

# EDITORIAL

## *What is network science?*

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### Abstract

This is the beginning of *Network Science*. The journal has been created because network science is exploding. As is typical for a field in formation, the discussions about its scope, contents, and foundations are intense. On these first few pages of the first issue of our new journal, we would like to share our own vision of the emerging science of networks.

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### 1 Is there a science of networks?

Whether there is or is not a science of networks, and what should be the focus of such a science, may appear to be academic questions. We use this prominent place to argue the following three statements:

- These questions are more relevant than they seem at first glance.
- The answers are less obvious than have been suggested.
- The future of network science is bright.

Of course, the editors of a new scientific journal are going to predict that the future of their science is bright. Cambridge University Press is betting that it is. We do also think, however, that the field is still in formation and that its essential shaping is taking place *right now*. The development and steering of network science into a fertile and beneficial direction form our primary motivations for creating this journal and for assuming active roles in its leadership.

Network science, the field, permeates a wide range of traditional disciplines, and *Network Science*, the journal, will welcome contributions from all of them. In addition, we will indeed publish foundational research on theory, principles, philosophy, and mathematics of networks.

While there is much overlap in disciplinary network research, the inherent disciplinary boundaries still tend to create silos of different interests, methods, and goals. If network science is to be one science, rather than separate and scattered research communities, or a set of tools that researchers use to analyze networks, the silos need to be dismantled while at the same time recognizing existing disciplinary practices and values.

We write this editorial to help establish common grounds for our journal and its field—grounds which should allow *Network Science* to excel above and beyond disciplinary boundaries. We envision our commons as much wider than some current interpretations of the term *network science*. We will therefore try to delineate the uniting elements rather precisely on the next few pages.

Our major statement is that we view *network science* as the *study of the collection, management, analysis, interpretation, and presentation of relational data*. But first, a few remarks on our perceptions of the current state of the field.

The claim that “networks are everywhere” has become almost routine. Frequently mentioned examples of “everywhere networks” include the Internet and other infrastructure networks, social, political and economic networks, scientometric and text-representational networks, as well as food webs and molecular-level biological networks. And there is a host of other, less commonly mentioned networks in many more research areas.

Networks and hence the network paradigm have become scientifically relevant across disciplinary boundaries. But many have asked: Is the network paradigm nothing more than an in vogue buzz phrase? Clearly, a *science* of networks requires a scientific commonality that creates a foundation for these different research streams. We must ask: Is there such a unity? And if there is, does this unified, shared element really contribute something relevant to science, or does it only appear to do so by virtue of the fact that “networks are hot?”

These questions are important to answer because out of this acclaimed relevance grows a promise—a promise of a new scientific discipline.

When we are surrounded by networks, with many of them arising from topics of the highest societal relevance, we certainly feel the need to understand them. Some researchers, at their most enthusiastic, have gone as far as proclaiming that network science is not just helpful, but essential. In a televised documentary (on *Australian Broadcasting Corporation* (ABC), Australia, in 2008), Duncan Watts said it very bluntly:

“Networks are important because if we don’t understand networks, we can’t understand how markets function, organizations solve problems, or how societies change.”

In a mathematical sense, this statement implies the *necessity* of network science. Given the many reports and commentaries flirting with the idea that network science may hold the key to just about every important problem, one is tempted to think that it could even be *sufficient* (again, in a mathematical sense).

While we are skeptical about the singularity and uniqueness of network science, we do acknowledge its potential relevance. It is quite amazing how many researchers, from different disciplines, have stated in survey and position papers that their research and discipline are being revolutionized by the increased use and importance

of the network paradigms. Political Science is a good example—network science has had a tremendous impact on this field, just in the last five years.

If anything, network science is a revolution a long time in the making. Despite frequent claims by some, network science did not suddenly appear when it was realized in the mid-1990s that networks could be models of complex systems. Such a limited definition of network science is simply inappropriate—it is important to recognize the many scientific antecedents of what we do. Network approaches have developed in many areas over the past two decades (physics, biology, economics, for example) because a relational perspective clearly added relevance to the discipline.

The roots of network science are particularly strong in social psychology, sociology, and anthropology, which has led to another misperception, namely that network science is the application of network analysis in disciplines other than the social and behavioral sciences. Sometimes the phrase *social network analysis* (“SNA”) is used to label everything that is network-related, even when the network aspects of the work are clearly not analysis at all (e.g., network theory). Acronyms may be appealing, but if all we do is “analysis,” we simply will not be able to create a real network science, fulfilling grand promises.

The network perspective allows us to address deep questions about human, biological, economic, and other systems that exhibit interdependent organization. As network researchers, and as editors of this journal, we do commit to the above promises, despite knowing that many of them will always remain promises.

At this stage of our science, there are too many areas in which we cannot point to empirical results that convincingly meet the claims being made. The Human Connectome Project is but one example that is just barely allowing us to study meaningful network connections in the human brain. Moreover, results of network studies are seldom tested against alternative conceptualizations—just as alternative approaches seldom test themselves against a network approach.

We want the science of networks to develop beyond claims and promises. We do not want to see the field degenerate into a scientific fad, leaving behind discredited theories and ideas. With this journal, we will try to advance the unity of a scientific, non-metaphoric perspective, and thus help bring its promises to fruition.

As we shall explain, the single, deepest point that unites us is not a toolbox of methods but a conceptualization that appears way before there is anything to analyze at all.

## 2 Network science and network theory

The above mentioned claim that “networks are everywhere” implies that the many phenomena jointly referred to as “networks” belong to a common category. For the diverse phenomena being studied this is only possible by means of abstraction so that a network and the phenomenon referred to as the network are generally distinct. The diagram in Figure 1 shows the role of abstraction as a conceptual prerequisite for representation in data.

Consequently, a network model should be viewed explicitly as yielding a network *representation of* something. While the model manifests itself in a network representation, it is obtained via the following two steps:

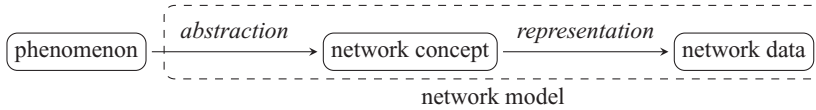


Fig. 1. The elements of network models.

1. A specification of how the phenomenon (in general, i.e., more generally than this particular instantiation) is abstracted to a network.
2. A specification of how this conceptual network is represented in data (e.g., measured or observed).

As representation is usually defined via an isomorphism, i.e., a one-to-one mapping between structures preserving relations, a phenomenon cannot be represented directly but needs to be conceptualized first.

Of course, this is by no means an unusual division in science or other areas of knowledge. Possibly because of the graphic and metaphoric connotations of the term network, the implications of a preceding abstraction step are often overlooked or blurred. Sometimes this may be on purpose for terminological convenience. More often, there appears to be a lack of awareness. We feel, however, that this distinction is crucially important for serious applications of network science to the understanding of substantive phenomena as it points to the delicacy of interpreting the results of network data analysis.

Interpretation essentially reverses the process of abstraction and representation to get back to the phenomenon so that substantive theory is required to secure conclusions. Abstraction facilitates generalization and comparison but at the same time presents an obstacle in this reverse direction, when statements about a network representation are interpreted in terms of the original phenomenon. The means to overcome this obstacle are necessarily disciplinary. We therefore consider network science to be the study of particular kinds of representations; issues relating to conceptualization, however, form an integral part of the application of network science to substantive problems.

#### *Claim 1*

Network science is the study of network models.

We emphasize that, in our view, network models are unlikely to generalize across domains. We hence remain open to, but rather sceptical about any Grand Unified Network Theory (GrUNT) that ignores research contexts. On a related note, we find it very unfortunate that many network studies are referred to as “social network analysis” just because the methods applied are commonly used for social network models. If the network under scrutiny models, say, gene regulation, the term is hardly appropriate.

Network theory builds on the assumption that a cause, an effect, or an association between aspects involve something that can be conceptualized as a network. Testing of hypotheses derived from network theory requires instantiation of the network model. While the abstraction yields the format in which a phenomenon will be represented, its actual representation is in terms of data that is typically obtained via empirical observation.

According to our framework there are actually two aspects to network theory. On the one hand, network theories can suggest and explicate, for given research domains, how to abstract phenomena into networks. This includes, for example, what constitutes an individual entity or a relationship, how to conceptualize the strength of a tie, etc. In such applied network science, the corresponding theories are epistemological—network theories bound to specific classes of phenomena. On the other hand, network theories can deal with formalized aspects of network representations such as degree distributions, closure, communities, etc., and how they relate to each other. In such pure network science, the corresponding theories are mathematical—theories of networks.

### *Claim 2*

There are theories about network representations and network theories about phenomena: both constitute network theory.

Establishing network theory can be a challenge in disciplines that have a highly individualized history. But without a theory about how to conceptualize a phenomenon as a network, there is no meaning to a formal theory of network data. We conclude that networks are not just an add-on to existing approaches—e.g., a means to add a little more explained variance in a social science research project—but require new theorizations and different thinking.

A network abstraction involves ontological commitment to a few basic features that are seen as scientifically relevant to the representation of a phenomenon. The features of a network abstraction include at least the following: individual elements; pair-wise relationships between those elements; and a global or macro- patterning that can be considered as network structure. This basic description may not be sufficient for all circumstances (e.g., think of longitudinal phenomena) and can be extended in many different ways, but these are fundamental features if we are to call the abstraction a network.

For example, a friendship network is a way of abstracting a social phenomenon into a comparatively simpler and much more general form of relationships between actors. The actual phenomenon is, of course, much richer: We are abstracting already quite substantially just by conceiving of the individuals as comparable entities of a common kind.

By postulating a friendship network in (say) a school classroom of 25 students, we have taken a theoretical step that is non-trivial. We have supposed that separate individuals are not an adequate representation, moreover that even separate dyads are insufficient; rather, that there is a unity within the classroom that makes it proper to talk of “a” network, not 25 children or 300 dyads.

To conceptualize the classroom in network terms is an implicit (and strong) claim that connectedness across individual elements is fundamentally important so that the classroom can be thought of as one “system.” If we accept that ontology, scientific inference is available at multiple levels: the students, the dyads, and indeed the network as a whole. Moreover, the inferences at one level cannot be simply combined (e.g., averaged) to derive inferences at other levels; the networked system is more than a simple aggregation of its constituent elements—it is patterned, not summed.

So the claim that “networks are everywhere,” if it is meaningful as network science, is not just a statement that we can see many things in the world in relational terms, but an implicit theoretical statement that scientific explanation of many phenomena is aided by abstraction to such a connected, systemic representation. Otherwise, it is no more than a statement that we can see the world in particular ways: after all, colors are everywhere, too, but no one to date has thought it scientifically helpful to understand classroom processes in shades of pink and purple.

The essential point must be that the abstraction into a network is helpful to scientific inference, permitting knowledge to develop. It need not be the case that this will always be so. But we need an empirical base to show that the network representation gives scientific traction.

*Claim 3*

Network science should be empirical—not exclusively so, but consistently—and its value assessed against alternative representations.

### 3 Network data

We have argued that networks are abstractions represented in data, but we have yet to discriminate them from other conceptualizations. We are now going to do so by first looking at characteristics of standard types of data to be able to then highlight the defining features of network data.

The input to data analysis consists of values of variables. Variables are generic placeholders characterizing the essential features of an abstract concept, thus allowing to formulate analytical steps generically as well. The instantiating values are usually obtained via some form of observation such as measurement. Note, however, that different original phenomena may yield the same representation in data.

Our definition of what constitutes network data hinges entirely on how the involved variables are related. It is thus independent of the phenomena being represented, the ranges of values that can be assumed, and the techniques used to analyze the data. The significance of the following claim will be established in three steps below.

*Claim 4*

What sets network data apart is the incidence structure of its domain?

The third step will also unveil the essential correspondence between the signature of network variables and the defining interest in network science.

*Claim 5*

At the heart of network science is dependence, both between and within variables.

#### 3.1 Step 1: Data tables

In data analysis, variables are generally associated with a set of entities (e.g., individuals), so that the same attribute is measured for all entities. The entities form a (sample from a) population and the variables corresponding to the same attribute are combined into a vector indexed by the entities. Variables for different

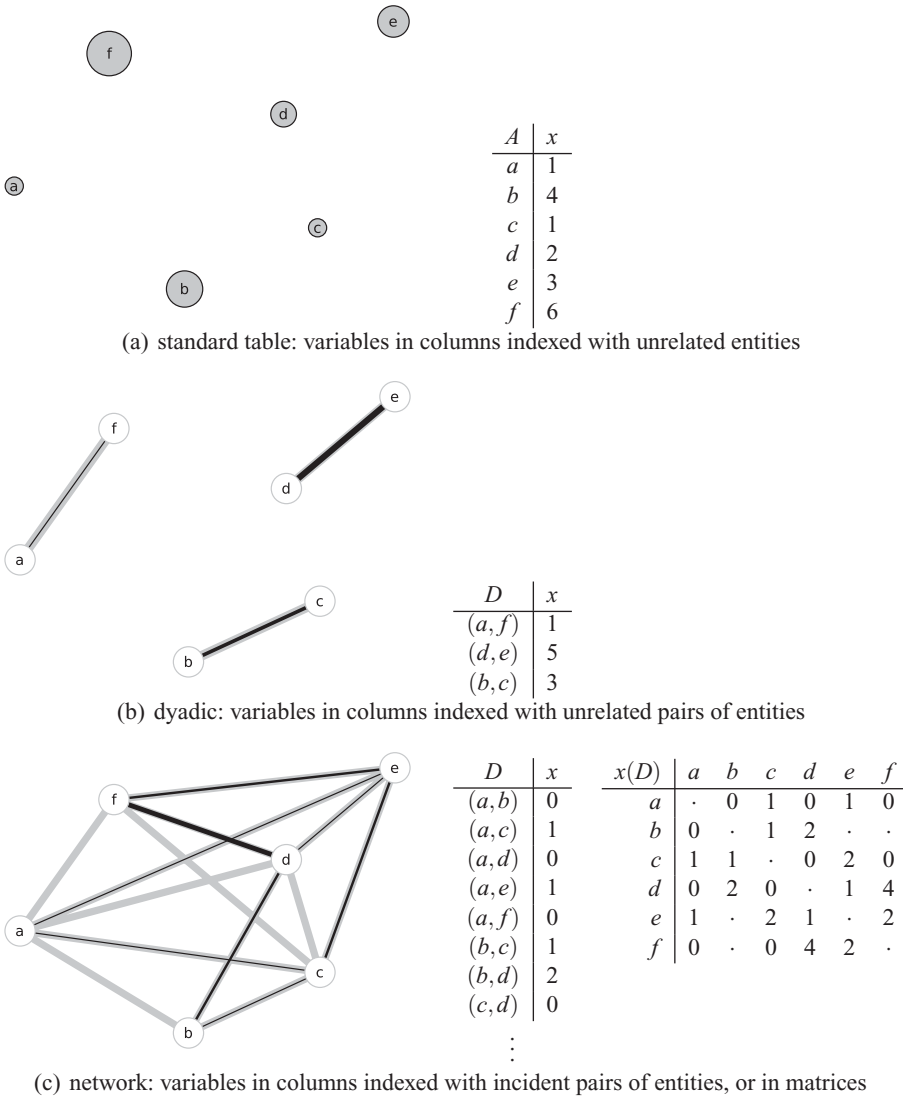


Fig. 2. Data formats distinguished by the structure of the domain.

attributes are conveniently organized in a matrix where each column corresponds to all variables representing the same attribute and each row corresponds to all variables associated with the same entity. This is illustrated in Figure 2(a).

A prototypical example would be a set  $A$  of individuals with variables gender, education, and income, where, e.g., a variable  $income_i$  represents the gross income of an individual  $i \in A$  in Euros per year. The data for one attribute is thus combined in a vector with index set  $A$ . But one alternative representation is that of a mapping  $income : A \rightarrow R$ , where  $R$  is an interval containing possible values. More generally, the notation  $x : D \rightarrow R$  declares a mapping (representing the variable)  $x$  that assigns to each element in the domain  $D$  a value in the range  $R$ . The elements of the domain are units of observation or analysis.

In the above example, variables gender, education, and income are of different types: While all are defined on the common domain  $A$ , the range of values they may assume is different. Even more importantly, these ranges exhibit a different level of structuring. The range of gender, for instance, is binary on a nominal scale, i.e., the only defined relation is an equality predicate. In other words, the comparison of two values yields either equality or inequality, and this is the only information we can get out of comparison. For instance, we cannot add or rank values of gender variables.

Assume now that education refers to the highest degree obtained by an individual. It may then be valid to compare two values and conclude that one indicates a higher level of education than the other, and this relation could be transitive. In this case, the range is ordered and the variable is on an *ordinal scale* of education. Finally, we may compare income by amount, but it may also be meaningful to compute differences and ratios. The range of the variable income can therefore be considered to be a continuous *ratio scale*. If, however, 0 is not meaningful for a continuous range as in, e.g., measuring IQ, it is not appropriate to calculate ratios and the scale is called *interval*.

The interesting thing to observe is that a range is usually not just a set of possible values but a set with additional relations such as an ordering or operations, i.e., *structured*. The structure of a range is crucial to know about because it determines the kinds of analyses and interpretations that are justified.

While the range of attributes is structured, in much of science, the domain on which variables are defined is assumed to have no structure, i.e., simply a set. This may be for good reason. If we are interested in associations between, say, education and income controlled for age, we actually do not want there to be relations between individuals that also moderate the association. Much of statistics is in fact concerned with detecting and eliminating such relations.

This is the single most important difference with network science, where the domains of at least some variables are explicitly set up to have structure. The potentially resulting dependencies are not a nuisance but more often than not they constitute the actual research interest.

### 3.2 Step 2: Dyadic data

Before introducing the structure of network-variable domains, consider as an intermediate step *dyadic* variables, i.e., variables defined on pairs of items. A classic example of this kind is the study of (populations of) couples. Here variables, such as duration of marriage, number of common children, etc., are associated with the couples, whereas further variables, such as age, occupation, etc., are associated with the individuals that make up the couples.

As illustrated in Figure 2(b), the domain of couple-level variables is therefore composed of pairs of individuals that cannot be treated as a new, atomic unit because it is important to maintain individual identities to be able to find between-variable associations in individual- and couple-level data. Similarly, attributes of couples cannot be represented in individual-level variables because this means eliminating, for instance, possible between-variable associations of individuals and marriages that are moderated by attributes of spouses.



A domain representing couples is structured but only minimally so. The only relation is a pairing of individuals in dyads. For the statistical analysis to work, it is usually desirable that these dyads be disjoint and independent. For example, having several individuals appear in two or more distinct dyads may invalidate findings about associations between, say, age differences and the number of common children. In this respect dyadic data is not all that different from standard data tables.

### 3.3 Step 3: Network data

While the units of observation for network data (the entities with which attributes are associated) are dyadic as well, it is by design that these dyads are *overlapping*, i.e., they intersect. Two dyads with a common member are called *incident*. See Figure 2(c) for an illustration.

If we are interested in, for instance, the effects of friendship among children of a school class, and we observe friendship ties for each pair of them, then the mere fact that the same child appears in several dyads creates a potential dependency between the attributes of those dyads. This is of course not a defect of the study design. Rather, the patterns found in data on incident dyads are the essence of what we are after because they may help explain, e.g., which particular children can be considered crucial for the integration of the class.

Concretely, we can define a network variable as a mapping  $x : D \rightarrow R$  from a domain of non-disjoint dyads  $D$  to a range  $R$ . In the common case of *interaction domains*  $D \subseteq A \times A$ , the units of observation are pairs of entities, or actors, from a set  $A$ . A relation  $x$  then corresponds to a one-mode network that can be represented, for instance, as a graph or a square matrix. Note that there may be so-called *structural zeros*, i.e., entries  $(k, l) \notin D$  that are not part of the analysis, often the diagonal entries.

The domain can be more general, though. An *affiliation domain*  $D \subseteq A \times S$  relates actors in  $A$  (e.g., directors) with settings in  $S$  (e.g., company boards). The two-mode networks defined on such domains can be represented, for instance, in a rectangular matrix, a bipartite graph, or a hypergraph. An ensemble of ego networks can then be considered as a special two-mode network in which each alter in  $A$  is affiliated with exactly one ego in  $S$ , i.e., dyads overlap only on the ego side.

Diametral to standard forms of data analysis, dependencies between the elements of the domain are at the heart of network representations. Of course, we most often think of two attributes being dependent on, or associated with, each other. For instance, it is possible that income may be associated with age. In standard terms that is an association between the distributions of two variables, homogeneous with respect to individuals. It does not matter whether individual  $i$  is rich or old (or both): rather, if there is an association between the two variables, then wherever  $i$  is located on one of the distributions (age or income) tends to be associated with  $i$ 's location on the other distribution; moreover, this association is in some sense an average across all such individuals  $i$ .

As a consequence that may not immediately be obvious, an incidence-structured domain leads to interesting questions also about *within-variable* associations, or *patterned relations*, beyond distributional analyses. The first conceptual extension is that the income of  $i$  may be related specifically to the income of  $j$ , e.g.,

because they are good friends who share information relevant for their salary negotiations. In other words, rather than being a dependence between two different types of variables, now we have a dependence within the values for one type of variable. This is a complex dependence because it cannot be aggregated or averaged in distributional terms. It corresponds to the kind of dependency analyzed in spatial statistics (with proximity rather than friendship as the underlying mechanism).

Yet, network dependence goes further because dependence does not just stop at actor attribute variables. It may apply within the set of network variables as well. Any network variable is defined on a domain of pairs of individuals (i.e., the dyads), and the incidence structure of the domain captures the potential for within-variable dependencies. A network tie variable takes a value, often binary, sometimes valued, indicating whether there is or not a tie between its two individuals. The crucial point is that the presence of one tie may influence the presence of another. In other words, ties are not necessarily moderating variables, but there may be dependencies within the tie variable themselves. While this will appear an unfamiliar point of view to some, it is merely a statement that networks may be systematically patterned. Without dependence among ties, there is no emergent network structure.

In the explicit form of stochastic models, these ideas entered network analysis from spatial statistics. They are deeply at the heart of network theory, even if seldom overtly addressed. Entire sets of methodological approaches, such as exponential-family random graph models, depend on modeling tie dependence appropriately.

With independence among network tie variables, we would be left only with the simple random networks known as Bernoulli graphs, Erdős-Renyi graphs, or the  $\mathcal{G}(n, p)$  model. It should be noted that this view does not require a statistical perspective; combinatorial invariants of graphs that represent networks are of interest exactly for the same reason as descriptors of structural features.

Because almost all the networks that we observe bear little resemblance to simple random graphs, tie dependence is empirically very common. For instance, a familiar network process is that of preferential attachment, whereby actors “prefer” to be attached to popular actors so that the rich get richer. The presence of many ties centered on one popular individual may attract the presence of additional ties to that same individual.

Dependence among ties is thus the means whereby network structure self-organizes and evolves, or emerges, but it is not simple. This is why network science is often referred to as the study of *complex networks*. It remains a research question to establish plausible types of tie dependence. Theories or methods that wish away these dependencies are ignorant of the structure of the domain, and thus contradictory to a network model.

While the choice of representation is indeed a matter of convenience and hence relative to any given scenario, we think that the data-oriented perspective of a structured domain is leaner than, for instance, the common strategy of defining networks in terms of graphs. Graphs may be one of the most common forms of representation but they do not make the most distinguishing feature of network data apparent. The edges display the structure of an observation, not of the conceptual setup that led to it.

At *Network Science*, we anticipate to publish work on all kinds of network data, including ego networks. We also hope to receive contributions on network sampling techniques, possibly defining the domain on the fly, and even fundamental theoretical work on structured dyadic domain.

Contributions using other forms of data, simulations, or analytical approaches that focus on building theory, illustrating practical data concerns, or fleshing out nuances not recognized in standard representations are welcome as well. Likewise is rigorous qualitative research which could offer insight into process and meaning that can be missed otherwise. With all articles, the quality of data and the appropriate use of it to answer the questions put forth about relational, complex phenomena is the most important criterion.

### 3.4 Discussion

Our characterization of network data focuses on the structure of the domain of variables irrespective of their range. We have built our exposition on this definition because it carves out the essential distinction from standard data and allows for a more uniform description of different network types. A further advantage is the clear distinction between dyads for which no data is available (because they are not in the domain) and dyads for which the data indicates the absence or nullity of a relationship.

Statistics is often defined as the study of data, involving anything from its collection, preparation, and management to its exploration, analysis, and presentation. In this view, our definition of network science delineates a subarea of statistics concerned with data of a peculiar format. This implies that, like general statistics, network science is not tied to any particular substantive area. The disciplines for which area editors have assumed responsibility should therefore not be viewed as limiting the scope of submissions.

Areas such as machine learning or data mining are distinguished from other areas of statistics by the tasks addressed. Operations research is distinguished mostly by the subject matter and its consequences for data and tasks. In contrast, it is the special data format that causes network science to be markedly different from other areas in statistics. First, the abstraction to a different category of concepts introduces a combinatorial structure on the domain of variables. This structure leads to alternative representations that ask for more combinatorial approaches than distributions and graph theory in particular. Second, there is an inherent focus on interdependence and (in contrast to time series analysis: non-linear) within-variable associations.

#### *Claim 6*

Network science is evolving into a mathematical science in its own right.

Throughout this section we have advanced the argument in mathematical and quantitative or combinatorial terms, so as to make the point precisely, but we hasten to add that the same considerations apply to qualitative network approaches. A qualitative approach, perhaps even more so, is sensitive to the issues of connectivity, systematicity, and dependence. For network science, the point is not whether one is

researching in a qualitative or quantitative way, but that the understanding of the phenomenon treats relational connectivity and dependence as central.

#### 4 The emerging science of networks

In light of the above discussion, we hope that this journal will provide a shared intellectual space for network scientists working in many different fields to communicate with each other about relational data.

To get there, we must recognize our various shared and disparate histories, recognize that this field is quick-evolving, commit to compatible languages about networks, and be willing to speak outside narrow disciplinary interests to broader communities of scholars. The benefit, we believe, will be well worth the effort.

As editors of a journal attempting to encompass a broad field with a long and storied history, we have already rejected the idea that network science “began” with some kind of new discovery or even a Kuhnian paradigm shift tipped off by work originating from physics, no matter how interesting or influential. Network science is neither tied to nor “owned” by any other field.

We should not be ignorant of the forebears of our emerging science, and decades of empirical research. The past 15 years have seen a boom of interest in networks that does not overtly trace its roots to, for example, the sociometry of Moreno or the sociology of Simmel. Even this older tradition has long borrowed from other fields such as graph theory, physics, or statistics as it has developed.

Neither are these the sole progenitors of what we now recognize as network science. Many streams of research are converging to create this new flow. The economic problem of transshipment, or finding the most economical routes to transport goods, is one of these streams. Seriation, or a method of relative dating of archaeological artifacts is a 19th century splash that turned into a stream. Gene regulatory networks have their own distinct research history since the late 1960s and have led to the development of specific network models to account for transcription rates. And there are many more examples showing that network science does not begin with the advent of networks as models for complex systems, but as a perspective focusing on interdependent relations that was developed in many areas.

The interest in models and tools applied to increasingly available large data sets brought to bear by physics, biology, and socio-technical networks has brought with it methodological and technological innovation. There is so much opportunity to draw from work across fields, and so much history to be aware of. The journal values work that points out the various streams of research that have informed a particular field so that the intellectual relationships that shape the network of network science can be made visible.

##### *Claim 7*

Network science is itself more of an evolving network than a paradigm expanding from a big bang.

It is our intention to help the field of network science develop a canon of research moving forward by publishing the most promising and widest-reaching work in the field.

This goal transcends disciplinary boundaries but we do have disciplinary goals as well. Our major fields of editorial coverage (with area editors in parentheses) include information science (Adamic), computer science and mathematics (Brandes), communication, engineering and management (Contractor), economics (Goyal), political science and psychology (Robins), public health and medicine (Valente), physics (Vespignani), and statistics and sociology (Wasserman). Each editor has identified key topics and debates within their area that they would like to see addressed in the coming issues of *Network Science* and that list follows this editorial as an attachment. Consider these an open call for work, but also consider *Network Science* as welcoming of work that pushes this new science forward.

We are excited by the prospects of this new journal, *Network Science*. We believe there is a distinctive science of networks that crosses traditional disciplinary boundaries. It is ready to be brought together in a coherent form that transcends disciplinary silos. We encourage all our readers to contribute to the journal to help achieve these goals.

### Acknowledgments

Part of the research that led to this editorial was funded by Deutsche Forschungsgemeinschaft under grant Br 2158/6-1 and the Social and Cognitive Networks Academic Research Center of the US Army Research Laboratory.

### Notes from the area editors

#### *Lada Adamic, editor for information science*

Information is an interdisciplinary field, just as network science. Therefore, a broad range of topics can fall under this heading, including networked information (e.g., the web, Wikipedia, citation networks), information dynamics in online, organizational, and other social networks, and networks that can be constructed by representing relationships between data (e.g., health, scientific, or historical data). We invite contributions that include novel theoretical models, empirical studies, and methods and applications pertaining to information networks.

#### *Ulrik Brandes, editor for computer science and mathematics*

We invite articles presenting original research in structural and computational network science. This includes the study of network representations, algorithms, data management, and visualization. A typical theory paper uses graph theory, combinatorics, algorithmics, machine learning, information retrieval, or computer graphics methods, whereas a systems paper concentrates on design aspects, implementation, and performance assessment. Novel uses of network approaches in application areas, and in particular those relating to social media, may also be suitable for the information science area.

*Noshir Contractor, editor for communication, engineering, and management*

**Management.** The last few decades have witnessed the emergence of new organizational forms based on fluid, dynamic multi-level socio-technical networks. We invite contributions that advance our understanding of the emergence and outcomes of these novel forms of organizing both within traditional and informal intra- and inter-organizational contexts. We also invite submissions that investigate how we can use these insights to design more effective networks. In all of these areas we seek to publish a broad range of articles that make significant theoretical, computational, empirical, and/or methodological advances.

**Communication.** Digital technologies have significantly enhanced the modalities and affordances we use to communicate at the interpersonal, group, organizational, societal, intercultural, and global levels. These new developments prompt a reconsideration of extant—and exploration of new—communication theories and methods. We invite submissions that utilize novel network perspectives to advance our multi-level understanding of the antecedents and outcomes of communication structures and processes. In all of these areas we seek to publish a broad range of articles that make significant theoretical, computational, empirical, and/or methodological advances.

**Engineering.** Across various engineering disciplines there has been a growing interest in understanding phenomena from a network perspective. These include contexts as diverse as transportation networks, production networks, supply chain and logistic networks, telecommunication networks, traffic networks, data networks, mobile ad hoc networks, content distribution networks, peer-to-peer networks, sensor networks, neural networks, nano networks, and regulatory networks. In all of these diverse contexts, we seek theoretical, methodological, computational, and empirical contributions that examine engineering issues such as network architecture, flows, protocols, reliability, performance, optimization, routing, and congestions.

*Sanjeev Goyal, editor for economics*

In the field of economics, we would like to publish articles which explore the economic origins and consequences of networks. We are also keen to publish articles which explore network themes that lie at the intersection of economics and other disciplines such as computer science, physics, statistics, psychology, and sociology.

*Garry Robins, editor for psychology and political science*

**Psychology.** We invite articles based in social psychology, social relations, and social cognition but within an explicit social network or social system framing. We are also interested in the structure of brain networks, including the network-based modeling of empirical neuroscience data pertaining to brain connectivity; the structure of cognitive networks (e.g., memory associations); organizational psychology, with an emphasis on individual outcomes within a network-based organizational system, or on the structure and outcomes of different types of organizational systems; leadership within network-based social systems; small group studies of networks;

and interaction of individual attitudes, traits and behaviors, and social network ties, including network-based social influence. Finally, we are also interested in the perception of social networks, network structures typical of different age groups, or of other social categories; network-based social support and mental health; and social networks and culture.

**Political science.** We hope to see theoretical, empirical, or computational studies relating to network-based political science, policy networks, network governance, including management of environmental systems, and dispersion of political attitudes or policy-related behaviors across community social networks. Also welcome are articles about health system networks, international networks linking nations, historical network analysis, networks relevant to social movements, network-oriented social media, and hyperlink analysis of political issues.

*Thomas Valente, editor for public health and medicine*

We invite manuscripts addressing all aspects of how networks relate to health, well-being, and disease across all ecological levels and/or environmental systems. Original scientific studies, as well as reviews are welcome. We also invite manuscripts that develop novel measures, algorithms, perspectives, or insights that relate to health and disease incidence, prevalence, progression, or transmission.

*Alessandro Vespignani, editor for physics*

Physicists specialize in the study of complex systems, both theoretical and applied. The methods of physics are well suited to the problems arising in such systems; if these systems happen to involve relational information, then network science benefits from this research. We invite manuscripts from physicists studying networks, either empirically or theoretically, particularly those interested in properties of networks as a whole—shape, signature, or topology. Physics journals have published much of the foundational work in network science over the past 15 years; we hope that *Network Science* will be seen as a proper venue for such research.

*Stanley Wasserman, editor for sociology and statistics*

**Sociology.** We invite manuscripts using sociological theory and methods to study network relationships among social actors, and the patterns and implications of these relationships on groups and society. Network analysis is of course rooted in sociology and social psychology—many advances over the past decades have come from researchers in these fields. We hope that *Network Science* will be a leading publication venue for sociological structural scientists.

**Statistics.** Network science is inherently a discipline rooted in data. Since statistics is the science of data, we welcome research on both statistical theory of networks and the statistical modeling of data arising from network studies. Network theories have advanced over the decades because of development and quantification of hypotheses that can be studied with statistics.