CHAPTER 5

RETHINKING SOCIAL NETWORKS IN THE ERA OF COMPUTATIONAL SOCIAL SCIENCE

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SOCIAL network analysis and theory has proliferated rapidly across the social sciences, shifting our analytical focus from individuals or groups to social relations or "ties." Such ties have been conceptualized in four distinct ways. Theories of group process and team dynamics often depict social networks as patterns of *sentiments*, or thoughts and feelings in the minds of individuals directed at others, such as liking, hatred, or trust. Theorists interested in network positions as sources of power often think of ties as *access,* an enduring opportunity to obtain resources or information from another (even if the party never uses the opportunity). Theorists interested in social influence or contagion often think of networks as behavioral *interaction* that actually occurs between actors, such as temporally aggregated communication, support, gifts, sex, or citations (ignoring possible contacts that never occurred). Most classic work on social networks has measured *role relations* where two parties have a socially constructed relationship associated with distinct norms and expectations for role-related behavior, such as marriage, friendship, or coauthorship. Although these four approaches consider different kinds of theoretical objects, they similarly treat the network as a temporally continuous and enduring latent structure.[1]

An alternative perspective focuses on time-situated events linking actors, including interactions such as conversations, meetings, or transactions. This focus is growing in social network research because of two revolutions, one in data collection and one in data analysis. First, new telecommunications and sensor technologies allow researchers to collect data on events connecting actors with unprecedented volume and granularity. Electronic traces, such as logs of messages sent and received, telephone calls, meetings recorded on electronic calendars, exchanges in online commerce or sharing sites, or sensor data, allow researchers to observe social dynamics in fine time grain. In the second revolution, innovations in statistical methods are uniquely fit to make sense of these streaming data, by explicitly modeling temporal interdependence of relational events (Butts, 2008), including interaction behavior. This confluence of cutting-edge methods and dynamic behavioral data implies exciting frontiers of empirical research. However, it also challenges social network theory, which has been largely predicated on a view of networks as relatively stable configurations of interpersonal relationships. After describing these two revolutions, we investigate the mapping between streaming interaction data and social network concepts to identify implications for network theories.

We show how a deeper understanding of temporal dynamics can also enhance our understanding of traditional social network lenses. In particular, new frontiers inspire rigorous attention to scope conditions on theories developed for alternative network concepts, such as social influence network theory (Friedkin & Johnsen, 2011) for interaction networks, structural balance theory (Cartwright & Harary, 1956) for interpersonal sentiments, or network exchange theory (Cook et al., 1983) for structures of access or opportunity. We also describe nascent efforts to develop dynamic structural theories to fit the new breed of timestamped event data. This often means eschewing the concept of ties to focus on social processes operating in time.

Four Conceptualizations of Network Ties for Social Network Theory

We will elaborate an analytic typology developed by Kitts (2014), distinguishing four basic approaches to defining networks. The four usages of the social network concept offer building blocks for distinct theories, and all have supported decades of fruitful research. This typology certainly does not represent the approaches as mutually exclusive, and they often overlap empirically as illustrated in Figure 5.1. Some empirical ties may involve two or more of these features, but the four types remain distinct in theory because they apply to distinct theoretical mechanisms with corresponding scope conditions. Social network analysts often ignore the differences between these four conceptualizations, as if they are interchangeable, such that we can measure one and apply it to a theory developed for another. For example, they may use a measure of electronic messages sent and received (interaction) and apply a theory such as homophilous attraction or structural balance (which apply to sentiments) or centrality and power in exchange (which apply to structures of access and opportunity).

In briefly discussing these four traditions, we will highlight a couple of analytical issues that prove relevant under revolutionary modes of data collection and analysis. First, how does a network concept represent *null ties*, such as non-coauthors (role relation), impossible exchange partners (structure of access or opportunity), nonrecipients of phone calls (interaction), or nonliked others (sentiment)? Second, what is the connection of the social network concept to *time*? In particular, does the conceptualization of network ties assume temporal *continuity*? By continuity in time, we mean that for a given time interval on which a tie is defined, the tie is assumed to exist from start to finish including all time points

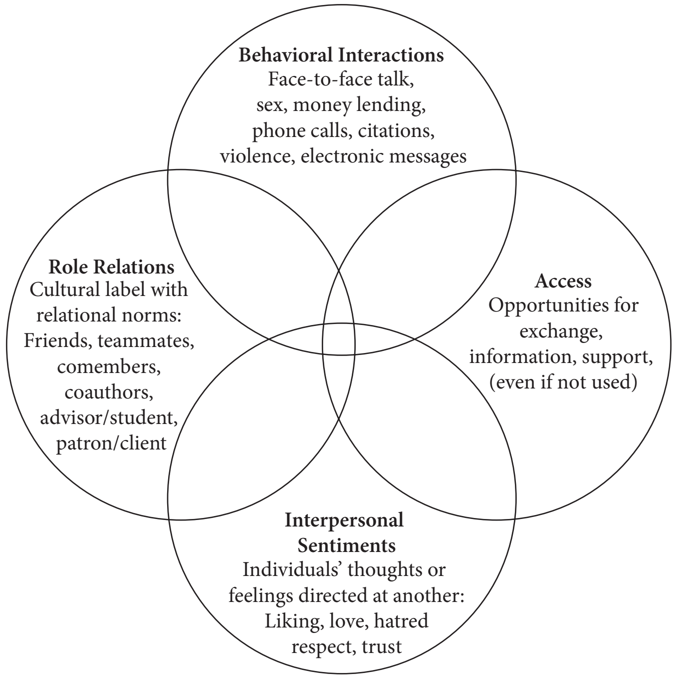

FIGURE 5.1 Four conceptualizations of social networks.

within the interval.[2] For example, if one person reports being a friend with another person in a given survey wave, this is assumed to be true for all time within the wave.

Social Ties as Access or Opportunity

A substantial body of theory assumes that social networks are opportunity structures, where a party has an enduring access to resources (Molm, Whitham, & Melamed, 2012) or information from another (even if the party never uses the opportunity). Knowing the set of alters accessible in such a way to any given ego allows a researcher to construct a graph of possible paths by which goods or information *might* flow among actors. Classic measures of closeness or betweenness centrality (Freeman, 1979) are defined on geodesics, or the shortest paths that can be traversed between any two nodes in a network. An actor connected to others by relatively short paths is assumed to have access to more accurate and timely information, and an actor who lies on many shortest paths of access among peers is assumed to have power to control flows of information in the network (Bonacich, 1987).

Researchers in sociological exchange theory have offered valuable insights into the dynamics of exchange given exogenous structures of access or opportunity (Cook et al., 1983). Although this usage is prevalent in network theories and this interpretation is imposed on social network data of all forms, it has been poorly aligned with observational social network data. There are not many cases where naturally collected data on interpersonal sentiments, role relations, or interaction are interpretable as structures of access or opportunity. Potential interaction partners may be difficult or impossible to observe empirically because most links may never be realized. For example, researchers may observe patterns of electronic messages sent or money lent among actors, but not the set of alters who *could have* sent messages or lent money. In fact, much of the empirical work that has aimed to investigate social networks as access to resources or information has been in the domain of laboratory experiments, where investigators can control such access. For example, a prominent contemporary online experiment (Centola, 2010) assigns network ties ("health buddies") as information sent by the investigator to ego about alter's choice (even where parties are anonymous and will never interact, no sentiments are felt, and ego never reads that information).[3]

Social Ties as (Time-Aggregated) Behavioral Interactions

In many cases, researchers are not interested in where interaction could occur, but instead where two parties actually share overt behavior or one directs behavior at another. Theories of social influence (Friedkin & Johnsen, 2011) and diffusion (Valente, 1995) typically apply to interaction networks. Researchers studying the spread of HIV naturally focus on networks of risk behaviors, such as sex or needle sharing. Generative theories of social networks may also be driven by assumptions about interaction. For example, arguments that spatial and sociometric propinquity leads to formation of dyadic ties (C. C. Liu & Srivastava, 2015) and triad closure by chance (Stephens & Poorthuis, 2015; Lewis, Gonzales, & Kaufman, 2012) are driven by an assumption that ties are composed of behavior that occurs in time and physical or social space.

Classic social network analysis and theory has focused on temporally continuous and stable relationships as measured by sociometric surveys. By contrast, interaction behavior is explicitly rooted in time and so behavioral interaction data are typically ill-suited to this view of networks as timeless abstractions. To develop conventional social network data from interaction records, researchers interpret aggregations of observed or self-reported interaction histories (Heidler et al., 2014; Vargas, 2011) as temporally continuous relationships that may be amenable to social network analysis. Aggregation produces a set of dyadic event counts (such as the number of electronic messages sent within a month), and thus coarsens the observation of interaction, but does not change the nature of the data. They are still events. Dyadic event counts do not naturally imply continuity and thus do not resemble a network of relationships. To make these data amenable to conventional social network analysis, scholars typically take a step beyond aggregation to convert those dyadic event counts into a set of "ties" that are assumed continuous in time. For example, researchers may define a *friend* as "a person whom the user has directed at least two posts to" (Huberman et al., 2009) or a *communication network* as a set of ties represented by at least one reciprocated phone call in a month (Eagle, Macy, & Claxton, 2010) or in 18 weeks (Onnela et al., 2007). Aggregating timestamped events into counts is a methodological choice to reduce the temporal pattern into a static constant (Brashears & Quintane, 2018); interpreting that temporally aggregated event count as a continuous "tie" or relationship is an ontological leap with deep implications for theory. This method may be repeated over successive time periods to derive a series of such structures, turning episodic temporal aggregations into panel network data.

Social Ties as Interpersonal Sentiments

Classic theories of network dynamics interpret social ties as interpersonal sentiments (Homans, 1950), which are thoughts or feelings that social actors have about others. As sentiments exist in the minds of individual perceivers, they are inherently directional. They may be positive (liking or trust), negative (hatred or jealousy), or neutral (awareness or acquaintance), and they may or may not be symmetric with sentiments felt by the other party.

Sentiments may be interconnected with but distinct from social interaction. For example, according to theories of homophilous attraction (Byrne, 1961), individuals are drawn to peers who are similar to themselves, grow to like them, then choose them as interaction and relationship partners. The triadic theory of structural balance (Cartwright & Harary, 1956; Marvel et al., 2011) is built on an assumption that ties represent positively or negatively valenced sentiments. Dissonance arises when positively tied actors disagree (or negatively tied actors agree) in the sign of their tie to a third actor. This dissonance leads to instability in the network, and resulting reconfigurations may lead to a more stable balanced state (where triads are either all positive or have a positively tied pair that is negatively tied to a third). In all of these cases, the "tie" exists in the subjective thoughts or feelings of the actor(s).

Social Ties as Socially Constructed Role Relations

Much social network research has depicted networks as sets of *role relations*, cultural labels assigned to dyads as distinct relationships (such as friendship, kinship, marriage, etc.) or shared involvement in some higher-order social unit (teammates, officemates, housemates, coauthors). These relations operate as relational norms, expectations, and repertoires for how actors behave within the role. For example, research on the meaning of friendship among adolescents (Kitts & Leal, 2020) shows that friendship is typically construed as relational norms, including behavioral prescriptions (e.g., "sticks up for me when others are against me") and proscriptions (e.g., "would never hurt me"). Although we might thus infer relationships from patterns in role-related behavior, more often researchers simply ask individuals to identify their friends or other relations in surveys or interviews, or find archival data that records these relationships.

There is no theory about the social processes producing role relations generally (applying across disparate categories of friendship, kinship, combatant, plaintiff-defendant, and vendor-client relations), and few theories even for more specific role relations. However, because role relations are simple to measure with surveys or archival data, they are often used as proxies for any of the other three types of ties. Theories developed to explain the dynamics of interpersonal sentiments, access, or behavioral interaction have been applied to role relation data (such as friendship or coauthorship), even though these theories have nothing to say directly about role relations.

Comparing These Four Conceptualizations

Treatment of Ties and Null Ties

Researchers have conflated theories and data across these four distinct conceptualizations of social networks with impunity because they have focused exclusively on *ties*. It is instructive to redirect our attention to *null* ties to interrogate the mapping of one network concept to another.

Work based on structures of access or opportunity—including theories of structural power and centrality in exchange networks—is predicated on an interpretation of null ties as loci where interaction is strictly impossible. It is rarely recognized that this implies a weak or ambiguous interpretation of *ties,* where interaction might occur (but might not). If we represent the network as a sociomatrix, most of the analytical leverage comes from a strong interpretation of the zeros. Any uncertainty about those zeros is a fundamental problem: a long path through social ties may be unimportant if the first node could simply contact the last node directly (as if traversing null ties). Uncertainty about the null ties in a network propagates along each step in a path, such that long paths (and metrics that depend on them) become questionable.

In the case of sentiments and especially role relations, the focus is entirely on ties, so null ties are poorly defined and rarely observed in any explicit way. For example, if a survey allows students to identify their best friends among students in their school, we have some insight into the alters who are nominated as best friend but little information about the alters not so nominated. In fact, the non-best friends could be enemies, strangers, siblings, lovers, neighbors, or just very good friends. The problem is not peculiar to friendship and is shared for a great variety of role relations as well as for sentiments. We may make some reasonable assumptions about the behavior of a coauthor, client, or friend-with-benefits relation, but how do we interpret non-coauthor, non-client, or non-friend-with-benefits? Investigating null ties in role relation and sentiment network measures is an open frontier for future research, and we will discuss this frontier later. Until we have more purchase on what null ties mean for a given role relation or sentiment we should be very careful in applying theories or metrics that depend importantly on null ties when using role relation or sentiment data.

Defining networks as temporally aggregated interaction histories offers a concrete, clear, and strong definition of social *ties*: we know whether or how much a given mode of interaction (email, phone conversation, sex, lending) has been observed on this time interval. Null ties in temporally aggregated interaction data also have an explicit interpretation: interaction of this form did not occur between these actors during this time interval. However, null ties still cannot carry the theoretical weight that they carry for structures of access. Taking aggregated interaction as a proxy for access requires us to interpret lack of observed interaction on a time interval as observed impossibility of interaction on that interval.

Temporality

Ties conceived as role relations, sentiments, and access all have had little relationship to time in previous work. Until recently, almost all social networks research involved a timeless analysis of a fixed structure of relations. All ties were assumed to operate continuously for the duration of the research. This assumption of continuity at the tie level implies two related properties at the graph level, stability and concurrency. By network *stability*, we mean an absence of network change on the interval. By *concurrency,* we mean that all ties within the period of continuity are simultaneously active, and thus all paths described by the graph can be traversed for the entire interval. Accordingly, we can employ a centrality or centralization metric, a clustering coefficient, or an index of homophily, modularity, or structural cohesion to describe the network structure. Longitudinal studies were rare until recently and have typically applied the same timeless lenses to repeated cross-sections. Within each time interval, all ties are assumed to be present (or absent) continuously and concurrently, even as the network changes between discrete time steps.

It is rarely possible to identify a start or stop time for a role relation, sentiment, or access. An exception, such as legal marriage, may have a well-defined beginning and ending, but those time points may have little to do with the underlying sentiments and behaviors of matrimony. A couple may love each other and live together years before marrying, and they may move out and hate each other a long time before divorcing. Similarly, coauthorship is a role relation that typically implies interaction over time, but interaction involved in developing the article may be separated by years from the observed publication time, coauthors may not even work on the project at the same time, and some may not work on it at all.

Unlike most interpretations of sentiments, role relations, and access structures, interaction behavior—such as conversations, money lending, sex, and fighting—occurs at specific times. But the canon of social network theory, developed largely for static networks, has little to say about time. Thus, although we see the temporality implicit in interaction data as an opportunity to develop more nuanced processual theories of social networks, scholars have historically treated time as an ignorable nuisance by aggregating interaction data over time, interpreting the resulting data as cross-sectional networks just like those collected through sociometric surveys. More recent research on social interaction has aggregated events into coarse panels, defining a tie as a quantity of interaction exceeding some threshold (e.g., at least n phone calls in a month) and defining a null tie as a lesser quantity of interaction in that time interval.

Let us consider the implications of the width of those time intervals, a seemingly innocuous methodological choice. The wider the time interval monitored, the more events may be included in each interval, the greater likelihood that social ties will be identified, and the denser the network. Shrinking intervals of aggregation breaks event series into separate intervals, reduces within-interval event counts, eliminates ties, and reduces network density. In the limit as intervals shrink, the network disappears altogether. By contrast, temporally continuous relationships will not be eliminated by shrinking the width of panels. Even an instantaneous snapshot of a network of relationships is still a network.

Observing interaction event histories situated in continuous time without temporal aggregation may produce sparse and unstable ties with only vacuous null ties. Aggregating events in time gives more stable impressions of ties and more meaningful interpretations of null ties. The tradeoff is that, in developing these robust images of network structure by aggregation, researchers also destroy details of the sequence and timing of interaction. Interestingly, constructing networks from dynamic interaction data necessarily implies these tradeoffs between observing the dynamic process (by dissolving the network) and observing the structure (by obscuring the process). In this chapter, we point to new analytical lenses that resolve this dilemma through explicit dynamic structural analysis of relational events.

Dilemmas of Mapping Theories to Data across Discrepant Conceptualizations of Networks

Given that research has so rarely acknowledged the discrepancies between these four ways of conceptualizing networks, there has been hardly any attention to the conditions under which we can employ a theory developed for one conceptualization to data drawn from another. Consequently, researchers often face a mismatch between the form of their network data and the network theory they aim to employ. Social influence or diffusion theories developed for behavioral interaction have been applied to role relation data, such as modeling contagion on a friendship network or social influence among coworkers. Structural balance theory and homophilous attraction, developed for sentiment structures, have been applied to socially constructed role relations or even behavioral interaction networks such as electronic messages or phone calls. Similarly, theories of network exchange and structural power, developed for structures of access or opportunity, have been applied to role relations or behavioral interaction data. Let us examine some challenges for crossing these boundaries in connecting theory to data and then think about scope conditions for when it may be acceptable to do so.

It seems that there are 12 possible ways that theory and data can mismatch across these four conceptualizations, but we focus on the 5 ways that are common in the literature. Given the ease of measuring role relations using surveys (and the lack of general theories for role relations), early researchers generally used role relations as proxies to apply theories of interaction, access, and sentiments. In more recent years, especially with the advent of digital trace data (Golder & Macy, 2014; Malik, 2018), interaction data are readily available with little effort or expense, so researchers use them as proxies to apply theories of access and sentiments. We focus on these five cases where researchers commonly employ a theory from one network conceptualization to data derived from another.

Can We Use Role Relation Data to Investigate Theories of Social Interaction, Access, and Sentiments?

Interpreting a role relation graph (kin, friend, lover, classmate, teammate, coworker, comember, neighbor) as an interaction graph is making dual assumptions that the specific role relation implies interaction and that the lack of that specific role relation implies noninteraction. For many relations, the former assumption may be questionable, while the latter is often absurd. People do not always interact with their friends, neighbors, or parents, and we cannot assume that non-friends, non-neighbors, or non-kin never interact. Thus, a role relation network will at best offer a subset of the true structure of interaction, and some key role relations may not represent regular interaction at all.

If researchers interpret null ties in the role relation graph as null ties in the interaction graph, this likely induces "false negatives" where interaction occurred despite an absent role relation. Rather than conventionally assuming this risk away, let us begin to explore scope conditions where it may be reasonable to assume that a nonrelationship does in fact reflect noninteraction. Consider a small bounded population with a high baseline level of interaction, such as a school classroom. In this context it seems indefensible to assume that non–best friends never interact with one another. By contrast, if the network boundary is very broad and the baseline level of interaction very low, such as in a large city, then it is more reasonable to assume that non-best-friends never interact. Stated more generally, interpreting a role relation network as an interaction network is more problematic if the network boundary is set around a population with a high expectation of interaction.

We avoid repetition here, but all of these points apply at least as strongly for interpreting role relation networks as access networks. In light of this challenge, it seems hard to motivate a study of structural power (e.g., depicting a central actor as lying on the shortest paths among peers) for a network of close friends in a classroom or in a small team of employees, because a theory of access places great weight on null ties, which carry little weight when the researcher has only measured a specific role relation in a population with high expectation of interpersonal access. This is a key challenge to a large body of work that has applied such theories, concepts, and metrics for specific role relations in classrooms, teams, or organizational units, where access is practically ubiquitous across the population.

We need similar scope conditions for applying role relation data to theories of sentiments. Consider applying structural balance theory to friendship networks among youth. Sentiments can be challenging to measure, especially negative sentiments. Many scholars interested in positive and negative sentiments have measured the role relation *friendship* (taken to represent positive sentiments) and assumed that peers not mentioned as friends or best friends are in fact negative ties. For example, Hallinan (1974) measured best friends among students and implicitly assumed that alters not nominated as best friends operated as negative sentiment ties, to apply structural balance theory. Following this logic, over four decades of studies have appealed to structural balance theory as an explanation for triad closure or transitivity in positive-sentiment relations (such as friendship). For example, Wimmer and Lewis (2010) describe a force to close triads among Facebook friends by structural balance, which requires the assumption that individuals who are not Facebook friends are joined by a negative tie. Much work follows from Holland and Leinhardt (1971), who argued that null ties (and even asymmetric positive ties) in positive sentiment networks can be interpreted as negative ties for the purpose of deriving transitive closure from balance theory. Later work following from theirs extended this argument to role relations (Hallinan, 1974). To be sure, transitivity and triad closure may be extremely prevalent in role relations of many kinds, but structural balance theory cannot explain this pattern unless null ties in the role relation (e.g., non-coauthor) are interpretable as negative sentiments.

Here we may offer an explicit scope condition for applying structural balance theory to role relation networks with an implication of positive mutual affect, like friendship. In a small group of densely interacting friends where nearly everyone is friends with everyone else, an anomalous pair of actors who do not call each other friends may be perceived as having negative sentiments toward one another. Or a pair of actors who have always called each other friends but cease doing so at a particular point in time may be perceived as having negative sentiments. In either case, it is the violated expectation of a positive role relation that implies negative sentiments.

Can We Use Aggregated Social Interaction Data to Investigate Theories of Access and Social Sentiments?

Given the ubiquitous challenges of measuring networks of access or opportunity outside the laboratory, researchers have often interpreted temporally aggregated interaction networks as access to apply theories of structural power or centrality metrics based on path lengths. However, because those theories rely on a strong interpretation of null ties, they are generally difficult to apply to aggregated interaction data. First is the problem that interactions may have occurred in some other mode not measured (say, two students may not send each other emails on the university server because they communicate on Gmail or Instagram instead, so their lack of measured emails does not represent lack of access). A person is unlikely to follow a long path of past email partners to say something to a teammate or classmate who is immediately accessible some other way. Second is the interplay between time aggregation and the interpretation of null ties, which are crucial to theories of access. If aggregated interaction data are already hard to defend as a measure of impossibility of interaction, aggregating interactions into shorter time intervals further weakens this interpretation of null ties and thus makes the interpretation of interaction as access even more untenable. Simply aggregating interaction into brief intervals will make the entire population seem inaccessible, and without aggregation raw interaction event data generally cannot be represented as access at all.

We previously discussed how structural balance theory has been inappropriately used to account for triad closure in role relations. Recently researchers have appealed to structural balance theory to explain the phenomenon of triad closure in temporally aggregated behavioral interaction networks (e.g., if i tends to send electronic messages to j, and j sends to k, then i also tends to send to k). The link to the classic theory is tempting, but recall that the motivational drive in the theory is the dissonance created by the (negative) valence of ties. Applications of structural balance theory to positive or neutral social interaction data such as email communication networks (Kossinets & Watts, 2009) must assume that noninteraction on a time interval is equivalent to a temporally continuous negative sentiment tie on that interval, an assumption that at least needs to be defended. We believe this slippage from a theory for positive and negative sentiments to an analysis of neutral interaction events is a telling example of why the careful thought in this chapter is needed.

In a contrasting example, Kitts (2010) identifies scope conditions under which structural balance theory may be applied to triad closure in social interaction data (i.e., conditions in which noninteraction might be plausibly interpreted as negative sentiments): envision an interaction form that is socially construed as reflecting positive sentiments (e.g., children playing together, adults having each other over for dinner with family), operating in small groups with a very high baseline level (high expectation) of social interaction. In those conditions, for dyads where such interaction is anomalously missing, the parties may be perceived as avoiding each other and implicitly having a negative tie. Similarly, if two parties interact regularly and then cease interacting together, this could imply or signal a negative sentiment. In either case, it is the tension between the *expectation* of interaction and surprising lack of interaction that implies a negative tie to social perceivers, and implied or perceived negativity does have implications for structural balance theory. By contrast, for a large university community, the absence of emails exchanged between any two students does not imply a negative sentiment to anyone because it does not violate any expectation. Thus, in those cases we have no justification to use structural balance theory to explain triad closure in networks of positive or neutral interactions. Such patterns could instead be explained more parsimoniously through propinquity (i.e., proximity in physical or social space), through shared memberships in classes, clubs, or other foci (Feld, 1981), as a byproduct of homophily (Goodreau, Kitts, & Morris, 2009) or status hierarchy (Feld & Elmore, 1982).

In the next two sections we will introduce a pair of revolutions, in data and methods. We first describe the implications of new sources of streaming data for each of the network conceptualizations defined earlier. Then we present a methodological revolution that allows us to go beyond interpreting aggregated interactions as ties, and instead to directly investigate structural-temporal interdependencies in behavior.

A Revolution in Data Collection: Computational Social Science

Decades of previous research on interaction networks were constrained to either manually observe interaction behavior (and then aggregate it into "social ties") or to ask survey questions about typical interaction partners (such that survey respondents mentally aggregate over events). Tools of computational social science allow direct measurement of social interaction behavior in continuous time, employing a new universe of timestamped interaction data, which form the behavioral substrate of what we call social networks. These data include traces of electronic messaging and interactions using social media, as well as streaming data from location-aware devices, fixed and wearable sensors, biometric monitoring, and the like.[4] Several recent articles have highlighted the key theoretical, methodological, or institutional challenges in using such digital trace data in the social sciences (e.g., Golder & Macy, 2014; Kitts, 2014; Lazer & Radford, 2017). Many scholars have represented aggregated interaction event data as social networks, applying the same theories developed for understanding sociometric nomination patterns. In the following section, we ask how these new sources of data correspond to the four traditional conceptualizations in social network theory and analysis.

Computational Social Science and Role Relations

Contact lists such as those on Facebook, Google, or LinkedIn should be classified minimally as role relations in the aforementioned typology because they are temporally continuous dyadic roles defined by the social media platform. Like other role relations, the data are convenient but only weakly correspond to theoretically motivated network concepts. Some links on some platforms may imply interaction, sentiments, or access, but this is likely to be idiosyncratic and inconsistent, so it is difficult to fit such data to scope conditions of any behavioral theory without extensive processing. For example, while some Facebook contacts might indeed interact socially or have relationships with one another deeper than a contact list on the website, many or most such online contacts apparently never interact (even on the website itself), are not mutually acquainted, and some are not even people. If Facebook pages can represent not only persons but also organizations, clubs, babies, cats, or deceased people, then we are unlikely to find a meaningful social or behavioral theory that applies to networks of this kind.

Early research on online relationships (e.g., Adamic & Adar, 2003) tended to examine sparse networks where most actors had only one or two connections, which researchers assumed were close friends or colleagues. Connections on social media years later have become less costly (usually just a click of a mouse), so they are both more numerous and less significant (Dunbar, 2016; Golder, Wilkinson, & Huberman, 2007; Huberman, Romero, & Wu, 2009; Yang & Yu, 2014), with some ties connecting complete strangers. To derive an interpretable social network, scholars have used a variety of ways to carve out a subset of a digital contact list that plausibly fits a conventional social tie concept. For example, Golder et al. (2007) recommend filtering the set of Facebook friends to identify only those who send each other electronic messages or comment on each other's materials. Their goal is to remove noninteracting "friends" and thus make these ties more like offline friendships (which they assume include communication). Similarly, Gilbert and Karahalios (2009) use exchange of photos as well as public and private messages to identify tie strength in Facebook relationships. Wimmer and Lewis (2010) aim to restrict the list of Facebook friends to substantive relationships by only selecting friends from one cohort at the same college, and regard the friendship as existing (one-way) only after one party tags the other in a photo posted to Facebook. This restriction implies that they are genuine people who have some face-to-face interaction.[5] Xie et al. (2012) similarly propose ways to equate offline relationships with patterns of posting on Twitter. We see that researchers may develop a composite measure intersecting an arguably ambiguous role relation (such as Facebook friends) with a temporally aggregated behavioral interactions to find a more interpretable relationship. Even so, such composite measures are problematic for null ties, as they impose a strong equivalence assumption between total strangers and close friends who fail to interact on the platform in a given time interval, which may not always be defensible.

Computational Social Science and Sentiments

Although most have focused on the wealth of electronic trace data representing social interactions, innovations in computational social science can also provide digital data on interpersonal sentiments. We might naively assume that a tag such as a "friend" or a "like" on

Facebook entails a positive sentiment, but users may employ those tags for a variety of reasons and even the meaning of a “like” is unclear (Sumner, Ruge-Jones, & Alcorn, 2017). Interpersonal sentiments are not commonly available in digital form, although particular social media may invite users to rate each other positively or negatively (Leskovec et al., 2010; State, Abrahao, & Cook, 2016).

A challenging but rewarding approach is to analyze text in messages or posts using natural language processing tools for sentiment analysis (Stieglitz & Dang-Xuan, 2013; B. Liu, 2015; Pozzi et al., 2016). For example, text analysis of social media posts allows for identification of emotional expressions and examination of temporal patterns in moods (Dodds et al., 2011; Golder & Macy, 2011) and also for identification of dyadic similarity in sentiments toward social objects to drive recommender systems (Yang, Huang, & Wang, 2017). Sentiment analysis of Facebook status updates (Coviello et al., 2014) has allowed observation of emotional contagion on networks of Facebook contacts. The same tools can be applied to text directed from one actor to another to provide measures of interpersonal sentiments. Fuhse et al. (2020) analyze transcribed verbal and nonverbal reactions to speech (e.g., laughter, applause, objections) as recorded in parliamentary proceedings to identify sentiments of alliance and conflict among parties, and O’Connor, Stewart, and Smith (2013) analyzed news reports of events to infer valence in international relations.

An exciting but less developed frontier is collecting electronic trace data on sentiments using biometric sensors. For example, researchers may monitor galvanic skin response, pupil dilation, or heart rate (Palaghias et al., 2016; Salah et al., 2011); employ brain imaging (O’Donnell & Falk, 2015); or monitor hormones in saliva or urine samples such as oxytocin (Doom, Doyle, & Gunnar, 2017; Grebe et al., 2017) or cortisol and testosterone (Ketay, Welker, & Slatcher, 2017; Kornienko et al., 2014; Mehta et al., 2017). They may also automatically monitor sentiment-related nonverbal behavior, such as eye gaze or body posture (Schmid Mast et al., 2015), response latency (Iyengar & Westwood, 2015); analyze speech features in audio recordings (Gu et al., 2017; Rachuri et al., 2010); use accelerometers to detect laughter (Hung, Englebienne, & Kools, 2013); use chest bands to monitor breathing patterns during conversations (Rahman et al., 2011; Ejupi & Menon, 2018); use infrared thermography to infer emotions from facial microexpressions (Clay-Warner & Robinson, 2015); or reflect radio-frequency signals off of the body to detect emotional states through physiological responses (Zhao, Adib, & Katabi, 2016).

Computational Social Science and Behavioral Interactions

Among the most commonly collected data forms attributed to computational social science are records of behavioral interactions: timestamped logs of phone calls (Eagle et al., 2010; Onnela et al., 2007; Raeder et al., 2011), emails (Kleinbaum, Stuart, & Tushman, 2013; Kossinets & Watts, 2009), electronic calendar meetings (Lovett et al., 2010), or credit card purchases (Dong et al., 2018); online arenas for dating (Lin & Lundquist, 2013), gaming (Szell & Thurner, 2010), resource sharing (State, Abrahao, & Cook, 2016), writing reviews and commenting on them (Goldberg, Hannan, & Kovacs, 2016), exchanging questions and answers (Vu, Pattison, & Robins, 2015), and crowdsourced editing (Crandall et al., 2008). Face-to-face interactions have been similarly monitored using wearable sensors that detect conversations (Harari et al., 2019; Nakakura, Sumi, & Nishida, 2009; Wyatt et al., 2008) or physical proximity (Eagle, Pentland, & Lazer, 2009; Pachucki et al., 2015) and mutual orientation (Jang et al., 2017). The advent of location-aware devices allows for inference of interaction events by colocation (Lee et al., 2013) or mobility patterns as sequences of locations (Cranshaw et al., 2010). In parallel to the emergence of new sources of digital data coming directly from computer-mediated interactions, the digitalization of more traditional sources of interaction data has also enabled access to fine-grained temporal information about persons and organizations offline. For example, radio communication transcripts (Butts, Petrescu-Prahova, & Cross, 2007), citations (Peng, 2015; Shwed & Bearman, 2010; Foster, Rzhetsky, & Evans, 2015), and gang member fatal shootings (Papachristos, Hureau, & Braga, 2013) also provide timestamped event records of interaction.

The availability of timestamped interaction data offers rigorous ways to operationalize classic social network concepts such as tie *strength*. These methods range from simple, such as the total time spent in phone calls (Onnela et al., 2007) or the frequency of two-party face-to-face conversations (Wyatt et al., 2008) during a time interval, to very complex, such as automatically collected measures of interaction intensity, intimacy, reciprocal giving, emotional support, and relational duration (Gilbert & Karahalios, 2009). Similarly, continuous monitoring of interaction using sensors allows new measures of node *position* in networks. Wyatt et al. (2008) use sensor-recorded speech to develop a temporally sensitive measure of closeness centrality, considering how information flows through paths of conversations (where nodes are "closer" to the extent that they are connected by short paths with more talking time and "farther" to the extent that they are connected by long paths with little talking time). It may also allow researchers to link these social positions to fine-grained interaction behavior. For example, they find that individuals change their speech patterns (syllable rate, vocal pitch, speaking turn length) when talking with peers who are central in the network of temporally aggregated conversations and when speaking through "weak ties" (infrequent conversations) in that network. Of course, we challenge such literatures to stretch these ideas a step further, beyond ties and networks, to directly theorize, measure, and model the structural temporal dependencies in social behavior.[6]

Computational Social Science and Structures of Access or Opportunity

Many core social network concepts, measures, and theories are predicated on the notion of the network as a structure of access or opportunities. This has been easy to implement in experiments, where researchers can control who is able to interact with or receive information from whom, but hardly any observational study actually measures null ties as complete prohibition of relevant interaction. That interpretation is especially untenable in small-scale contexts such as face-to-face interaction among classmates or close colleagues. Thus, implementation of access networks in observational empirical research is a largely open frontier, where computational social science promises to deliver new insights. There are two avenues by which computational social science may lead to important theoretical developments.

First, digital data may mitigate the dearth of research on structures of access or opportunity by providing new ways to monitor users' access to information on a network. Although the form of data may be idiosyncratic and specific to particular social media, in many cases a medium may allow or require users to define privacy preferences, identifying what information is public or private, and even identify discrete sets or social circles of alters who are privy to different levels of shared information, or ability to exchange messages (Anthony, Campos-Castillo, & Horne, 2017; Golder & Macy, 2014; Lewis, 2011). This could be developed in further work to give natural field observation of networks more directly interpretable as access to information.

The second avenue represents a deeper rethinking of the concept of access. In interpreting observed interaction networks as access, researchers have strayed from the crucial scope condition that gives access networks analytical leverage, that is, that relevant interaction is strictly impossible through null ties, requiring information or resources to travel through other actors in the network. Ironically, some of these same researchers have data relevant to the concept of access. For example, they may have measures of the physical proximity of actors in a network, or the fact that some actors share a primary language and others do not, or that some actors may be more available to one another because of their work schedules, or the locations of their offices or homes, or their positions in the organizational chart. These variables constrain availability for interaction and are often a more faithful representation of the access concept than is the observed interaction network. But they are typically treated either as *control variables*, a nuisance to be ruled out as researchers investigate some other structural force (like assortative mixing or triad closure), or as *determinants* of the network (such as the effect of physical distance on the odds of forming a tie). These features of the interaction context may instead be seen as composing a latent access network. As Kitts (2014) has argued, the next step is to extend the concept of networks-as-access to latent ties with continuous rather than discrete values (where interaction is more or less costly, risky, or difficult) and to refine the theories and measures to reflect this step. Operationalizing the access network as a structure of impediments, challenges, and barriers to interaction could mean building a network without conventional sociometric data like role relations or interaction records, but instead measuring and modeling the structure of access. Researchers may apply theories of access (such as structural power or network exchange) to those data on distance or impediments, rather than using questionable proxies based on role relations or observed interaction.

The new developments in computational social science—especially the advent of location-aware devices and geotagging of locations for interaction and routine activities—may often offer such fine-grained measures of relatively exogenous access networks. Rather than implementing null ties as strict prohibition of interaction, we can model a continuum like transaction costs or friction, which makes interaction more or less feasible. This generalization will facilitate applying theories and concepts of network exchange to behavioral interaction outside the laboratory, where impediments to exchange may be relative rather than absolute. Such impediments make some exchanges costly or undesirable, but not strictly impossible.

A Revolution in Data Analysis: From Aggregating to Modeling Relational Events

The emerging continuous measures of interaction challenge us to consider more deeply issues of temporal dynamics in underlying social processes. Preliminary efforts extend previous work on networks composed of temporally aggregated events. Moody, McFarland, and

Bender-deMoll (2005) demonstrate how aggregating behavior in slices of time allows networks to be tracked over time visually. Kossinets and Watts (2009) construct network snapshots based on temporally aggregated email exchanges, with a variety of different thresholds to define ties, then investigate changes in these networks over time. Martin (2009) proposes a "quantitative ethology" in which interpersonal dominance acts are aggregated within discrete periods to describe the development of status hierarchies among adolescents.

Statistical modeling approaches also typically operate on temporally aggregated data. For example, researchers use exponential family random graph models (ERGMs) to explore forces that underlie structural patterns in static networks (Butts et al., 2014; Cranmer & Desmarais, 2010; Goodreau et al., 2009; Harris, 2013; Lewis, 2016). Stochastic actor-oriented models (SAOMs) or temporal exponential family random graph models (TERGMs) aim to use discrete time network panel data to make inferences about generative processes that account for the changing structure (Leifeld & Cranmer, 2015; Snijders, Van de Bunt, & Steglich, 2010). However, these methods do not offer a framework for directly modeling fine-grained interdependent dynamics of relational behavior.

Temporal aggregation obscures generative dynamics because it necessarily removes a wealth of information about timing or sequence, as well as changes in the composition of nodes in the network. Diffusion paths that appear in aggregated networks may be impossible if the sequencing or timing of interaction prevents transmission. For example, if B interacts with C and then A interacts with B, the path from A to B to C appears in a temporally aggregated network but is meaningless given the constraints of timing and sequence (Moody, 2002). Indeed, producing a static network by aggregating over a sequence of interactions, such as sex contacts in a high school (Bearman, Moody, & Stovel, 2004), can severely distort social processes such as contagion and diffusion. Aggregation also assumes that all actors were available during the entire time interval. Hence, aggregating interactions and then using conventional tools to analyze and interpret the networks is likely to be misleading. Notably, aggregating timestamped event data into panel data to use tools like SAOM or TERGM destroys the very fine-grained information that could provide direct insight into the processes researchers are trying to model. By retaining the event data, future work can lead to theoretical insights that illuminate mechanisms of change.[7]

Recent developments in statistical methodology make it possible to preserve the temporal information present in relational event data. Inspired by event history analysis, the relational event modeling (REM) framework (Butts, 2008) was developed as a way to statistically capture temporal dependencies inherent in behavioral interaction data while respecting coarser social interdependencies between actors. These models predict the occurrence of the next event in a sequence of events, where past events form a context that shapes the propensity for future events. The framework allows specification of statistics that capture social processes, such as reciprocation or transitive closure. Such social interdependencies violate the conventional assumption of independent observations for cross-sectional networks but are not a problem in the REM framework due to the temporal ordering of events. Each event is taken to be independent of the others, conditional on the realized history of events.

Relational event modeling is employed by Butts (2008) to describe radio communications in the World Trade Center disaster. Variants of this model have been applied in a variety of interaction forms: computer-mediated group interactions (Leenders, Contractor, & DeChurch, 2016; Pilny et al., 2016), online discussions in Massive Open Online Courses (Vu et al., 2015) and computer games (Schecter et al., 2018), phone calls among students

(Pilny et al., 2017), cosponsorship of bills in Congress (Brandenberger, 2018), international events coded from news reports (DuBois & Smyth, 2010), and patient transfers among hospitals (Kitts et al., 2017). Alternative frameworks or extensions have been proposed to serve specific needs of researchers in handling sequences of relational events. For example, recent efforts to combine REM and SAOM aim to model the coevolution of event sequences with individual-level attributes or behaviors (Stadtfeld & Block, 2017; Stadtfeld, Hollway, & Block, 2017). Alternatives or extensions incorporate exogenous events and multiple event types at the ego level (Marcum & Butts, 2015), combine multiple event sequences through hierarchical modeling (DuBois, Butts, McFarland, & Smyth, 2013), or integrate stochastic blockmodeling with relational event models (DuBois, Butts, & Smyth, 2013). Finally, slightly different approaches to modeling relational event sequences have been presented through multilevel modeling (DeNooy, 2011) or alternative modifications of linear or logistic regression models (De Nooy, 2015; Doogan & Warren, 2017; Vu et al., 2011).

In traditional dynamic network analysis (Snijders et al., 2010), social processes are assumed to follow the same form of time dependence, which remains stable over historical time. A key advantage of modeling event sequences is that researchers can explore how relational events may depend on past events over distinct time horizons, aligning the analytical method with the time grain of the social processes. Static properties of networks such as reciprocity and transitivity can be recast as dyadic and triadic patterns of history dependence in events (e.g., *i* may be more likely to give to *j* again if *j* reciprocates quickly vs. slowly, or if *j* has a long history of reciprocating to another actor, *k*). Authors have used different assumptions about history dependence, specifically the retrospective time horizon that may affect current events. Butts (2008) considers that only the most recent event (or the previous event of a certain type) can be used to predict the next event. Kitts et al. (2017) show how short-term and long-term history dependence may reflect distinct processes, moving beyond *reciprocity* as a property of ties to theorize *reciprocation* as nuanced patterns of history dependence. Some authors also weight events by their distance in retrospective time, such as by a continuous decay in importance (Amati, Lomi, & Mascia, 2019; Brandes, Lerner, & Snijders, 2009; Leenders et al., 2016). These approaches have benefits and drawbacks: Selecting only the most recent event or a certain kind of event severely constrains the questions that can be asked about history dependence. Distinguishing the short term from the long term allows that processes may operate differently over these time horizons but requires the researcher to distinguish the two horizons for substantive or theoretical reasons. Time weighting avoids this choice, but researchers must instead specify a decay function. (For an exploration of the boundary between discrete-horizon and continuous decay approaches, see Kitts et al., 2017, p. 876).

The temporal expression of a given social process may be affected by the context. Researchers typically apply the concepts of inertia, reciprocity, or transitive closure in the same way, regardless of the type of underlying relational data. For example, triad closure is applied in different contexts such as interpersonal sentiments (e.g., Newcomb, 1961), radio communication during emergency situations (e.g., Butts et al., 2007), or interorganizational alliances (Gulati & Gargiulo, 1999). In these cases, the time horizons of history dependence may apply to years for the context of strategic alliances between firms, to months for changes of interpersonal sentiments, and to minutes or seconds for radio communications. Recognizing these different time horizons might enable us to theorize more about temporal shapes of dyadic and triadic history dependence for different modes of interaction. For example, in a longitudinal study of the coevolution of multiple modes of interaction (phone calls, coworking, social visits, wearable sensor measures of dyadic and multiparty face-to-face conversations), Kitts (2010) teases apart propinquity and structural balance as explanations for triad closure by exploiting the theorized time horizons of these processes. This analysis compares interaction forms implying colocation like multiparty face to face conversations and team meetings with isolated interaction like phone calls and dyadic meetings and also compares sentiment-laden interaction forms like social visits with affectively neutral interaction forms like working together. The comparison across modes of interaction reveals stronger triad closure on a short time scale to the extent that interaction joins third parties into shared locations, consistent with propinquity theory. Consistent with balance theory, triad closure increases over a long time scale, but only for interaction modes laden with affect.

In closing, the analytical lenses described here can be extended and applied to discover the interplay of dynamic social interaction patterns with coarser socially constructed relationships, interpersonal sentiments, or access over time, all largely unexplored frontiers. With the advent of computational social science, we now see some researchers monitoring and modeling several of these phenomena simultaneously. For example, researchers analyze perceived friendships based on self-reports in tandem with measures of interaction using phone call records (Pilny et al., 2017) or Bluetooth sensors (Oloritun et al., 2013). Further, Eagle et al. (2009) infer friendships based on spatiotemporal patterns of proximity and communication (i.e., phone calls, close proximity off campus in evenings and on weekends) and compare those to self-reported friendships. Zhang & Butts (2017) infer friendships and group comemberships in the same data using correlations of activity sequences in dyads, as detected by mobile devices. Park and Kim (2017) analyze interaction events (gift exchange) overlaid on a network of "friends" in an online community. West et al. (2014) examine interpersonal evaluations among Wikipedia editors (positive, neutral, or negative votes for each other's candidacy for administrator) in tandem with sentiment analysis of their comments. Stadtfeld and Pentland (2015) examine the interplay between two forms of role relation—romantic partnerships and friendships—using longitudinal survey data that is paired with mobile phone data (enabling future research on how multiple role relations interoperate with behavioral interaction). Wyatt et al. (2011) combine surveys with automatic conversation detection using audio; Bahulkar et al. (2017) combine surveys with records of calls and text messages and Bluetooth measures of colocation; Matic, Osmani, and Mayora-Ibarra (2012) use a combination of proximity using Wi-Fi signals and relative body orientation using embedded accelerometers, orientation sensors, and gyroscopes. Such research often presents one measure as ground truth for the purpose of evaluating the other as a measure of the true social network. Although that is a fruitful step, we expect new data and methods will lead to fundamental discoveries resulting from investigating how role relations, interactions, sentiments, and access interrelate in time.

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Notes

1. To bound our discussion, we consider social networks as sets of social actors and links between them (in behavior, sentiments, access, or socially constructed roles). Social network analysis can also be applied to so-called two-mode networks that could be seen as conventional rectangular data, such as persons and their opinions, theaters and the films they show, or documents and their topics. Some such networks may be projected to form conventional social networks (such as partners in a conversation or comembers of a team). In other cases, one-mode projections do not form social networks as we use the term here, such as persons linked by having similar opinions, theaters linked by showing similar films, or documents linked by sharing topics. We focus here on four coherent domains of research, where all nodes represent social actors and all links represent behavior, sentiments, access, or roles connecting actors. We do not consider mere similarity to be a social tie (cf. Bail, 2016; Borgatti et al., 2009).
2. Gross and Jansa (2017) refer to this property of continuity as "persistence." Our approach follows Kitts (2014) in using continuity because persistence may be confused with another dimension of temporality: the *duration* of a tie. The assumption of tie continuity is orthogonal to duration, as a tie may exist continuously on a brief interval.
3. That study prohibits contact, communication, observability, or even personal information about the peer to ensure that all network ties are anonymous strangers who will never directly encounter or have feelings for one another; they either receive a single email notice for each peer that joins an online forum (Centola, 2010) or they receive updates about a peer's ongoing health behavior (Centola, 2011). In this pure application of networks-as-access, interaction and sentiments are eliminated as potentially confounding factors in estimating the causal effect of social ties (as access). Later online experiments (e.g., Centola et al., 2018) induce interaction among research subjects, in the form of one-shot coordination games with a series of different partners. The players never meet, communicate, or learn anything about each other, so once again this design aims to cleanly investigate a single dimension of network ties.
4. The term *computational social science* is used to represent multiple fields of inquiry that are as yet hardly integrated. One of these fields (see Macy & Willer, 2002) focuses on computational modeling of social processes, aiming to clarify theory through formalization, often without empirical data. Another of these fields focuses on methods derived from computer science and machine learning for analyzing socially relevant data, such as natural language processing of text (Bail, 2016; Evans & Aceves, 2016), often agnostic to social scientific theories or data sources. A third usage (see Lazer et al., 2009; Golder & Macy, 2014; Salganik, 2019) describes new sources of digital trace data), often agnostic to either theory or analytical method. In this chapter we refer to the third movement (defined on data sources and data collection) but suggest that the other computational social science communities could as well add purchase to the challenges identified in this chapter.
5. That said the lead author just mentioned to one Facebook-using friend that Facebook pages could as well be cats or dead people, and she responded by showing him her dead cat's Facebook page. Princess has been dead for seven years but still has 28 Facebook friends (including 27 persons and one dead dog), is tagged in photos with them, and continues to send and receive messages, posts, comments, and likes after her death. Conventional social network analysis may be applied to these data, but no general behavioral theory applies to such phenomena.

6. For example, whereas the approach by Wyatt et al. obscures sequential constraints by aggregating over time, see Falzon et al. (2018) discuss extensions and applications that explicitly take sequence of interactions into account.
7. Even when relational events are aggregated, information in the timestamped data may be exploited before aggregation to yield new insights. For example, Oloritun et al. (2012) examine aggregated interaction networks collected using Bluetooth sensors but differentiate structures of short interactions from lengthy interactions, arguing that short and long interactions reflect different generative processes, producing distinct structures.

References

Adamic, L. A., & Adar, E. (2003). Friends and neighbors on the web. *Social Networks, 25*(3), 211–230.

Amati, V., Lomi, A., & Mascia, D. (2019). Some days are better than others: Examining time-specific variation in the structuring of interorganizational relations. *Social Networks*, *57*, 18–33.

Anthony, D. L., Campos-Castillo, C., & Horne, C. (2017). Toward a sociology of privacy. *Annual Review of Sociology, 43*(1): 249–269.

Bail, C. A. (2016). Combining natural language processing and network analysis to examine how advocacy organizations stimulate conversation on social media. *Proceedings of the National Academy of Sciences*, *113*(42), 11823–11828.

Bahulkar, A., Szymanski, B. K., Chan, K., & Lizardo, O. (2017). Coevolution of a multilayer node-aligned network whose layers represent different social relations. *Computational Social Networks*, *4*(1), 11.

Bearman, P. S., Moody, J., & Stovel, K. (2004). Chains of affection: The structure of adolescent romantic and sexual networks. *American Journal of Sociology*, *110*(1), 44–91.

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology*, *92*(5), 1170–1182.

Borgatti, S. P., Mehra, A., Brass, D., & Labianca, G. (2009). Network analysis in the social sciences. *Science, 323*(5916), 892–895.

Brandenberger, L. (2018). Trading favors—Examining the temporal dynamics of reciprocity in congressional collaborations using relational event models. *Social Networks*, *54*, 238–253.

Brandes, U., Lerner, J., & Snijders, T. A. B. (2009). Networks evolving step by step: Statistical analysis of dyadic event data. In *International Conference on Advances in Social Network Analysis and Mining* (pp. 200–205), IEEE.

Brashears, M. E., & Quintane, E. (2018). The weakness of tie strength. *Social Networks*, *55*, 104–115.

Butts, C. T. (2008). A relational event framework for social action. *Sociological Methodology, 38*(1), 155–200.

Butts, C. T., Morris, M., Krivitsky, P. N., Almquist, Z., Handcock, M. S., Hunter, D. R., . . . Bender de-Moll, S. (2014). *Introduction to exponential-family random graph (ERG or p*) modeling with ERGM.* Florence, Italy: European University Institute.

Butts, C. T., Petrescu-Prahova, M., & Cross, B. R. (2007). Responder communication networks in the World Trade Center disaster: Implications for modeling of communication within emergency settings. *Journal of Mathematical Sociology*, *31*(2), 121–147.

Byrne, D. (1961). Interpersonal attraction and attitude similarity. *Journal of Abnormal and Social Psychology, 62*(3), 713.

Cartwright, D., & Harary, F. (1956). Structural balance: A generalization of Heider's theory. *Psychological Review*, *63*(5), 277–293.

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science, 329*(5996), 1194–1197.

Centola, D. (2011). An experimental study of homophily in the adoption of health behavior. *Science*, 334(6060), 1269-1272.

Centola, D., Becker, J., Brackbill, D., & Baronchelli, A. (2018). Experimental evidence for tipping points in social convention. *Science*, 360(6393), 1116-1119.

Clay-Warner, J., & Robinson, D. T. (2015). Infrared thermography as a measure of emotion response. *Emotion Review*, *7*(2), 157–162.

Cook, K. S., Emerson, R. M., Gillmore, M. R., & Yamagishi, T. (1983). The distribution of power in exchange networks: Theory and experimental results. *American Journal of Sociology, 89*(2), 275–305.

Coviello, L., Sohn, Y., Kramer, A. D. I., Marlow, C., Franceschetti, M., Christakis, N. A., & Fowler, J. H. (2014). Detecting emotional contagion in massive social networks. *PLoS One*, *9*(3), e90315.

Crandall, D., Cosley, D., Huttenlocher, D., Kleinberg, J., & Suri, S. (2008). Feedback effects between similarity and social influence in online communities. In *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 160–168). New York, NY: ACM.

Cranmer, S. J., & Desmarais, B. A. (2010). Inferential network analysis with exponential random graph models. *Political Analysis, 19*(1), 66–86.

Cranshaw, J., Toch, E., Hong, J., Kittur, A., & Sadeh, N. (2010). Bridging the gap between physical location and online social networks. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (pp. 119–128). New York, NY: ACM.

de Nooy, W. (2011). Networks of action and events over time. A multilevel discrete-time event history model for longitudinal network data. *Social Networks*, *33*(1), 31–40.

de Nooy, W. (2015). Structure from interaction events. *Big Data & Society*, *2*(2).

Dodds, P. S., Harris, K. D., Kloumann, I. M., Bliss, C. A., & Danforth, C. M. (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *PLoS One*, *6*(12), e26752.

Dong, X., Suhara, Y., Bozkaya, B., Singh, V. K., Lepri, B., & Pentland, A. S. (2018). Social bridges in urban purchase behavior. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *9*(3), 33.

Doogan, N. J., & Warren, K. (2017). A network of helping: Generalized reciprocity and cooperative behavior in response to peer and staff affirmations and corrections among therapeutic community residents. *Addiction Research & Theory*, *25*(3), 243–250.

Doom, J. R., Doyle, C. M., & Gunnar, M. R. (2017). Social stress buffering by friends in childhood and adolescence: Effects on HPA and oxytocin activity. *Social Neuroscience*, *12*(1), 8–21.

DuBois, C., Butts, C. T., McFarland, D., & Smyth, P. (2013). Hierarchical models for relational event sequences. *Journal of Mathematical Psychology*, *57*(6), 297–309.

DuBois, C., Butts, C., & Smyth, P. (2013). Stochastic blockmodeling of relational event dynamics. In *Proceedings of the 16th International Conference on Artificial Intelligence and Statistics* (pp. 238–246).

DuBois, C., & Smyth, P. (2010). Modeling relational events via latent classes. In *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 803–812). New York, NY: ACM.

Dunbar, R. I. (2016). Do online social media cut through the constraints that limit the size of offline social networks? *Royal Society Open Science*, *3*(1), 150292.

Eagle, N., Macy, M., & Claxton, R. (2010). Network diversity and economic development. *Science*, *328*(5981), 1029–1031.

Eagle, N., Pentland, A. S., & Lazer, D. (2009). Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences*, *106*(36), 15274–15278.

Ejupi, A., & Menon, C. (2018). Detection of talking in respiratory signals: A feasibility study using machine learning and wearable textile-based sensors. *Sensors*, *18*(8), 2474.

Evans, J. A., & Aceves, P. (2016). Machine translation: Mining text for social theory. *Annual Review of Sociology*, *42*, 21–50.

Falzon, L., Quintane, E., Dunn, J., & Robins, G. (2018). Embedding time in positions: Temporal measures of centrality for social network analysis. *Social Networks*, *54*, 168–178.

Feld, S. L. (1981). The focused organization of social ties. *American Journal of Sociology*, *86*(5), 1015–1035.

Feld, S. L., & Elmore, R. G. (1982). Patterns of sociometric choices: Transitivity reconsidered. *Social Psychology Quarterly*, *45*(2), 77–85.

Foster, J. G., Rzhetsky, A., & Evans, J. A. (2015). Tradition and innovation in scientists' research strategies. *American Sociological Review*, *80*(5), 875–908.

Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215–239.

Friedkin, N. E., & Johnsen, E. C. (2011). *Social influence network theory: A sociological examination of small group dynamics* (Vol. 33). New York: Cambridge University Press.

Fuhse, J., Stuhler, O, Riebling, J. & Martin, J. L. (2020). Relating social and symbolic relations in quantitative text analysis. A study of parliamentary discourse in the Weimar Republic. *Poetics, 78*.

Gilbert, E., & Karahalios, K. (2009). Predicting tie strength with social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 211–220). New York, NY: ACM.

Goldberg, A., Hannan, M. T., & Kovács, B. (2016). What does it mean to span cultural boundaries? Variety and atypicality in cultural consumption. *American Sociological Review*, *81*(2), 215–241.

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881.

Golder, S. A., & Macy, M. W. (2014). Digital footprints: Opportunities and challenges for online social research. *Annual Review of Sociology*, *40*, 129–152.

Golder, S. A., Wilkinson, D. M., & Huberman, B. A. (2007). Rhythms of social interaction: Messaging within a massive online network. In Steinfield, C., Pentland, B.T., Ackerman, M., Contractor, N. (Eds.), *Communities and technologies* (pp. 41–66). London, UK: Springer.

Goodreau, S. M., Kitts, J. A., & Morris, M. (2009). Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. *Demography*, *46*(1), 103–125.

Grebe, N. M., Kristoffersen, A. A., Grøntvedt, T. V., Thompson, M. E., Kennair, L. E. O., & Gangestad, S. W. (2017). Oxytocin and vulnerable romantic relationships. *Hormones and Behavior*, *90*, 64–74.

Gross, J. H., & Jansa, J. M. (2017). Relational concepts, measurement, and data collection. In Victor, J. N., Montgomery, A. H., Lubell, M. (Eds.), *The Oxford handbook of political networks* (p. 175–201). New York: Oxford University Press.

Gu, J., Gao, B., Chen, Y., Jiang, L., Gao, Z., Ma, X.,. . . & Jin, J. (2017). Wearable social sensing: Content-based processing methodology and implementation. *IEEE Sensors Journal*, *17*(21), 7167–76.

Gulati, R., & Gargiulo, M. (1999). Where do interorganizational networks come from? *American Journal of Sociology*, *104*(5), 1439–1493.

Hallinan, M. T. (1974). A structural model of sentiment relations. *American Journal of Sociology*, *80*(2), 364–378.

Harari, G. M., Müller, S. R., Stachl, C., Wang, R., Wang, W., Bühner, M.,. . . & Gosling, S. D. (2019). Sensing sociability: Individual differences in young adults' conversation, calling, texting, and app use behaviors in daily life. *Journal of Personality and Social Psychology*. Advance online publication. http://dx.doi.org/10.1037/pspp0000245

Harris, J. K. (2013). *An introduction to exponential random graph modeling* (Vol. 173). Thousand Oaks, CA: Sage Publications.

Heidler, R., Gamper, M., Herz, A., & Eßer, F. (2014). Relationship patterns in the 19th century: The friendship network in a German boys' school class from 1880 to 1881 revisited. *Social Networks*, *37*, 1–13.

Holland, P. W., & Leinhardt, S. (1971). Transitivity in structural models of small groups. *Comparative Group Studies*, *2*(2), 107–124.

Homans, G. C. (1950). *The human group*. New York, NY: Harcourt, Brace & World.

Huberman, B. A., Romero, D. M., & Wu, F. (2009). Social networks that matter: Twitter under the microscope. *First Monday, 14*(1).

Hung, H., Englebienne, G., & Kools, J. (2013). Classifying social actions with a single accelerometer. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 207–210). New York, NY: ACM.

Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. *American Journal of Political Science*, *59*(3), 690–707.

Jang, H., Choe, S. P., Gunkel, S. N., Kang, S., & Song, J. (2017). A system to analyze group socializing behaviors in social parties. *IEEE Transactions on Human-Machine Systems*, *47*(6), 801–813.

Ketay, S., Welker, K. M., & Slatcher, R. B. (2017). The roles of testosterone and cortisol in friendship formation. *Psychoneuroendocrinology*, *76*, 88–96.

Kitts, J. A. (2010). Dynamics of networks within groups. Paper presented at the Group Process Conference, Atlanta, Georgia.

Kitts, J. A. (2014). Beyond networks in structural theories of exchange: Promises from computational social science. *Advances in Group Processes*, *31*, 263–298.

Kitts, J. A., & Leal, D. F. (2020). What Is(n't) a friend? Dimensions of the friendship concept among adolescents. Forthcoming in *Social Networks.*

Kitts, J. A., Lomi, A., Mascia, D., Pallotti, F., & Quintane, E. (2017). Investigating the temporal dynamics of interorganizational exchange: Patient transfers among Italian hospitals. *American Journal of Sociology*, *123*(3), 850–910.

Kleinbaum, A. M., Stuart, T. E., & Tushman, M. L. (2013). Discretion within constraint: Homophily and structure in a formal organization. *Organization Science*, *24*(5), 1316–1336.

Kornienko, O., Clemans, K. H., Out, D., & Granger, D. A. (2014). Hormones, behavior, and social network analysis: Exploring associations between cortisol, testosterone, and network structure. *Hormones and Behavior*, *66*(3), 534–544.

Kossinets, G., & Watts, D. J. (2009). Origins of homophily in an evolving social network. *American Journal of Sociology*, *115*(2), 405–450.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A. L., Brewer, D., . . . Jebara, T. (2009). Computational social science. *Science*, *323*(5915), 721–723.

Lazer, D., & Radford, J. (2017). Data ex machina: Introduction to big data. *Annual Review of Sociology*, *43*, 19–39.

Lee, Y., Min, C., Hwang, C., Lee, J., Hwang, I., Ju, Y., . . . Song, J. (2013). Sociophone: Everyday face-to-face interaction monitoring platform using multi-phone sensor fusion. In *Proceedings of the 11th Annual International Conference on Mobile Systems, Applications, and Services* (pp. 375–388). New York, NY: ACM.

Leenders, R. T. A., Contractor, N. S., & DeChurch, L. A. (2016). Once upon a time: Understanding team processes as relational event networks. *Organizational Psychology Review*, *6*(1), 92–115.

Leifeld, P., & Cranmer, S. J. (2015). A theoretical and empirical comparison of the temporal exponential random graph model and the stochastic actor-oriented model. *arXiv preprint arXiv:1506.06696*.

Leskovec, J., Huttenlocher, D., & Kleinberg, J. (2010). Signed networks in social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1361–1370). New York, NY: ACM.

Lewis, K. (2011). The co-evolution of social network ties and online privacy behavior. In *Privacy online* (pp. 91–109). Berlin, Heidelberg, Germany: Springer.

Lewis, K. (2016). Preferences in the early stages of mate choice. *Social Forces*, *95*(1), 283–320.

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences*, *109*(1), 68–72.

Lin, K. H., & Lundquist, J. (2013). Mate selection in cyberspace: The intersection of race, gender, and education. *American Journal of Sociology*, *119*(1), 183–215.

Liu, B. (2015). *Sentiment analysis: Mining opinions, sentiments, and emotions*. New York: Cambridge University Press.

Liu, C. C., & Srivastava, S. B. (2015). Pulling closer and moving apart: Interaction, identity, and influence in the US Senate, 1973 to 2009. *American Sociological Review*, *80*(1), 192–217.

Lovett, T., O'Neill, E., Irwin, J., & Pollington, D. (2010). The calendar as a sensor: Analysis and improvement using data fusion with social networks and location. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (pp. 3–12). New York, NY: ACM.

Macy Michael, W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, *28*(1), 143–166.

Malik, M. M. (2018). *Bias and Beyond in Digital Trace Data* (Doctoral dissertation, Carnegie Mellon University). Retrieved from http://reports-archive.adm.cs.cmu.edu/anon/isr2018/abstracts/18-105.html.

Marcum, C. S., & Butts, C. T. (2015). Constructing and modifying sequence statistics for relevent using informR in R. *Journal of Statistical Software*, *64*(5), 1.

Martin, J. L. (2009). Formation and stabilization of vertical hierarchies among adolescents: Towards a quantitative ethology of dominance among humans. *Social Psychology Quarterly*, *72*(3), 241–264.

Marvel, S. A., Kleinberg, J., Kleinberg, R. D., & Strogatz, S. H. (2011). Continuous-time model of structural balance. *Proceedings of the National Academy of Sciences*, *108*(5), 1771–1776.

Matic, A., Osmani, V., & Mayora-Ibarra, O. (2012). Analysis of social interactions through mobile phones. *Mobile Networks and Applications*, *17*(6), 808–819.

Mehta, P. H., DesJardins, N. M. L., van Vugt, M., & Josephs, R. A. (2017). Hormonal underpinnings of status conflict: Testosterone and cortisol are related to decisions and satisfaction in the hawk-dove game. *Hormones and Behavior*, *92*, 141–154.

Molm, L. D., Whitham, M. M., & Melamed, D. (2012). Forms of exchange and integrative bonds: Effects of history and embeddedness. *American Sociological Review*, *77*(1), 141–165.
Moody, J. (2002). The importance of relationship timing for diffusion. *Social Forces*, *81*(1), 25–56.
Moody, J., McFarland, D., & Bender-deMoll, S. (2005). Dynamic network visualization. *American Journal of Sociology*, *110*(4), 1206–1241.
Nakakura, T., Sumi, Y., & Nishida, T. (2009). Neary: Conversation field detection based on similarity of auditory situation. In *Proceedings of the 10th workshop on Mobile Computing Systems and Applications* (p. 14). New York, NY: ACM.
Newcomb, T. (1961). *The acquaintance process.* New York, NY: Holt, Reinhard & Winston.
O'Connor, B., Stewart, B. M., & Smith, N. A. (2013). Learning to extract international relations from political context. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 1094–1104). ACL.
O'Donnell, M. B., & Falk, E. B. (2015). Linking neuroimaging with functional linguistic analysis to understand processes of successful communication. *Communication Methods and Measures*, *9*(1–2), 55–77.
Oloritun, R. O., Madan, A., Pentland, A., & Khayal, I. (2012). Evolution of social encounters in ad-hoc mobile face-to-face interaction networks. In *2012 International Conference on Social Informatics* (pp. 192–928). IEEE.
Oloritun, R. O., Madan, A., Pentland, A., & Khayal, I. (2013). Identifying close friendships in a sensed social network. *Procedia-Social and Behavioral Sciences*, *79*, 18–26.
Onnela, J.-P., Saramäki, J., Hyvönen, J., Szabó, G., Lazer, D., Kaski, K., . . . Barabási, A.-L. (2007). Structure and tie strengths in mobile communication networks. *Proceedings of the National Academy of Sciences, 104*, 7332.
Pachucki, M. C., Ozer, E. J., Barrat, A., & Cattuto, C. (2015). Mental health and social networks in early adolescence: a dynamic study of objectively-measured social interaction behaviors. *Social Science & Medicine*, *125*, 40–50.
Palaghias, N., Hoseinitabatabaei, S. A., Nati, M., Gluhak, A., & Moessner, K. (2016). A survey on mobile social signal processing. *ACM Computing Surveys (CSUR)*, *48*(4), 57.
Papachristos, A. V., Hureau, D. M., & Braga, A. A. (2013). The corner and the crew: The influence of geography and social networks on gang violence. *American Sociological Review*, *78*(3), 417–447.
Park, P. S., & Kim, Y. H. (2017). Reciprocation under status ambiguity: How dominance motives and spread of status value shape gift exchange. *Social Networks*, *48*, 142–156.
Peng, T. Q. (2015). Assortative mixing, preferential attachment, and triadic closure: A longitudinal study of tie-generative mechanisms in journal citation networks. *Journal of Informetrics*, *9*(2), 250–262.
Pilny, A., Proulx, J. D., Dinh, L., & Bryan, A. L. (2017). An adapted structurational framework for the emergence of communication networks. *Communication Studies*, *68*(1), 72–94.
Pilny, A., Schecter, A., Poole, M. S., & Contractor, N. (2016). An illustration of the relational event model to analyze group interaction processes. *Group Dynamics: Theory, Research, and Practice*, *20*(3), 181.
Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (2016). *Sentiment analysis in social networks*. Cambridge, MA: Morgan Kaufmann.
Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C., & Aucinas, A. (2010, September). EmotionSense: A mobile phones based adaptive platform for experimental social psychology research. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (pp. 281–290). New York, NY: ACM.

Raeder, T., Lizardo, O., Hachen, D., & Chawla, N. V. (2011). Predictors of short-term decay of cell phone contacts in a large scale communication network. *Social Networks*, *33*(4), 245–257.

Rahman, M. M., Ali, A. A., Plarre, K., Al'Absi, M., Ertin, E., & Kumar, S. (2011). mconverse: Inferring conversation episodes from respiratory measurements collected in the field. In *Proceedings of the 2nd Conference on Wireless Health* (p. 10). New York, NY: ACM.

Salah, A. A., Lepri, B., Pianesi, F., & Pentland, A. S. (2011). Human behavior understanding for inducing behavioral change: Application perspectives. In *International Workshop on Human Behavior Understanding* (pp. 1–15). Berlin, Heidelberg, Germany: Springer.

Salganik, M. (2019). *Bit by bit: Social research in the digital age*. Princeton, NJ: Princeton University Press.

Schecter, A., Pilny, A., Leung, A., Poole, M. S., & Contractor, N. (2018). Step by step: Capturing the dynamics of work team process through relational event sequences. *Journal of Organizational Behavior*, *39*(9), 1163–1181

Schmid Mast, M., Gatica-Perez, D., Frauendorfer, D., Nguyen, L., & Choudhury, T. (2015). Social sensing for psychology: Automated interpersonal behavior assessment. *Current Directions in Psychological Science*, *24*(2), 154–160.

Shwed, U., & Bearman, P. S. (2010). The temporal structure of scientific consensus formation. *American Sociological Review*, *75*(6), 817–840.

Snijders, T. A., Van de Bunt, G. G., & Steglich, C. E. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, *32*(1), 44–60.

Stadtfeld, C., & Block, P. (2017). Interactions, actors, and time: Dynamic network actor models for relational events. *Sociological Science*, *4*, 318–352.

Stadtfeld, C., Hollway, J., & Block, P. (2017). Dynamic network actor models: Investigating coordination ties through time. *Sociological Methodology*, *47*(1), 1–40.

Stadtfeld, C., & Pentland, A. (2015). Partnership ties shape friendship networks: A dynamic social network study. *Social Forces*, *94*(1), 453–477.

State, B., Abrahao, B., & Cook, K. (2016). Power imbalance and rating systems. In *Proceedings of the 10th International AAAI Conference on Web and Social Media (ICWSM).*

Stephens, M., & Poorthuis, A. (2015). Follow thy neighbor: Connecting the social and the spatial networks on Twitter. *Computers, Environment and Urban Systems*, *53*, 87–95.

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—Sentiment of microblogs and sharing behavior. *Journal of Management Information Systems*, *29*(4), 217–248.

Sumner, E. M., Ruge-Jones, L., & Alcorn, D. (2017). A functional approach to the Facebook Like button: An exploration of meaning, interpersonal functionality, and potential alternative response buttons. *New Media & Society*, *20*(4), 1451–1469.

Szell, M., & Thurner, S. (2010). Measuring social dynamics in a massive multiplayer online game. *Social Networks*, *32*(4), 313–329.

Valente, T. W. (1995). *Network models of the diffusion of innovations*. Cresskill, NJ: Hampton Press.

Vargas, R. (2011). Being in "bad" company: Power dependence and status in adolescent susceptibility to peer influence. *Social Psychology Quarterly*, *74*(3), 310–332.

Vu, D. Q., Hunter, D., Smyth, P., & Asuncion, A. U. (2011). Continuous-time regression models for longitudinal networks. In *Advances in Neural Information Processing Systems* (pp. 2492–2500). NIPS.

Vu, D., Pattison, P., & Robins, G. (2015). Relational event models for social learning in MOOCs. *Social Networks*, *43*, 121–135.

West, R., Paskov, H. S., Leskovec, J., & Potts, C. (2014). Exploiting social network structure for person-to-person sentiment analysis. *Transactions of the Association for Computational Linguistics*, *2*, 297–310.

Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documented on Facebook. *American Journal of Sociology*, *116*(2), 583–642.

Wyatt, D., Bilmes, J., Choudhury, T., & Kitts, J. A. (2008). Towards the automated social analysis of situated speech data. In *Proceedings of the 10th International Conference on Ubiquitous Computing* (pp. 168–171). New York, NY: ACM.

Wyatt, D., Choudhury, T., Bilmes, J., & Kitts, J. A. (2011). Inferring colocation and conversation networks from privacy-sensitive audio with implications for computational social science. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *2*(1), 7.

Xie, W., Li, C., Zhu, F., Lim, E. P., & Gong, X. (2012). When a friend in Twitter is a friend in life. In *Proceedings of the 4th Annual ACM Web Science Conference* (pp. 344–347). New York, NY: ACM.

Yang, D., Huang, C., & Wang, M. (2017). A social recommender system by combining social network and sentiment similarity: A case study of healthcare. *Journal of Information Science*, *43*(5), 635–648.

Yang, D. H., & Yu, G. (2014). Static analysis and exponential random graph modelling for micro-blog network. *Journal of Information Science*, *40*(1), 3–14.

Zhang, X., & Butts, C. T. (2017). Activity correlation spectroscopy: a novel method for inferring social relationships from activity data. *Social Network Analysis and Mining*, *7*(1), 1.

Zhao, M., Adib, F., & Katabi, D. (2016). Emotion recognition using wireless signals. In *Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking* (pp. 95–108). New York, NY: ACM.