighting the "to–from" path. For example, if A seeks advice from B, A has a directed advice tie to B (A→B). Networks with directional ties are called *directed networks* or *digraphs*. In some cases there is no directionality in a link. For instance, A communicating with B is not conceptually distinct from B communicating with A. It is therefore defined as a nondirectional tie and the link does not include any arrows. Such networks are called *nondirected networks*. Relations can also vary in terms of their *strength*. They could be binary (present or absent), signed (such as a positive/like versus a negative/dislike relationship), or *valued* (such as the frequency or duration of communication). Networks that include more than one type of relation are said to be *multirelational* (such as advice seeking and friendship). Networks that are multimodal and multirelational are called *multidimensional networks* (Contractor, Monge, & Leonardi, 2011).

For purposes of analysis, network data are often represented as a matrix, known as a *sociomatrix*. In sociomatrices, the rows and columns refer to the actors, and the inner cells represent the relationships from the actor in a particular row to the actor in a particular column. A sociomatrix with only binary links (denoted by 0 and 1) is called an *adjacency matrix*. Sociomatrices with nondirectional ties are always symmetric (if A is friends with B then B has to be friends with A), whereas networks with directional ties can be asymmetric. For bipartite networks, the rows and columns represent the two types of actors. For instance, rows could be readers and columns could be encyclopedia entries. The cell entry would indicate if the individual listed in a specific row read the entry listed in a specific column. A three-dimensional network would be required to represent a tripartite network.

As is the case in other emerging scientific arenas, the vast majority of the initial scholarship on networks focused on description. Researchers have described networks at five levels: individual, dyadic, triadic, subgroup and global. The individual level, also referred to as the actor level, consists of network metrics for every actor in the network, whereas the dyadic and triadic levels measure characteristics of collectives of two and three nodes, respectively. The subgroup level of analysis looks at larger collectives of nodes that are subsets of the overall network, and the global level looks at the entire network.

Individual

At the individual network level there has been considerable interest in measuring the centrality of an actor in the overall network. The influential work of Freeman and his colleagues has demonstrated that an individual's centrality is more nuanced than it might appear. An individual could be deemed central by the number of links he/she has with other individuals. This measure is called *degree centrality*. A person with high degree centrality in a Facebook friendship network could be characterized as a *connector* in the network. If the network is a directed network (such as followers on Twitter), one can measure an actor's centrality by counting the number of ties they receive (*indegree centrality*) and the number of ties they send out (*outdegree centrality*). A person with high indegree centrality in the Twitter network would indicate a popular person and a person with high outdegree centrality in the Twitter network would indicate an expansive person who follows many. When a node lacks any tie, directed or otherwise, it is said to be an *isolate*.

There are three more nuanced measures to describe an actor's network centrality that go beyond a count of the direct network ties. *Closeness centrality* measures the extent to which an actor is able to reach all other actors in the network either via direct connections or indirectly via the fewest number of intermediaries. Hence, while two actors might have the same degree centrality (number of direct ties), they may vary in their closeness centrality since those with whom they have direct ties might provide them differential indirect access to the rest of the network. If the network is directed, there are two measures of closeness centrality in terms of incoming and outgoing ties. In general individuals with high closeness centrality are attuned to the pulse of the network since they have access to all actors in the network via the shortest number of intermediaries. Hence, they are sometimes referred to as *pulse takers*. In a directed network, individuals with a high incoming closeness centrality could be the first to find out about any information such as some gossip or a rumor, and those with a high outgoing closeness centrality are best positioned to initiate the flow of information, by perhaps starting a rumor or spreading gossip.

Betweenness centrality measures the extent to which an actor is on the shortest indirect path between two actors who are not directly connected. Here again, while two actors might have the same degree centrality (number of direct ties) to others, they may vary in their betweenness centrality since those with whom an actor has direct ties might also be directly connected to each other, thereby reducing the actor's betweenness centrality. If the network is directed, there are two measures of betweenness centrality indexing the directionality in the flow of information. In general individuals with high betweenness centrality have the potential to serve as *brokers* in a network. In the case of directed networks they have the ability to leverage two opportunities. Actors with high betweenness based on incoming ties have the unique opportunity to generate creative ideas and innovations by combining ideas they obtained from those with whom they have direct ties – actors who are by definition not directly connected to each other and hence cannot explore the combination of their ideas. Actors with high betweenness based on outgoing ties have the opportunity to exercise greater autonomy – assured in the knowledge that what they tell one person is not likely to reach the other person since they are not directly connected.

Finally, *prestige centrality* measures the extent to which an actor is connected to others who are in turn connected to others who are in turn connected to others, and so on. As mentioned previously in discussion of the page rank algorithm used by Google search, this seemingly circular metric can be mathematically computed as the *eigenvector centrality* for each actor in the network. An individual with high prestige may not have many direct ties but may be efficient by connecting to a few well-connected individuals, who are in turn connected to a few well-connected individuals. Prestige measures can also be computed for directed networks. Jon Kleinberg at Cornell University distinguished between nodes that were *authorities* and those that were *hubs*. An actor has a high authority score if it receives ties from actors that have high hub scores. An actor has a high hub score if it sends ties to many actors with high authority scores. Here again, what appears to be a circular definition can be mathematically computed as a separate hub and authority score for each actor in the network. Kleinberg developed these metrics in the context of website networks, where each node was a website with possible links among them. In this case, put simply, a good hub website steers you to many good authoritative websites, and an authoritative website is linked by many good hub websites. Portals tend to be good hubs pointing to authoritative websites such as Wikipedia, and authoritative websites such as Wikipedia are pointed to by portals that are good hubs. In the context of organizational networks, an individual with a high hub score is one who directs ties to others who have a specific expertise (authorities). These individuals with a specific expertise have a high authority score because they receive links from those who have a high hub score. As such, hubs in these organizational networks are not necessarily the experts, but they can point you to the experts, and experts are not necessarily the hubs in the network, but you could reach them via the hubs in the network.

Dyadic measures of geodesic distance, MAN scores, and structural equivalence

Networks can also be described by taking two nodes at a time. These are known as dyads in a network. A *dyad* is defined as two nodes and any possible ties that may or may not exist between them. The simplest dyad is the presence of a direct tie between a pair of actors. The shortest path between two actors is a measure of their degrees of separation. This is referred to as their *geodesic distance*. When two actors are directly connected they have a geodesic distance of 1. When two nodes are indirectly connected via a single intermediary, they have a geodesic distance of 2. If the shortest path between A and D is via two intermediaries (B and then C), then the geodesic distance between A and D is 3. It is possible that there may be multiple shortest paths between two actors. For instance, A may also be indirectly connected with D via one or more different intermediaries (A and then B or C and then B, respectively). The number of distinct geodesics (or shortest paths) between two actors provides the dyad's *redundancy* score. The higher the redundancy measure, the more likely it is that information will travel between the two nodes.

In a directed network such as Twitter, a tie might exist from actor A to B but not from B to A. In such cases we can conduct a dyad census that counts the MAN scores for all possible dyads in the network. MAN refers to the number of mutual, asymmetric, and null dyads in the network. A dyad is *mutual* if there is a directed tie from each of the actors to the other actor. A dyad is *asymmetric* if there is a directed tie from one actor to the other but not in the other direction. A dyad is *null* if there are no directed ties between them. The MAN scores for a network can be compared to the MAN scores computed for random versions of the network that have the same number of nodes and ties but whose ties are randomly assigned between nodes in the network. Networks where the number of mutual dyads is significantly larger than the number of mutual dyads in equivalent random networks suggest a strong structural tendency for reciprocity. However, networks where the number of asymmetric dyads is significantly larger than the number of asymmetric dyads in equivalent random networks would suggest a strong structural tendency for hierarchy or the presence of hubs in the observed network.

Whereas geodesic distance and MAN scores focus on the direct or indirect ties between two actors, *structural equivalence* measures the degree to which two nodes share similar positions in the network, irrespective of their direct or indirect ties to each other. If two actors are connected to the same other individuals and also not connected to the same other individuals, they are deemed structurally equivalent. Two actors may be somewhat, but not perfectly, structurally equivalent if they communicate and not communicate with some but not all of the same other actors in the network. Ron Burt, who first developed this concept, showed that actors who were structurally equivalent in a communication network would often adopt similar attitudes and behaviors even though they did not communicate directly. This is because being structurally equivalent exposed them to the same sources of information from all others in the network.

Triadic

Networks can also be described by taking three nodes at a time, known as a triad. A *triad* is defined as a set of three nodes and all possible ties that might exist among them. In an undirected network, a triad that has all three nodes connected to each other would indicate closure. We can count the number of triads in the network (actors taken three at a time) that exhibit closure and compare this count with the number of triads exhibiting closure in random networks that have the same number of nodes and ties as the observed network. If the count of triads with closure is significantly higher in the observed network than in random versions of that network (with the same number of nodes and ties), we would conclude that actors who are linked to the same actor are more likely to be linked to each other. This is exactly what we would expect if actors were more likely to be friends with their friends' friends. A related measure, the *clustering coefficient*, is computed as the proportion of triads in which an actor is engaged that have closure to the total number of possible triads in which an actor could have closure. Actors in small world networks have, on average, much higher clustering coefficients than what would be found in random networks of the same number of nodes and ties.

In directed networks, a triad is described as being *transitive* when A directs a tie to B who in turn directs a tie to C, and we also observe that A directs a tie to C. Here again we can do a triad census by comparing the proportion of transitive triads to all possible triads in the observed network with the proportion of transitive triads in random versions of the network with the same number of nodes and ties. The presence of more transitive triads than those observed in random networks suggests a modicum of hierarchy. This may occur in advice networks where it may be the case that A goes to B for advice, B goes to C for advice, and A also goes directly to C for advice, suggesting a hierarchy where A is at the low end and C at the high end.

A directed network can also be measured at the triadic level in terms of its cyclicity. A triad is *cyclical* if A directs a tie to B who directs a tie to C who directs a tie back to A, thereby creating a cycle. If a triad census indicates more cyclicality in the observed network than random versions of the same network, it indicates a lack of hierarchy. In some contexts it indicates the presence of generalized exchange or what Wayne Baker, a network scholar at the University of Michigan, refers to as the *reciprocity ring*, where A helps B who helps C who in turns closes the ring by helping A. In information seeking networks, this could represent an unhealthy informational closure with the blind leading the blind.

Subgroup

Networks can also be described at the level of groups that are subsets of the network. One such subgroup, a *component*, is defined as the largest set of actors that are all directly or indirectly connected to one another. If all actors in a network are directly or indirectly connected to one another, the network has one component that constitutes the entire network. This is not uncommon in communication networks. Often, however, there is a large subset of actors that are all connected with one another directly or indirectly (sometimes called a *giant component*), but there are a few peripheral actors in the network that are either isolates (not connected to any other actors) or connected directly or indirectly to only a few other actors. Networks often have one giant component and a handful of smaller components made up of one or a few actors. In directed networks, a *strong component* is defined as the largest subset of actors where each actor can reach each other actor following the direction of the network tie. A *weak component* is defined as the largest subset of actors where each actor can reach each other actor regardless of the direction of the tie. For instance, A, B, and C would be in the same weak component if A directs a tie to B who directs a tie to C. However they will not be in the same strong component since C is unable to reach B or A, and B is unable to reach A.

A clique is a subgroup that has a more stringent requirement. A *clique* is the largest subgroup of actors in a network, wherein all members are directly connected to each other. Actors in a clique can still be connected to actors outside the clique and can have membership in multiple cliques. An actor is not part of a clique if it does not have a direct tie to every single actor in that subgroup. This strict definition of a clique is relaxed by defining an *n-clique* as the largest subset of actors that can reach all other actors in the subgroup directly or indirectly via no more than *n* steps. This allows for cliques where members have two, three, four, and so on, up to *n* degrees of separation between them. An *n-clan* has the additional requirement that any two members of an *n*-clique must be connected indirectly in *n* steps that include intermediaries who are also in the subgroup. A *k-plex* is the largest subgroup of actors that relaxes the strict definition of a clique by allowing the actors to be connected to all but *k* members of the subgroup. For example, a 3-plex is the largest subset of actors where actors in the subgroup are directly connected to no less than three of the other actors in the network. Each of these measures describes various facets of cohesiveness in the network. An organizational communication network with many distinct and disparate cliques might identify strongly with their cliques but have challenges identifying with the larger organization. Another useful subgroup descriptor, a *k-core*, is the largest subset of actors where all actors must be connected to at least *k* other actors. This is a very useful metric for describing the so-called core–periphery structure that is often found in organizational communication networks. These networks are often characterized by a group of core insiders who interact more with one another, and to a smaller extent, with the rest of the actors on the periphery of the network.

Global

Finally, a network can also be described in its entirety. We have already covered two of these metrics while chronicling the intellectual history of network science (small world and scale-free networks). However, the oldest and most common global metric of a network is its density. The *density* or *connectedness* of a network is defined as the proportion of actual links to the number of possible links. A network in which there is a high degree of connectedness is said to be *dense*, whereas a network with a low density is *sparse*. Having high density in an organizational communication network would be a healthy sign if tasks required a high degree of interdependence, but might suggest a lack of trust in cases where connectedness is being used to "check" on one another.

Diameter is another global descriptor of a network. It refers to the largest geodesic distance between any pair of nodes. The geodesic distance was previously defined as the shortest direct or indirect path between any pair of actors. Hence the largest geodesic distance is the largest shortest path between any pair of actors in the network. In effect, it measures the largest indirect path that would be required to connect two actors within the network. In organizational contexts, it provides a measure of the worst-case reachability in a network.

A set of frequently used global metrics to describe networks is based on the afore-mentioned measures of degree, betweenness, closeness, and prestige centrality for actors in directed and undirected networks. *Network centralization* is a metric used to describe the network as a whole based on the variability in actors' centrality scores. A high degree network centralization score describes a network where one or a few actors have very high degree centrality while the rest have low degree centrality (akin to the afore-mentioned scale-free networks). Likewise a high betweenness, closeness, or prestige network centralization score describes a network where one or a few actors have high betweenness, closeness, or prestige centrality scores while the rest have low betweenness, closeness, or prestige centrality scores, respectively.

Explaining networks: Theoretical advances

While there has been – and continues to be – a robust body of research to describe networks, there has also been a growing awareness for the need to move from description to explanation (Monge & Contractor, 2003). It is interesting to be able to describe the extent to which networks exhibit closure, density, centralization, small world, or scale-free properties, but this description begs some more fundamental questions: Why do these structures emerge? Why do actors create, maintain and dissolve links and with what consequences? Put simply, why do certain networks form and how do they perform? The theoretical advances described in this section are helping to address those fundamental questions. Complementary methodological advances are discussed briefly later.

Self-interest

Theories of self-interest are based on the premise that people make rational choices in order to maximize gains and minimize losses. In terms of networks, actors driven by self-interest would create ties in order to gain social capital. Just as financial capital is indexed by individuals' wealth, and knowledge capital is estimated from their education, *social capital* is measured as the access to resources available to actors from those in their social network (Coleman, 1988). Social capital can be amassed by enlarging one's network, thereby granting access to more resources from more people. However, a large number of network ties is not sufficient for obtaining high levels of social capital, as most networks consist of dense, homogeneous clusters, filled with redundant information. Novel information is often obtained by accessing contacts in different clusters. The space between two clusters is called a *structural hole* that, if filled, can contribute to the actor's social capital (Burt, 1992). An actor who fills a structural hole is called a *broker*, and gains advantages in terms of information access, timing, and referrals. *Access* refers to the broker's ability to obtain privileged information and filter out unwanted information. The advantage of *timing* gives brokers priority access to crucial information. Brokers may also receive significantly more *referrals* as actors who are aware of the broker's structural advantage will often seek them out for mutual benefit. Brokers can fulfill a number of different roles in a network, such as being *coordinators* if they are a member of a subgroup and pass on information to other disconnected members within the same group. If they are not a member of the subgroup in question, they can act as *consultants* by transferring messages between two unlinked members of the same group. Brokers can be *gatekeepers* of a subgroup by controlling outsiders' access to members within the group. Conversely, brokers can act as *representatives* of their subgroup, regulating insiders' access to outsider information. *Liaisons* act as a mediator between two entirely separate subgroups in which they are not a member.

Exchange theories

While individuals may strategically strive to pursue self-interest, others not responding favorably may foil their efforts. A more fruitful strategy might be to seek ties with those who offer you something you need and to whom in turn you offer something they need. Theories of exchange focus on the supply and demand of resources among actors, and the extent to which actors conduct cost–benefit analyses of trading their resources with others. Major theories of exchange, which include social exchange (Emerson, 1976), resource dependency (Pfeffer & Salancik, 2003), and network exchange (Cook & Whitmeyer, 1992), seek to explain the creation of ties for exchanging resources among individuals and organizations, as well as their consequences. The motivation to create exchange ties requires the ability of both parties to perceive accrual of benefits that offset the costs they incur. This calculation is shaped by levels of trust between the actors as well as norms of reciprocity and equity. While there might be some appeal, in terms of reduced coordination cost, in relying exclusively on an exchange tie with only one actor, there are also some critical downsides. An overreliance on one actor for an exchange tie could create an unhealthy co-dependence. This is why it is often in the interest of individuals and organizations to forge exchange ties with others who are not connected with each other in a coalition or cartel. This provides them greater flexibility in negotiating terms that are favorable to them. On the other hand, it is in the interest of the "alters" (the actors' connections) to seek a coalition in order to improve their negotiating hand.

Collective action

There are occasions where actors do not create ties with others because it maximizes their self-interest or because they get something from another actor and that other gets something from them (social exchange). Instead, actors create ties with another actor because they believe this gives the two of them the best opportunity to gain something from a third party. This logic is at the foundation of theories of collective action (Olson, 2009). Public goods theory is the most developed and employed theory of collective action in communication (Fulk et al., 1996). *Public goods*, sometimes referred to as the "commons," are resources that are accessible to everyone and are seemingly endless in supply, although they can suffer a loss in quality due to crowding and overuse. The theory of public goods is primarily concerned with convincing people – particularly noncontributors or "free riders" – to contribute to the creation and maintenance of public goods. Individuals could be convinced to become contributors by the features of the public good, individual and group characteristics, and the action processes that make the good available. In communication networks, *connectivity* (the extent to which people are able to contact each other) and *communality* (the extent to which people store and share information) are public goods. Individual characteristics that are necessary in creating and maintaining these public goods include having an *interest* in the good (i.e., seeing its inherent value), and possessing the necessary *resources* to create and maintain it (time, money, energy, expertise). These characteristics are seldom found in high amounts within a single individual (although when they are, it can make an immense difference), making the collective interest and resources of a group invaluable to supporting public goods. Public goods are also more likely to come to fruition when information about them is spread through cliques with strong ties. The faster and more widespread the adoption of the good, the more likely it is to reach *critical mass*, at which point there are enough people contributing so that the good is self-sustained.

Contagion

The three families of theory mechanisms outlined above – self-interest, social exchange, and collective action – are strategies actors use to form networks that will perform well. However, there are other theories that are not strategic but reflect human propensities to form networks which may or may not perform. The remainder of the theories described here fall into this latter category. Theories of contagion state that actors are susceptible to becoming "infected" with certain beliefs, behaviors, and attitudes by virtue of their relations in a network. The process by which actors become more similar is known as *convergence*. Contagion explains why individuals are influenced by the network to change their attitudes and behaviors and has been used extensively to explain the communication and diffusion of innovations (Rogers, 1983). Research has shown that the influence of others is not always a simple additive function based on the attitudes or behaviors of those in one's network. Burt (1987) showed that contagion was more likely to occur when two individuals were connected to the same other individuals (structural equivalence) in the network rather than being connected to each other (cohesion). Valente (1995) showed that individuals often changed attitudes or behaviors only after the input from their network had reached a threshold or tipping point.

In addition to influencing individuals' attitudes and behaviors, contagion also influences the formation of new network ties. For instance, when actors first join a network they are more likely to seek network ties with those who are already well connected. This is because, by virtue of contagion, they are mimicking what others in the network are doing. This tendency for preferentially attaching to those who are already well connected is one plausible explanation for the widespread prevalence of scale-free networks.

Cognitive theories

Cognitive theories of communication networks are based on individuals' perceptions of the network as opposed to the "ground truth" (i.e., their actual observed interactions). Theories of cognition include semantic networks among actors, semantic networks of text, cognitive social structures, cognitive knowledge networks, and cognitive consistency.

Semantic networks among actors capture the extent to which actors share interpretations of messages, events, and/or artifacts (Monge & Eisenberg, 1987). Semantic networks help test assumptions about the extent to which communication among actors will necessarily lead to shared interpretations as well as the presence of differentiated interpretive lobbies within networks. Research shows that strategically ambiguous communication can lead to actors believing that they have shared interpretations (a strong semantic network tie) when in fact they do not – and that this might be a desirable outcome (Eisenberg, 1984). Semantic networks have also been used to describe and understand cultural and national differences in the interpretation of key communicative processes such as worker participation (Stohl, 1993).

A second, more active body of research has examined the *semantic networks of text*, where the nodes are words and the ties are typically co-occurrences in narrative or semantic similarity based on dictionaries. This tradition built on foundational work of Woelfel and Fink (1980) who developed the GALILEO system to spatially model relations among words based on multidimensional scaling, and Danowski's (1982) network modeling of the relations among words used in a computer bulletin board discussion system. Corman et al. (2002) developed an innovative technique for generating networks of noun phrases from a large corpus of text using centering analysis of communication. Their research demonstrates the utility of this approach to sift through vast amounts of text to identify key players and concepts. In an interesting nod to semantic networks among actors, they also demonstrate how this approach could be extended to generate semantic networks among actors where the links between actors reflected the similarity in the semantic networks of text they generated. The growth in digital data and computational capability and the development of software such as ConText (Diesner, 2014) promise to make semantic networks of text a major growth area in the network research enterprise.

Cognitive social structures, first introduced by Krackhardt (1987), is based on the premise that individuals' actions and interactions with you are based not on who you actually know but on who others *think* you know – and these are not always the same. While it might appear intuitive to assume that who you actually know should be the "ground truth," there is strong evidence that people act on their perceptions and hence it is their perceptions that should be privileged. Corman and Scott (1994) eschewed the methodological debate, proposing instead a model that theoretically linked perceived networks and observed communication through the use of triggered activity foci that actors shared.

Cognitive knowledge networks, first introduced by Contractor, Zink, and Chan (1998), are based on the premise that individuals' actions and interactions with you are based not on what you actually know but what they *think* you know – and these are not always the same. This concept, analogous to cognitive social structures, provides an apparatus to map individuals' perceptions of what information, skills, and/or expertise any human or nonhuman agent possesses. Hollingshead and Contractor (2006) argue that cognitive knowledge networks lend themselves well to testing propositions based on theories of *transactive memory systems*, which argue that in order to be effective, individuals must specialize in different areas of expertise, know the areas of expertise of others on the team, and help grow others' expertise by routing knowledge to them that is relevant to their expertise.

Cognitive consistency theories dating back to Heider's work on balance theory posit that actors seek cognitive consistency in their relationship with people and concepts. In terms of networks, it results in actors choosing to forge ties, for instance, with friends of their friends. More generally, in a communication network, if two actors have inconsistent perceptions of a third actor, then they will alter their evaluations of the said actor or of their dyadic relationship, in an attempt to achieve balance. Studies have shown that individuals who are embedded in organizational networks where they are friends with the friends of their friends tend to have high levels of job satisfaction even if their friends do not report high levels of satisfaction. It is important to note that this closure is the antithesis of Burt's (1992) theory that self-interest would propel you to bridge structural holes where you connect with people who are not connected to each other. The research suggests that, in general, actors *form* network ties with the friends of their friends in order to improve cognitive consistency but in so doing they may not *perform* as well, which is aided by bridging structural holes.

Homophily

Homophily is often referred to via the epigram "birds of a feather flock together," meaning that individuals tend to create network ties with similar others (McPherson, Smith-Lovin, & Cook, 2001). *Similarity* is based on a number of individual attributes such as age, gender, socioeconomic status, race, nationality, education, and sexuality. The theory of *self-categorization* states that individuals seek to legitimize their social identity by sorting themselves into the afore-mentioned categories. The *similarity attraction hypothesis* posits homophily results from individuals' desires to connect with others who share their self-categorized identity in order to reduce psychological discomfort and avoid conflict. Even though these theories accurately note humans' propensity to form networks on the basis of homophily, there is evidence that these ties do not always perform as well as diverse ties (Page, 2008).

Proximity

Physical proximity increases the likelihood that individuals will communicate by virtue of having more opportunities to interact with each other. Monge and colleagues (1985) were among the first to document the effects of proximity on communication networks.

More recently, Kabo et al. (2014) found that outcomes of scientific collaboration in an organizational setting were influenced much more by the extent to which two individuals' paths overlapped in visiting public spaces such as elevators, stairs, and restrooms than the distance ("as the crow flies") between their offices. The advent of ubiquitous communication technologies has called into question the primacy of proximity. However, research suggests that proximity continues to influence the formation of network ties because we are more likely to use communication technologies with individuals close to us than those far away. That said, there is evidence that while proximate ties are more likely to form, distributed ties are more likely to perform (Jones, Wuchty, & Uzzi, 2008).

Explaining networks: Methodological advances

Clearly there is a plethora of theoretical explanations for why networks form and perform. Until recently, there was a paucity of network analytics methods to statistically test these theories. Traditional statistical methods often make fundamental assumptions about the independence of observations which are violated by network data, hence making them unusable. However, in the past two decades there have been substantial advances in the development of new methods to statistically test the extent to which these theories explain the formation and performance of networks. They are all based on the premise that if actors are operating on the basis of a specific theory, then certain structural signatures unique to that theory should be seen more frequently in the network than one might expect by chance (Contractor, Wasserman, & Faust, 2006). In essence these techniques serve as a statistical MRI to decipher the extent to which the observed network is being differentially created by one or more theoretical mechanisms (see Carrington, Scott, & Wasserman, 2005).

Future directions

Theoretical

As we increasingly migrate our lives to the digital realm, we are generating vast amounts of digital trace data about our actions, interactions, and transactions (Mathur et al., 2012). These high-resolution data are motivating the development of new theories that utilize concepts and variables that were not part of our theoretical repertoire because we simply could not conceive of having access to those measures. Today, theories of team processes and outcomes that incorporate physical markers of affect such as eye gaze and nods, physiological markers of stress based on voice intonation and cadence, and text analytic markers of trust among individuals (Carter et al., 2015), are plausible, indeed promising, enterprises. Developments in high-precision, miniaturized, and unobtrusive wearable and ambient devices are revolutionizing the ability to collect network data.

Methodological

The availability of time stamped data is also motivating the development of new network methods that take advantage of such data. A recent example is the development of relational event network models that help us assess the extent to which theoretically derived sequential structural signatures can explain the probability of a specific relational event from one actor to another, at a specific point in time, as a function of all prior relational events between any pair of actors (Butts, 2008).

The glut of digital data is also (re)opening the door to two methodological approaches that were briefly considered a half-century ago before being relegated to the social scientific wilderness. First, it is the right time to reconsider the role of data driven approaches for the development of network theory. For decades, social science researchers have been skeptical of generating insights from so-called exploratory or data driven methods, often referring to them as "trying to read tea leaves to tell a fortune" (Bray & Kehle, 2011, p. 141). Two things make it worthwhile to incorporate data driven approaches into the ensemble of network analytic methods, which also include the afore-mentioned theory driven approaches. First, the magnitude of data makes it feasible to run data driven machine learning models on large amounts of "training data" and then test the robustness of the models on separate "test data." This was not a luxury available to prior social network research. Second, the insights offered from machine learning models are often far more nuanced and complex compared to the relatively linear insights generated by most traditional network methods. Engaging with these complex findings offers the promise of developing more nuanced theories about how social networks form and perform.

Second, the availability of empirical data and advanced computational capabilities behooves us to revisit the use of computational models to help refine network theories as well as anticipate their implications in a wide range of scenarios (Dooley & Corman, 2002). Systems dynamics models that were in vogue in the latter part of the 20th century were not well suited for networks because they were designed to model factors (or variables) and not actors (Macy & Willer, 2002). Recent advances in agent based computational models (Wilensky & Rand, 2015) are particularly well suited to articulate theories about network dynamics. Further computational models such as those used for the 1972 Club of Rome report titled *The Limits to Growth* were in part discredited because the parameters used to specify the effects of variables on one another were not grounded in empirical data, as those high-resolution data did not exist. However, recent methodological advances are making it possible to utilize the high resolution of data available to estimate parameters for computational models (Sullivan et al., 2015), thereby mitigating the earlier criticisms.

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SEE ALSO: Actor–Network Theory; Adoption and Diffusion; Alternative Forms of Organization and Organizing; Boundary Spanning; Cognition and Organizational Communication; Collective Action; Groups and Teams in Organizations; Interorganizational Communication; Leadership in Organizations; Social Capital; Social Support; Supervisor–Subordinate Communication; Transactive Memory; Trust

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