BEYOND NETWORKS IN STRUCTURAL THEORIES OF EXCHANGE: PROMISES FROM COMPUTATIONAL SOCIAL SCIENCE

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ABSTRACT

Purpose – *The research community currently employs four very different versions of the social network concept: A social network is seen as a set of socially constructed* role relations *(e.g., friends, business partners), a set of* interpersonal sentiments *(e.g., liking, trust), a pattern of behavioral* social interaction *(e.g., conversations, citations), or an* opportunity structure *for exchange. Researchers conventionally assume these conceptualizations are interchangeable as* social ties*, and some employ composite measures that aim to capture more than one dimension. Even so, important discrepancies often appear for* non-*ties (as dyads where a specific role relation or sentiment is not reported, a specific form of interaction is not observed, or exchange is not possible).*

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Methodology/approach – *Investigating the interplay across the four definitions is a step toward developing scope conditions for generalization and application of theory across these domains.*

Research implications – *This step is timely because emerging tools of computational social science – wearable sensors, logs of telecommunication, online exchange, or other interaction – now allow us to observe the fine-grained dynamics of interaction over time. Combined with cutting-edge methods for analysis, these lenses allow us to move beyond reified notions of social ties (and non-ties) and instead directly observe and analyze the dynamic and structural interdependencies of social interaction behavior.*

Originality/value of the paper – *This unprecedented opportunity invites us to refashion dynamic structural theories of exchange that advance "beyond networks" to unify previously disjoint research streams on relationships, interaction, and opportunity structures.*

Keywords: Social networks; social exchange; interpersonal sentiments; social interaction; online exchange; relational event modeling

Since the advent of social network analysis, scientists have been defining, measuring, and analyzing social networks in four fundamentally different ways. Some use social networks to refer to substantive *role relations*, whether represented as a cognitive category (such as friendship, kinship, and marriage) or shared involvement in some higher-order social unit (teammates, officemates, housemates, coauthors, comembers). By contrast, some use social networks to refer to patterns of *interpersonal sentiments* (liking, respect, trust, esteem, disesteem, hatred). Some define social networks as *behavioral interaction* (communication, advice, social support, citation, gift, or transaction). Lastly, researchers in sociological exchange theory often think of networks as *opportunity structures* for interaction (i.e., choice sets of possible exchanges, whether or not exchange is actually realized in any given dyad).

All four definitions of social networks – as role relations, sentiments, interactions, and opportunity structures – offer building blocks for distinct theories, and all have supported decades of fruitful research. Any of these interpretations may overlap with the others empirically, as friends or work partners may like one another, interact with one another regularly, and be available for some kinds of exchange. However, two people may like each other and regard each other as friends although they hardly ever interact or they may interact regularly without regarding each other as friends or liking each other, and some actors may be available to others as exchange partners without interaction, emotional attachments, or socially recognized friendships taking place. In studying "social networks," researchers often elide the distinction between these four conceptualizations in their measures, analyses, interpretations, and applications. Overwhelmingly (if implicitly) their use and interpretation of social network analysis assumes these four versions are interchangeable. I aim to show that strong assumptions are required to leap from one version of the networks concept to another, especially with regard to their treatment of *non*-ties (interpretation of the case where a tie is not observed). Rigorously identifying these boundary conditions for theory extension and application will offer an unprecedented opportunity to constructively integrate our diverse research programs.

Most foundation work in social network analysis and theory – including concepts, measures, and methods – has drawn from sociometric study of socially constructed role relations (friends, acquaintances, kin, coworkers, teammates, neighbors). A related approach has measured interpersonal sentiments (e.g., liking, hatred, trust, or esteem). Although there is room for fruitful research on the interplay between interpersonal sentiments and socially constructed role relations, I will generally characterize the research on "relationships" as encompassing these two approaches. Some common measures – such as close friendship – try to capture both role relations and sentiments. I will show that during a time interval on which a graph is defined, these approaches similarly assume temporal *continuity* (i.e., social ties are continually active on the interval) and temporal *stability* (i.e., the structure of ties is fixed on the interval). This foundation research on relationships has also been motivated by the assumption that relationships channel social interaction – with many theorists assuming that measured ties are proxies for interaction behavior – so studies of relationships rarely examine social interaction directly. Researchers who study relationships also implicitly assume that just as ties are continuously open for interaction, non-ties are continuously shut; that is, relevant social interaction can never occur outside of social ties.

Contrasting with studies of relationships (either role relations or interpersonal sentiments), some scholars have constructed networks of social interaction from observable relational behavior such as communication (e.g., e-mail, phone, face-to-face conversations), contact (e.g., colocation, meetings, sex), or resource exchange (support, advice, gifts, lending, drug needle sharing, scholarly citations). Having observed a sequence of behavioral interaction events, scholars typically aggregate those behaviors over time, then set a filter that transforms these event counts into a set of ties and non-ties. Beginning with data that could give us rich insight into fine-grained dynamics of interdependent interaction behavior, scholars collapse those data into categories and interpret the resulting ties as if they are temporally continuous and stable to fit the traditional conceptual lenses for network analysis of relationships.

Research on relationships (role relations or interpersonal sentiments) or social interaction has focused almost exclusively on *ties*, either ignoring dyads where no tie is observed or assuming that non-observed tie means non-tie. By contrast, researchers who view social networks as opportunity structures for exchange have relied on non-ties to carry the theoretical weight: Ties are sites where interaction may or may not take place and emotional attachments may (or may not) appear, whereas non-ties are precisely defined as vacuums, where interaction and sentiments are exogenously prohibited.

The porous boundaries between these four conceptualizations of social networks have allowed a healthy diversity of ideas and empirical research, but understanding general processes requires us to ask how these levels connect. I argue that a constructive step is to temporarily suspend use of the reified but vacuous concepts of social *ties* and *networks* – which represent some unspecified congeries of aggregated ideas, behaviors, and emotions – and instead directly consider the structural dynamics of interaction. Making sense of these decades of research requires theoretical lenses, methodological approaches, and empirical data that speak to one another, and are collectively suited to investigating dynamics.

I will show how tools from Computational Social Science – employing analysis of the fine-grained temporal dynamics of social interaction – may serve as a common language to integrate the various threads of networks research. Although some early work on social interaction has used field observation or time diaries to observe interaction directly, new telecommunications and sensor technologies allow researchers to systematically collect data on interaction behavior with unprecedented volume and granularity. Electronic traces, such as logs of e-mails sent and received, telephone calls, meetings recorded on electronic calendars, exchanges in online commerce or sharing sites, allow us to monitor social interaction in fine time grain. Meanwhile, there is a convergence in statistical methodology that is poised to address the wealth of longitudinal interaction data. Cutting-edge analytical methods allow us to abandon assumptions that our observations are independent, and to explicitly model various forms of temporal and relational dependence. This confluence of ideas, tools, and data allows us to consider the dynamic interdependence of interaction behavior for a set of social actors in continuous time.

New analytical tools and rich data on behavioral interaction offer promising applications for all areas of social networks research. Indeed, I show how analyzing interaction dynamics can deepen our understanding of socially constructed relationships, interpersonal sentiments, and opportunity structures for exchange. However, these new frontiers also demand attention to scope conditions on theories developed for alternative conceptualizations of networks, such as structural balance theory for interpersonal sentiments or network exchange theory for opportunity structures.

CONVENTIONAL VIEWS OF NETWORKS AS TEMPORALLY CONTINUOUS AND STABLE STRUCTURES

Decades of research in social networks has employed the directed or undirected graph as a way to represent a set of relationships (typically assumed to imply interaction) or interaction (typically assumed to imply relationships) or opportunity structures. This graph has often been reified, where substantively vacuous concepts like social ties have allowed slippage across these four levels (role relations, sentiments, interaction, opportunity structures) in conversations across theories or findings. Fig. 1 illustrates a conventional binary and static representation of a network as a graph. We can observe various features of the *ties* in this network: The tie A-B is *reciprocated* and the tie B→C is *unreciprocated*. A triad E-F-I of mutually tied actors is a *closed* triad, whereas the triplet D-E-I is *intransitive*, and so on. This typical basic representation includes no weight on the tie (all ties are uniform in strength), no consideration of dynamics (changes over time in either end of the relationship), and there has been no principled way to incorporate a dependence on history. These simplifying assumptions have allowed the use of elegant and powerful tools of social network analysis (Wasserman & Faust, 1994), but have limited our ability to think in more nuanced ways about the structural dynamics of exchange.

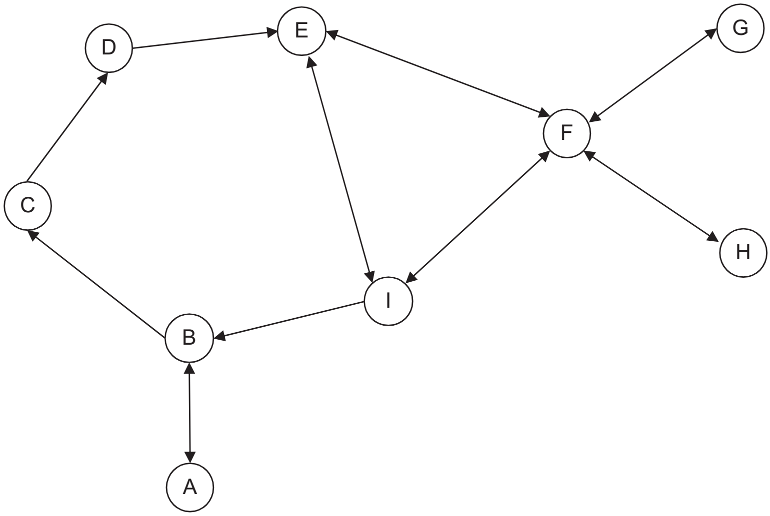

Fig. 1. Illustration of a Social Network as a Directed Graph.

Sociometric graphs are often constructed by a "relationship" measure (such as "close friends" among students) where ties are interpreted as continuously-available conduits, and non-ties are insurmountable barriers. For example, if Fig. 1 represents a network of best friends in a school class, authors read in the graph that because A is not friends with I (or E), A must "reach" I through a long path, with B always as an intermediary. Conceiving of the network as a flow of information leads us to interpret B's position as a source of power, because B may be able to withhold or manipulate information at will.[1]

The vast majority of this usage of the graph metaphor has presumed that the network is temporally continuous; that is, for the time interval in which the graph is defined, each tie is continuously active (available) during any moment within that interval; that is, there is no sequence of activation. Similarly common is the assumption that the graph is stable over that time interval, and this regularity motivates our use of terms like social *structure*. Lastly, conventional social network analysis often assumes that ties are interchangeable; that is, each friendship or coauthorship presents the same weight or dyadic diffusion potential as any other. These simplifying assumptions give us analytical leverage. For example, under these assumptions we can say that node B is *reachable* by node D by a *path* of length 3, which is three times longer than the path from F to G. We may then compute a centrality measure for each node (Bonacich, 1987; Freeman, 1978/1979), showing that a particular node lies on the most shortest paths connecting other nodes, or can reach other nodes by the shortest paths, or simply is connected to the most other nodes. We can also say that G and H are structurally equivalent (Friedkin, 1984) or that F's personal network spans structural holes (Burt, 1992) between {E,I} and {G,H}. Lastly, we can compute graph level metrics allowing us to show that one graph is more centralized or cohesive (Moody & White, 2003) than another based on patterns of ties and non-ties.

There are many ways to relax these assumptions, such as allowing that one tie may be more intense than another tie (with faster or more effective communication or influence, realized as a weight on the tie) or allowing that ties may be negative as well as positive, and these complications invite more nuanced measures and models. But the power and elegance of the simple graph metaphor in Fig. 1 makes this representation almost ubiquitous even when more fine-grained data are available. Notably, decades of research have shown the generality and analytical power of social network analysis tools, and they have spread rapidly across theoretical and empirical contexts.

I will be especially concerned about the usually implicit assumptions that ties are temporally continuous and stable over the time interval on which the graph is defined. Relaxing the assumption of temporal continuity would make all paths in the graph above ambiguous, as the simultaneity or sequencing of tie activation could make any path impassible. Allowing that the structure changes over time would require proliferating graphs. Either relaxation could make concepts like centrality, structural power, structural cohesion, or structural equivalence unwieldy.

A notable feature of the simple graph representation, which is rarely questioned or discussed, is the strong equivalency assumption for non-ties (such as A→I or B→I above), which are valued at exactly zero, representing zero behavioral interaction, zero sentiments, zero opportunity for exchange. These assumptions underlie our network metrics described above, but also imply important scope conditions for those same lenses. Our computing the length of the shortest path between node A and node I (through nodes B–E) is predicated on an assumption that interaction is strictly impossible among non-tied actors in this graph. The treatment of non-ties is a crucial issue with distinct implications for all four representations of social networks, and I will give it special attention.

FOUR CONVENTIONAL WAYS OF THINKING ABOUT SOCIAL TIES

Social Ties as Socially Constructed Role Relations

Most of the methodological and theoretical foundations of social network analysis were developed to suit social networks as sets of substantive *role relations*. These can be represented as a cognitive category (friendship, kinship, coauthorship) or shared involvement in some higher-order social unit (teammates, officemates, housemates). Examples include friendships among students (Kandel, 1978) or members of a fraternity (Newcomb, 1961) or karate club (Zachary, 1977), business ties or intermarriage among Florentine families (Padgett & Ansell, 1993), or coauthors of papers (Moody, 2004). In this usage, a social tie is measured as a labeled role relation operating at a level of abstraction above concrete social behavior. Scholars have often measured role relations as perceptions using surveys. For example, a conventional name-generator survey could ask the respondent, "list the names of your five closest friends."

The role relation has offered comfortable standing for the crucial assumptions of temporal continuity and stability supporting classical network analysis. Perceived relations like best friend, collaborator, spouse, comember, or teammate are plausibly continuous in time and relatively stable, such that we can use a graph to depict the structure of friendships in a college dormitory or shared corporate board memberships in a given month. Some role relations may also imply general patterns of sentiments and interaction behavior. For example, we often assume that friends like each other, talk with each other, spend time together, and trust and support each other, but friendship as a socially constructed category is not reducible to any of these dimensions and the correspondence from the relation label to any particular behavior or sentiment may be weak. For less culturally loaded role relations (such as comember or coauthor), the correspondence to behavioral interaction, sentiments, or opportunity structures is even more unclear. When role relations are measured using self-reported perceptions, the strong equivalency assumption for observed ties deserves critical consideration, as responses may depend on idiosyncratic and culturally or contextually contingent interpretations of the survey question.

Let us consider an example: The use of self-reported friendships to represent ties in a network has been extensively applied for children in school, where the term "friend" may presumably distinguish a student's closest alters from less close alters. Scholars have also applied this term to adults, assuming that friendships convey information, job opportunities, or social support; however, there is much ambiguity about how respondents interpret survey questions about their friendships. Indeed, there is mounting evidence that adult respondents' use of the word "friend" does not map onto social network researchers' concepts of strong or weak ties. Indeed, researchers find that respondents may employ friend as a generic category for miscellaneous associates who have no other more specific role label.

> [The label of 'friend'] is likely to be applied: to an overwhelming majority of non-relatives in a largely unsystematic way; to associates lacking other specialized role relations; to people of the same age; to people known a long time; and to people with whom respondents had primarily sociable, rather than intimate or material, involvements. (Fischer, 1982, p. 287)

The set of friends can thus be an *et cetera* category, which often does not include kin, lovers, coworkers, neighbors, people of different ages, or people who engage in material exchange, even when those other people may be more important emotionally and interact more frequently (i.e., stronger ties) than the people respondents actually label as "friend" on a survey. Research has shown us that although it seems easiest to measure a relationship by merely employing a name generator for a role relation, we must be very careful in interpreting such reports as interpersonal sentiments, behavioral interaction, or opportunity structures, and be attentive to the necessity of validating or defending these interpretations.

Much previous research has investigated what friendship *means* – in other words, how to interpret a "1" in a sociomatrix of relations – but a more serious problem for network analysis has hardly ever been acknowledged: When survey respondents *fail* to mention another person as a close friend (or partner, confidant, etc.) on a name generator, we are even less sure what this "0" in a sociomatrix means. Someone not mentioned as best friend is ostensibly not-a-best-friend, but it is still problematic to interpret such a non-observed-relationship as an observed-non-relationship. Moreover, just as scholars often conflate networks-as-relationships with networks-as-interaction in the positive case (assuming that relationships imply interaction), scholars often commit the same slippage for non-ties (assume that non-observed-relationships imply zero interaction) where this assumption is hardly ever defensible. In many applications of network analysis, researchers interpret a non-tie in a friendship network as no-communication, no-liking, no-time-spent-together. This is problematic in the Group Process tradition, where we apply network analysis in small populations. When these network nodes are students in a small class (or coworkers in a project team), where actors spend most of every day together, the interpretation that students can only transmit information to each other through long paths of best friends seems implausible. This is especially true when our measure of ties is a restrictive name generator such as five-closest-friends, and we have no direct observation or validation of non-ties. This kind of measurement error is extremely consequential for most conventional methods of social network analysis, as even a few "false-zeroes" in a sociomatrix can fundamentally distort graph-theoretic metrics like centrality.

This problem of interpreting non-reported relationships is highlighted when respondents give discrepant reports about whether or not they are friends with each other (Adams & Moody, 2007; Vaquera & Kao, 2008), resulting in the very common but awkward belief among network analysts that "friendship" is a directed relationship, where person C can be best friends with person D while D has exactly zero relationship with C. Scholars typically assume the one-directional friendship has been measured without error, that the "present" C→D tie works just like any other directed tie and the "absent" D→C tie works just like any other non-tie (Cheadle & Schwadel, 2012; Frank, Muller, & Mueller, 2013; Heidler, Gamper, Herz, & Eßer, 2014; Mouw & Entwisle, 2006).[2] With the ubiquitous slip of interpreting relationships as interaction, a scholar would then assume that C spends time with D but D does not spend time with C, C can send information to D but D cannot send information to C, etc. This dilemma gives another reason why the reified relationship graph should not be interpreted as a behavioral interaction graph. In particular, even when relationships plausibly imply social interaction, a non-tie in a relationship graph should not be interpreted as devoid of interaction, exchange, or communication unless these interpretations are also explicitly validated.

In summary, role relations were for many decades the easiest and most common measures of social ties, so role relations are well represented in the corpus of classical social network data. Because they operate at a level of abstract concepts, role relations are quite robust to issues of temporal continuity and stability, but they often rely on self-reports, which require some attention to measurement error. There is not much general theory about the social processes underlying role relations. However, the ease of measuring role relations has led researchers historically to regard them as proxies for interpersonal sentiments (e.g., applications of structural balance theory), behavioral interaction (e.g., application of social influence or contagion theories), or opportunity structures (e.g., applications of network exchange theory), even though none of these theories has anything to say directly about role relations. *Ties* in a role relation graph may in some cases correspond roughly to sentiments, interaction, or exchange opportunities – as friends may share positive sentiments and interact regularly, or collaborators may exchange feedback. *Non-ties* in a role relation graph (non-best-friends, non-coauthors, non-comembers) are rarely informative about sentiments, interaction, or exchange opportunities, and this is a principal obstacle to application of theories about sentiments, interaction, or opportunity structures to networks of role relations. At least, such applications demand attention to how the observe graph satisfies the scope conditions of the theory.

Social Ties as Interpersonal Sentiments

Another conceptualization of social networks has focused on interpersonal sentiments, such as liking, love, or respect. This has been seen as an alternative way to ask "Who are your friends?" Notably, direct measure of sentiments gives much more defensible grounds to investigate a theory about interpersonal sentiments, such as work on structural balance (Cartwright & Harary, 1956) or attraction (Smeaton, Byrne, & Murnen, 1989). This measure may be less vulnerable to some of the contaminants for a measure of perceived friendship – such as where individuals share very close positive relationships to their kin and lovers, but may not use the label *friends*. The sentiment measure may also be more interpretable in the case of disagreement in self-reported ties. Unlike friendship, marriage, or spending-time-together, interpersonal sentiments may be truly asymmetric so dyadic discrepancies are substantively interpretable.

To avoid the ambiguities of role relations like friendship, and to focus on sentiments as an internal directed state rather than behavioral interaction, some researchers have measured *aspirations* for social interaction. For example, Leinhardt (1972) asked school children "Who would you *like* to play with?" which is interpretable as a directed sentiment. By contrast, if we ask "Whom *do* you often play with?" we measure not sentiments but behavioral interaction (which reflect exogenous logistical, spatial, and sociometric factors). Also, the underlying reality for behavioral play must be mutual, whereas the aspirations may be one-sided.[3]

A unique strength of sentiment-based survey measures is their capacity to measure *negative* ties (dislike or disesteem) in a straightforward way, making them properly applicable to theories of network evolution based on structural balance (Cartwright & Harary, 1956; Marvel, Kleinberg, Kleinberg, & Strogatz, 2011). According to this broadly applied theory, social actors feel a drive to change their networks as a result of dissonance implied by having two positive ties to alters who are connected by a negative tie (having two friends who dislike each other), or having a positive and a negative tie to alters who are connected by a positive tie (having a friend who is friends with an enemy).[4]

Given the challenge of measuring negative relationships in surveys (as respondents are reluctant to describe negativity in their relationships), many scholars in this tradition have eschewed measuring negative ties and have instead employed a conventional name generator for role relations that imply positive sentiments (e.g., best friendship) and interpreted non-measured ties as measured-negative sentiment ties. In a representative study, Hallinan (1974) measures such sentiment relations ("best friends") for students in 51 classes from 14 schools, and (by applying balance theory) implicitly assumes that alters not nominated as best friends must operate as *negative* sentiment ties. I have already mentioned that interpreting non-measured ties as non-ties can often be a consequential mistake, but interpreting non-measured ties as *negative* ties is a step more extreme in this regard. Non-ties in a graph of relationships (e.g., for individuals not nominated as a friend on the survey) should not be generally interpreted as disliking. This should be read as a challenge to over four decades of studies that have appealed to structural balance theory as an explanation for triad closure or transitivity in positive-sentiment relations (such as friendship) following from Davis (1970) and Holland and Leinhardt (1970) but continuing to today (Frank et al., 2013). It is an even greater challenge to the widespread recent applications of structural balance theory to behavioral interaction networks, such as the phenomenon of triad closure in telephone or e-mail communication networks (Kossinets & Watts, 2009) or Facebook friends (Wimmer & Lewis, 2010). Applications of structural balance theory to positive or neutral social interaction data such as communication similarly assume that non-interaction is equivalent to a negative sentiment tie, an assumption that at least needs to be defended.

In a detailed study of triad closure using a combination of longitudinal survey data and wearable sensor data on physical locations, face-to-face conversations, phone conversations, social visits, and work projects, Kitts (2010) identifies boundary conditions in which non-interaction might be interpreted as negative sentiments. Outside those narrow boundary conditions, structural balance theory and similar models of relational dissonance should not be applied to positive relationship data or neutral behavioral interaction data. In such cases, we must rely on direct measures of sentiments.

Social Ties as Behavioral Interactions

Most foundation social networks research focused on relationships, whether role relations or sentiments (or implicit-sentiment role relations, such as best friends). But many researchers' substantive interest is in social interaction behavior, as it may transmit diseases, spread innovations, or offer job opportunities. There are reasons for caution in inferring behavioral interaction from observed relationships, as realized behavioral interaction may reflect many different (mostly unmeasured) roles – kin, friend, lover, classmate, teammate, coworker, comember, neighbor – as well as exogenous constraints and inducements due to scheduling and physical space. For these reasons, any role relation (even a strong relationship, such as best friend) will not capture a large portion of social interaction. Respondents may even apply a sentiment-charged label like "best friend" to a rarely seen alter such as a childhood friend. In order to narrow the set of closest friends to an interpretable subset of regular interaction partners, some researchers have included behavioral interaction as part of a self-report measure of relationships, such as Laumann (1973, p. 264) asking respondents to nominate "the three men who are your closest friends and whom you see most often." This composite measure narrows possible interpretations and more plausibly captures a set of alters that represent both positive sentiments and interaction. In trying to capture to both dimensions, however, it fails to capture either very well. It is not a measure of the most regular interaction partners (many of whom are not closest friends) or the most positive-sentiment ties (some of whom may not be called *friends* or may not be seen often). And a non-tie by this measure is hardly interpretable, as it could be a close friend who is not among the most frequently seen or a daily interaction partner who is only a casual friend.

Some researchers (Bailey & Marsden, 1999; Ruan, 1998; Uehara, 1990) have avoided ambiguity about role relations and instead employed name generators for specific interaction behaviors. They have asked about help with housework, borrowing money, borrowing household goods, discussing marital problems, discussing feelings of depression, frequently visit socially outside the home, or shared social visits, calling these "exchange" name generators.

Given the expense and difficulty of employing different name generators to measure networks for specific exchange behaviors, scholars have long hoped for an omnibus sociometric survey question that could capture the concept of strong ties overall, rather than trying to measure each individual exchange behavior. Granovetter's classic (1973, p. 1361) definition of the strength of ties includes not only the quantity of interaction but the quality of interaction (and associated sentiments):

> The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie.

Among the most extensive attempts has been the widely-used network measure from the General Social Survey, which asks respondents to think back to the last 6 months and report the names of people with whom they have discussed "important matters" during that time. The measure targets interaction behavior but researchers typically interpret these responses as strong ties (including close friends, and close kin).[5] However, just as earlier work had found that we should not see adults' self-reported friends as strong ties (because of how the label "friend" may be used as a residual category to apply to alters who are not particularly close or important to the respondent), recent empirical research has challenged the interpretation of the standard "core discussion network" name generator as a measure of strong ties:

> The core discussion network is not a representation of our strong ties; it is a combination of people we are close to, people we are not close to but who are knowledgeable about the matters we regularly find important, and people we are not close to but who are available because of our routine activities. (Small, 2013, p. 481)

In other words, this retrospective aggregation of past interaction reflects respondents' opportunistic use of available experts (advisors, therapists, accountants, computer support technicians, clergy, physical trainers, medical practitioners, etc.) as well as miscellaneous people who happen to be near us at times when we want a question answered, where in both cases the discussion partners themselves may not be either close or important to us. Using a single survey question to identify a respondent's social ties in a general way that is robust across cultures, genders, and life stages remains an elusive Holy Grail for social networks researchers. Whether we develop the question to focus on socially constructed relationships, sentiments, or social interaction, such a general and robust measure of a social tie has never been found.

In some cases, survey researchers (Cornwell & Laumann, 2011; Zachary, 1977) have used a conventional relationship measure but added a second survey question to identify the frequency or intensity of interaction within each tie. That is, respondents' self-reports of the frequency of interaction are used to represent how strong the observed ties are. Others may ask two independent survey questions, one to measure friend relations and a second for frequency of conversations or advice exchange (Coleman, Katz, & Menzel, 1957). Using two independent graphs allows researchers to observe regular interaction partners who are missed by the "friend" question and differentiate friends who are regular interaction partners from those who are seldom seen.

Alternatively, to appreciate the advantages of measuring sentiments directly (avoiding ambiguity of sentiment-charged role relations, and allowing for negative ties) – we can pair a measure of sentiments with an independent measure of behavioral interaction. This will be generally superior to an omnibus relation question or an interaction question alone. It will allow us to distinguish regular interaction partners from parents or childhood friends who not part of the respondent's day-to-day life, and also allow us to distinguish the level of emotional closeness among regular interaction partners. Oddly, this combination of sentiment and behavioral interaction measures has been used rarely, even in studies collecting sociometric data on several dimensions simultaneously. In a rare and often-cited example, Sampson (1968) measured *liking* and *disliking*, *esteem* and *disesteem, positive influence* and *negative influence, praise* and *blame* for a study of 18 monks in a monastery.

As social network lenses spread across scientific disciplines, many scholars are interested in social interaction behavior not as a feature of relationships but as a phenomenon in itself. Increasingly, researchers are employing direct measures of social interaction and constructing networks from the interaction data, but not measuring perceived relationships at all. Such researchers use social interaction as the operational definition of a social tie; that is, our ties are those others with whom we interact. When we are studying the diffusion of HIV on a network of partners in sex or intravenous drug use, a constructed network of those actual interpersonal risk behaviors may be a better focus of our attention than their perceived relationships.

Scholars interested in the underlying behaviors of social interaction may simply observe interaction over time and define a network as an aggregation of past interpersonal behavior. Qualitative field researchers informally aggregate observed sequences of interactions and interpret these aggregated interactions as measures of ties (Vargas, 2011). For example, Roethlisberger and Dickson's Bank Wiring Room study (1939) involved observations of various kinds of relational behavior (horseplay, arguments, helping, job trading) among employees. In his classic analysis of these data in *The Human Group*, George Homans (1950) treated these aggregated observations of interactions analytically as binary relationships. Just as the GSS asks the survey respondent to aggregate over a 6-month time window, the field observer similarly aggregates over a time window, ultimately turning interaction histories into inferred *ties* that may be analyzed using conventional tools of social network analysis. Unlike the survey data, however, the networks constructed from observed behavior can use a specific and rigorously applied definition of social ties, not vulnerable to differences of construal among the various survey respondents. Real-time applications can use multiple observers and sophisticated coding schemes to record social interaction for later aggregation into networks, and networks can even be constructed and analyzed from ethnographic or archived historical accounts (Heidler et al., 2014).

While employing the same temporal aggregation of interaction events, it is possible to cut a long time period into slices, defining a series of panel observations of networks. Moody, McFarland, and Bender-deMoll (2005) proposed ways of aggregating interaction behavior in time and then visualizing the resulting networks as "flip-books" or "movies" that represent a changing network over time. Following from Moody et al.'s "moving windows" approach to converting relational events into networks, Kossinets and Watts (2009) explore thresholds for defining network snapshots based on temporally aggregated e-mail exchanges, then investigate dynamic changes in these networks.

Social Ties as Opportunity Structures

Researchers in sociological exchange theory have offered valuable insights into the dynamics of exchange given exogenous *opportunity structures* (Cook et al., 1983) or *restricted access networks* (Marsden, 1983). For example, they have investigated the structural foundations of power, often focusing on negotiated exchange in "negatively connected" networks, where alternative exchange partners are mutually exclusive. In this research, there are elegant links between basic constructs, theoretical principles, and empirical findings. Ties and non-ties are unambiguously controlled by the investigator in laboratory experiments. In this usage, a tie is conceived as a location where exchange is possible, whether or not it actually occurs. For example, if A and B are tied and B and C are tied but A and C are not tied, then B can choose to interact with A or C (but A and C can only choose to interact with B). In this case, non-ties are precisely defined, whereas ties are dyads where exchange *might* occur. In the words of Thye, Lawler, and Yoon (2011, p. 407), "the network itself does nothing for individuals except generate a series of opportunities for and constraints on dyadic exchange."

The opportunity structures studied in network exchange theory – properly called "exchange networks" (Markovsky, Willer, & Patton, 1988; Willer, 1999) – may bear little resemblance to social networks as conventionally observed in studies of interaction and relationships. Studies of relationships aim to capture the network of socially constructed links among people (kin, coworkers, best friends, etc.) whereas observational studies of social interaction aim to capture behavioral exchanges that actually *occur* among individuals. Both approaches focus on the presence of ties and give little attention to non-ties. Neither approach allows observation of *impossible* partners. For example, in a deep study of the GSS name generator, Bearman and Parigi (2004) demonstrate that reporting zero peers as important discussion partners need not imply that respondents do not have any partners available.

Research on role relations, sentiments, or aggregations of observed behavior relies on a strong definition of ties with a weak or implicit definition of non-ties, and hardly ever validates non-ties as unavailable. By contrast, research on opportunity structures relies on a weak definition of ties with a strong interpretation of non-ties: Ties are dyads where exchange *might* occur, and actors cannot exchange through non-ties. This mismatch creates an obstacle for empirical application of exchange theories that focus so much weight on the assumption that exchange is impossible outside observed network ties. Indeed, empirical situations closest to exchange network studies are where there are complete barriers to interaction in some dyads (but not others). It is difficult to identify such situations, especially in contexts of interest to Group Process scholars, such as networks of friends or discussion partners in organizations.[6]

This raises a dilemma for empirical application of network exchange research, because many real-world informal social structures appear to be governed by voluntary choices, where alters may be more or less attractive or familiar but none are explicitly prohibited. Rather than a particular alter being available (tied) or strictly impossible (not tied) as in laboratory studies, empirical restricted access networks more often represent a continuum of accessibility. For example, alternative partners may vary in attractiveness, resourcefulness, geographic distance, environmental obstacles, regulatory restrictions, convenience of communication, or transaction costs. Indeed, Marsden (1983, pp. 690–691) explicitly noted that geographic distance, organizational structure, or other impediments (even "inertia" or "brand loyalty" in alternative partnerships)[7] can block exchange in a particular dyad.

Lawler et al. (2006) recently made a distinction between exchange relations that are forced by a lack of alternatives (i.e., the experimental design makes exchange unavailable in some dyads) versus exchange relations that are preferred by individuals because they provide superior terms of exchange. This distinction is easy to perform in the laboratory and may occur in the natural world primarily in fine time grain interactions due to scheduling constraints; for example, if B and C are prom dates on Friday night, then A or D cannot attend the prom with either B or C, so in this sense the A–B, A–C, B–D, or C–D interactions are rendered logistically impossible at that time. (Lawler et al. use a similar example of dyadic conversations occurring in two rooms at the same time.) Where interactions are not simultaneous, such logistical impossibilities are hard to identify. In the natural world it is rare for empirical exchange to be exogenously prohibited in any dyad. In coarse time grain, even explicit B–C commitments (say, B and C are married, which is hardly an exogenous constraint) are notoriously ineffective in prohibiting A–B contacts if the parties so prefer, provided that A and B can schedule an encounter when C is unable to observe their interaction. Actors may choose to refrain from exchanging with some others because of direct terms of exchange, or due to inertia that takes the form of emotional commitment or path dependent routines, or for strategic reasons (e.g., to avoid helping an enemy), all impediments that could be represented in the incentive structure. Even explicit prohibitions, such as state embargos, antitrust regulations, or restraining orders could be interpreted as disincentives rather than strict barriers to exchange, and contraband exchanges such as adultery, illegal drug sales, or political bribes are empirically common. Recognizing that these issues combine to form a continuum of constraints or incentives tends to blur the distinction between induced and enabled exchange relations, and whether a constraint is regarded as a structural disincentive or a prohibition is often a matter of framing. This guides our interpretation of Lawler's choice-process theory to either simultaneous interactions such as those in the laboratory (where barriers make exchange logistically impossible) or to situations where the incentive structure is *framed* as an externally binding situational constraint.

COMPUTATIONAL SOCIAL SCIENCE: NEW LENSES FOR STUDYING BEHAVIORAL INTERACTION

The advent of Computational Social Science (Lazer et al., 2009) has enabled recording of "Big Data" on social activities of millions of people. Among the most easily accessible are online contact lists, such as Facebook "friends," Twitter "followers," Google "circles," or LinkedIn "connections." Unfortunately, many or most such names on contact lists are not significant as either relationships or social interaction, as evidenced from research on Facebook "friends" (Golder, Wilkinson, & Huberman, 2007) and Twitter "followers" (Huberman, Romero, & Wu, 2009). Use patterns vary, and some such online contacts might indeed interact socially or have relationships with one another deeper than a contact list on the website, but many or most such online contacts apparently never interact (even on the website itself) and some are not even people. To carve through the junk data, scholars interested in relationships may use additional filters to identify significant links on online contact lists that may point to substantive relationships or interaction partners. For example, Wimmer and Lewis (2010) narrow their scope to Facebook friends that are colocated as students at the same university and appear in each other's tagged photos, a subpopulation of humans who are likely to interact at least occasionally (Lewis, Kaufman, Gonzalez, Wimmer, & Christakis, 2008). Golder et al. (2007) recommend focusing a network analysis of Facebook on the small subset of "friends" who send each other electronic messages or comment on each other's materials.

Whatever the meaning of these easily available user contact lists, industry or organizational partnerships can offer fine-grained privacy-sensitive data about social interactions. For example, researchers can analyze interactions through time-stamped records created by e-mail servers (Kossinets & Watts, 2009; Quintane & Kleinbaum, 2011), phone call logs (Onnela et al., 2007), radio communication transcripts (Butts, Petrescu-Prahova, & Cross, 2007), shared online calendars (Lovett, O'Neill, Irwin, & Pollington, 2010), or wearable sensors that detect face-to-face conversations (Wyatt, Choudhury, Bilmes, & Kitts, 2008, 2011) or physical proximity (Eagle, Pentland, & Lazer, 2009; Ingram & Morris, 2007).[8] Online arenas for dating (Lin & Lundquist, 2013), gaming (Szell & Thurner, 2010), exchange (Cheshire & Cook, 2004), and scholarly citations (Shwed & Bearman, 2010) also provide time-stamped event records that may represent instantaneous transactions organized according to fine-grained social dynamics.

Recall that traditional network analysis concepts and tools were developed for the study of temporally continuous and stable relationships, which construe networks as practically timeless abstractions (Gibson, 2005). Facing this incongruity between traditional sociometric tools and the world of time-stamped relational event data, CSS researchers who collect fine-grained interaction data have the problem of transforming their data to be conformable to tools derived from an age of sociometric surveys, simple graphs, and sociomatrices. For example, given a rich event history of contacts (phone conversations, e-mails, face-to-face conversations) for a set of actors, a researcher might aggregate the events into a simple matrix of counts, and then further apply a threshold filter: For a given period of time, more than *n* contacts within a period of time may be defined as a *tie* and fewer than *n* contacts may be defined as *no tie*. For example, Onnela et al. (2007) constructed a graph of interaction partners for millions of people using temporally aggregated records of calls on a cellular phone network, and Wyatt et al. (2008, 2011) used wearable sensors to record face-to-face conversations for a cohort of graduate students during a school year, but similarly aggregated rich micro-interaction data over time, and then treated those temporally aggregated interactions as if they were relationships.[9] Conaldi and Lomi (2013) observed the individual bug-fixing activities of software developers and Papachristos, Hureau, and Braga (2013) observe individual gang homicides, but all conventionally aggregate these behaviors into temporally continuous and stable social networks. Such aggregation of contacts may seem ad hoc, but see that it is in fact a more extensive and systematic version of the longstanding approach by qualitative field researchers who have tried to identify relations from observing and aggregating interaction histories. It is also analogous to the ways that sociometric surveys ask respondents to mentally aggregate over their own interaction histories to identify their important discussion partners. The new methods for automatically recording social interactions at least allow the aggregation of interaction data to be done in a transparent and rigorous way to avoid idiosyncrasies or inconsistencies in how observers or survey respondents perform this aggregation.

Of course, just as we should be cautious about interpreting sociometric relationship data as measuring social interaction, we should be cautious about interpreting aggregated interaction data as substantive relationships. Perusing our own records of e-mail or phone communication will illustrate that counts of contact events do not necessarily indicate our closest ties. Also aggregating events into counts destroys valuable information about temporal dynamics and action sequences. Although converting these fine-grained interaction dynamics into coarse ties is ubiquitous and unquestioned, it is not inevitable. In fact, the leap from conventional sociometric research to the world of Big (relational) Data invites us to deeply consider issues such as time grain in measurement, time frames of underlying social processes (Kitts, 2009; Quintane, Carnabuci, Robins, & Pattison, 2012), and short-term dynamics of interaction event sequences (Gibson, 2005; Kitts, Lomi, Pallotti, Mascia, & Quintane, 2013). We turn to these next.

BEYOND NETWORKS: CONSIDERING THE STRUCTURE AND DYNAMICS OF INTERACTION

There is clear value in studying relationships as socially constructed entities (including actors' perceptions of their friendships). There is also clear value in studying how opportunity structures for exchange affect important outcomes such as interpersonal power (Emerson, 1972) and commitment (Lawler, Thye, & Yoon, 2000). However, I advocate for a new generation of theoretical development and analysis of interaction dynamics. This includes direct measurement of behavioral social interaction (including time diaries, wearable sensors, and archival records such as telecommunication or online exchange) and should also include direct modeling of the structural and temporal dependencies of this relational behavior. Moving beyond temporally aggregating interaction behavior into *ties* will require employing and extending tools for dynamic relational data analysis. Fortuitously, there is a convergence in statistical methodology that is poised to address the wealth of longitudinal interaction data: Social network analysis, which models interconnections among actors, is being extended to consider changes over time (Desmarais & Cranmer, 2012; Snijders, Van de Bunt, & Steglich, 2010). Event history analysis, which models rates of events occurring as they may depend on the environment, including other events, is being extended to consider forms of statistical dependence across interconnected actors (Stewart, 2005). This confluence – recently articulated as relational event modeling (Butts, 2008; Stadtfeld, 2012) and applied to radio communications in the WTC disaster (Butts, 2008), postings in online Q&A communities (Stadtfeld & Geyer-Schulz, 2011), critics' reviews of new books (De Nooy, 2011), and reciprocity and generalized exchange in patient transfers among hospitals (Kitts et al., 2013) – allows us to consider the dynamic interdependence of interaction behavior for a set of social actors in continuous time.

As we consider a dynamic structural alternative to the static social network metaphor, we will observe another blind spot of typical relationship measures, which points to a constructive solution for several dilemmas raised here: Our use of relationships in dynamic theory and analysis is inherently limited because relationships are typically divorced from time. It is difficult or impossible to identify a specific time when a relationship starts and stops, as they are cognitive categorizations of role relations and/or interpersonal sentiments, not specifically linked to time. Even for the rare exceptions, such as legal marriage, the observable beginning and ending of the relationship (marriage and divorce) may correspond only weakly to the dynamic patterns of behavior and emotions assumed to underlie the network. Similarly, coauthorship is a socially constructed role relation but implies interaction over time. Moody (2004) observes a collaboration outcome – a coauthored paper – but this event identifies a coauthor relationship only after a delay, when interaction behavior may be finished. In this way, a network is constructed out of the set of coauthorship relations in a literature, although the underlying sequence and timing of interactions is still unknown.

The socially constructed categories that actors apply to their interpersonal lives are worthy of further study. However, analyzing the fine-grained dynamics of social interaction will give us more purchase on the social processes underlying what we intuitively understand as social networks, rather than aggregating interaction data and interpreting them as social ties. The perspective that I outline here is an important step to realizing the goals articulated by Walker et al. (2000, p. 333) that network exchange theorists "should begin to focus on network processes of self-organization, adaptation, and feedback."

We now have an opportunity to directly theorize, measure, analyze, and interpret patterns in the structure and dynamics of exchange. Extending the same conceptual tools that have proven useful in the study of social networks, we can focus our lenses on dynamic patterns in the structure of interaction (or structural patterns in the dynamics of interaction). Rather than studying reciprocity as a state (i.e., some number of ties are mutual in the graph), we can study the dynamic process by which individuals reciprocate communications, gifts, support, or other goods. The perspectives described here will bring our theories and field research on social interaction into closer dialog with ethnographic fieldwork on social interaction and also allow a clearer link to research in controlled laboratory settings.

These analytical lenses provide a new way of thinking about ties, as interaction events occurring in continuous time, depending on the history of previous interaction events and on states of the environment. Rather than defining an arbitrary threshold to identify non-ties (if interaction is not frequent enough), we can directly observe and analyze delays between interaction events. In the previous view of networks-as-aggregated-interaction, authors faced an often-unacknowledged dependence between the time grain of their aggregation (daily, weekly, monthly, yearly) and the structure and dynamics of their networks: If a researcher computes weekly interaction "networks" based on an aggregation of interaction events and applies a threshold (i.e., a tie is more than two conversations in a week), then ties will appear for some weeks and not for other weeks, and thus the apparent network is constantly changing. Using a coarser time grain (monthly or yearly) will result in a denser graph than using a finer time grain (daily or weekly) and will also result in a more stable structure. Such networks can thus be sensitive to arbitrary details of aggregation, and developing the most robust images of the overall structure (by more aggregation) will necessarily destroy most details of the sequence and timing of interaction.

For moving beyond the laboratory to observation of natural settings, I have instead argued for capturing and analyzing time-stamped interaction data, directly modeling the interaction event rates for all dyads. This will take advantage of all information we have about histories of exchanges, including delays between exchanges, dyadic and higher-order time dependence in exchanges (*i* may be more likely to give to *j* again if *j* reciprocates quickly versus slowly, or if *j* has a longer history of exchange with another actor, *k*). It also allows for characteristic structural sequences of interaction to be observed and analyzed. All this information is lost when we aggregate a history of time-specific social interactions into a matrix of assumed relationships (Moody, 2002). Indeed, producing a static network by aggregating over a sequence of contacts – such as sex in a high school (Bearman, Moody, & Stovel, 2004) – can lose crucial insights into social processes such as diffusion on the network.

I have explained that an important reason to move "beyond networks" in considering structural dynamics (or dynamic structures) is that we can consider the nuances of interaction patterns in time. Now I add that the same benefit applies to analysis of opportunity structures under this framework. The analytical perspective described here can advance the work in sociological exchange theory by providing a seamless and integrated way to monitor and model the rates of exchange across dyads as well as the constraints on exchange. This avoids arbitrarily defining ties versus non-ties in the observed interaction network (instead viewing them as continuous rates of interaction, or impediments to interaction) and avoids arbitrarily defining opportunity structures based on historically observed exchange events. The latter is a crucial generalization to a world where impediments to exchange may be relative rather than absolute. It may be that impediments make some exchanges relatively difficult or undesirable, but not strictly impossible, and those relative difficulties may be incorporated as continuous variation in the availability of partners (and alternative partners) within a model of exchange events. In other words, the simplifying assumption that drives much of the work in network exchange theory – that exchange relations are either *on* (available) or *off* (impossible) – is unnecessary under this framework. A matrix of dyadic geographic distances does represent a structure, and under the assumption that travel is costly could even be interpreted as (an input to) an opportunity structure for interaction. For example individuals who work in different buildings, have different schedules, speak different languages, or companies that operate in different regions or countries, may face higher transaction costs for exchange that make them less attractive (but not impossible) exchange partners. Rather than interpreting the observed history of interaction as an exogenous opportunity structure of ties and non-ties, the framework that I discuss here could be used to implement impediments or facilitators as continuous influences. It is a straightforward extension of formative ideas in network exchange theory (Marsden, 1983) to note that restricted access is actually a continuum, which makes exchange more or less feasible in a given dyad. Importantly, this generalization will bring us a step toward applying network exchange theory to behavioral interaction networks.

The theoretical and analytical lenses described here can be applied to discover the interplay of dynamic social interaction patterns with coarser socially constructed relationships, interpersonal sentiments, or opportunity structures over time, all largely unexplored frontiers. For example, individuals may strategically alter their networks of interaction to enhance their own (or neutralize someone else's) structural power in exchange. This could build on some earlier work that has combined methods – such as survey measures of relationships with time diary measures of interaction histories (Milardo, Johnson, & Huston, 1983; Nezlek, 1993). The age of Big Data offers tremendous leverage to extend this research program, such as combining sociometric surveys with direct measures of social interaction using wearable sensors of proximity (Eagle et al., 2009) and conversation detection (Wyatt et al., 2008, 2011) which allow us to model interdependence of exchange behavior over short and long time-spans.[10]

CONCLUSION

Social networks research has employed four qualitatively different approaches to the basic concept of the social tie – where ties represent *role relations*, *interpersonal sentiments*, *behavioral interaction*, or *opportunity structures*. Basic process theories have been developed primarily for sentiment structures (e.g., structural balance theory), interaction (e.g., social influence or contagion theories), and opportunity structures (e.g., network exchange theory). Although early work in Group Process explicitly targeted the dynamic interdependence of these structures, especially social interaction and sentiments (e.g., Homans, 1950; Newcomb, 1961), there has been much more progress within each domain than integrative work on how they fit together. This limited attention to how our concepts interrelate has impeded theoretical integration across distinct research programs and has occasionally led theorists in one camp to inappropriately generalize their arguments to empirical networks where their theories do not make sense (such as widespread application of structural balance theory to triad closure in neutral interaction networks). We must clarify what we all mean by social ties, and begin the process of identifying scope conditions under which theoretical arguments generalize across different network conceptualizations.

Much empirical work has employed measures of role relations (such as coauthors, comembers, or friends), which have historically been the easiest to measure, and often serve as a proxy in any kind of network study. However, the connection of role relations to sentiments, interaction, and opportunity structures is implicit, inconsistent, and often unclear, even for relations such as close friends that ostensibly imply positive sentiments and behavioral interaction. We have seen many reasons why role relations such as friendship are often inadequate as general measures of behavioral interaction (because most social interaction occurs outside the measured relations, and friendship often misses the strongest interaction ties), sentiments (because role relation measures may similarly miss the strongest sentiments), or opportunity structures for exchange (which role relations do not even attempt to measure). The fact that conventional relationship measures typically give no attention to non-relationships is a principal obstacle to generalizing to the other network concepts, where identifying dyads with negative sentiments, zero interaction, and blocked exchange may be crucial. Minimally, I have shown that strong assumptions need to be explicitly defended (especially about non-ties) to link theoretical propositions and findings across these levels. I thus begin the process of identifying scope conditions for which role relations may be applicable to general theories about network dynamics.

Increasingly, empirical work has constructed networks directly from behavioral interaction, such as communication or participation in shared activities, and these are becoming a new generic way to measure social ties. This tradition often aggregates interaction events (e.g., citations, e-mails, phone calls, or face-to-face conversations) over time and treats the resulting social ties as a proxy in any kind of network study. However, aggregated behavioral interactions also are not general measures of role relations, sentiments, or opportunity structures. Again, I begin the process for identifying scope conditions in which networks of interaction events may be applicable to our general theories about network dynamics.

Rather than continuing to organize our work using under-theorized and vague concepts like *social ties* or even *friendships*, I have advocated for maintaining distinct focus on social interaction behavior, interpersonal sentiments, and opportunity structures – none of which are generally represented by composite relationship measures. All three concepts play crucial roles in distinct bodies of theory, and can be operationalized clearly. Through studying them independently and jointly, we can understand their unique and interactive dynamics.

Traditional tools such as survey research are still important to allow us to simply measure both sentiments and interactions, and remain the best-developed ways to examine negative sentiments. Measures of sentiment can be used fruitfully in tandem with conventional measures of role relations and behavioral interaction. Assessing sentiments and interaction independently would give us a more strictly interpretable measure of strong ties in terms of emotional closeness and frequency of interaction, avoiding many problems of interpreting self-reported role relations (such as friendship) or core discussion partners as an omnibus measure of strong ties. This would also allow us to differentiate *non-interaction* from *disliking*, neither of which is measured from a conventional friends or discussion network name generator (and both of which are ubiquitous misinterpretations of non-observed ties in conventional relationship surveys).

As for the recent explosion of time-stamped longitudinal relational data (e-mails, phone calls, meetings, wearable sensors measuring colocation and face-to-face conversations) in CSS, I note that early work has aggregated these rich sources of interaction data into simplistic sociomatrices in order to apply classic network theories, concepts, measures, and methods. Aggregating the micro-social dynamics of interaction into coarse ties in networks follows a long history of such aggregation (whether the aggregation is performed implicitly by field observers or by respondents themselves in surveys). It is also motivated by a longstanding interest in durable structural patterns (such as who typically interacts with whom) rather than the fine-grained dynamics of their interaction within that structure. The new technologies of data collection and analysis make this distinction much less important, and allow us to investigate social dynamics within particular encounters using the same lenses that we use to study the evolution of typical-structures over long time-spans. I have advocated going beyond the traditional concept of the social network as a temporally continuous and stable structure. Rather than imposing the coarse-grained lens of locally stable networks to observe the structure of micro-interactions, I argue to generalize the fine-grained lens of micro-interaction research to longer time scales (constituting the network). The universe of time-stamped relational data and the lenses of dynamic relational event analysis make this possible for the first time. I have thus strongly advocated for analysis of the dynamic dependencies in interaction behavior using newly developed event-based frameworks. In moving beyond "network ties," we can now look at the short-term and long-term temporal dependencies of reciprocity and generalized exchange (Kitts et al., 2013), deference or dominance behavior leading to social hierarchies (Martin, 2011), and the continuous development of commitment in real-world exchange.

Now that we are able to move beyond the simplifying assumption that social ties are temporally continuous and stable binary states, we are ready for a qualitative shift in integrative theory development. For example, I have discussed sociological exchange theory, in which non-ties are dyads where exchange is exogenously blocked by the researcher in experiments, versus ties where exchange is allowed and may or may not occur. I show that this usage does not correspond to any of the traditional methods for conceptualizing or measuring interpersonal networks in natural settings. However, the new CSS lenses for monitoring and analyzing the dynamics of exchange provide a natural next step for carrying valuable insights from exchange theory out of the laboratory and into dialog with other networks research. Both the dynamic regularities in exchange and continuous or discrete constraints on exchange can be incorporated into the event-based lens. Barriers or impediments to exchange, such as geographic distance or resource complementarities that affect exchange values, as well as endogenous network processes that facilitate or obstruct exchange, can be explicitly modeled within this framework.

In discussing the four versions of social networks, I have often emphasized careful study of the dynamics of interaction behavior not because behavior is inherently more important than role relations, sentiments, or opportunity structures. Rather, it seems that a surge in empirical research on the dynamics of interpersonal behavior is inevitable: The advent of CSS allows us to easily collect copious and fine-grained data on behavioral interaction, whereas sentiments, socially constructed role relations, and opportunity structures may still be challenging to collect for most social contexts. This leaves us with two crucial frontiers: First, to the extent that we take advantage of the new wealth of behavioral interaction data, we can translate and extend some of our general theories for sentiments and opportunity structures by deriving implications for interaction behavior. We should do so carefully, with assiduous attention to scope conditions as discussed here. Second, we can develop fine-grained, longitudinal, scalable measures for sentiments, opportunity structures, and role relations. For example, we could go beyond surveys to employ automatic indicators of affect based on nonverbal behavior (eye gaze, facial expressions, body spacing, posture, gestures, speech prosody, response latency, etc.), biometric indicators (brain imaging, hormone analysis, etc.) or natural language processing of electronic messages. Notably, some online spaces already allow us to observe populations of individuals interacting over time while also evaluating each other, and some may even allow experimental manipulation of opportunity structures by researchers. We must of course scrutinize the generalizability of findings from research in these settings, where both interaction and sentiments can be quite thin, but the opportunity for large-scale observational and experimental research is unprecedented.

I have addressed a broad range of social networks research, mostly outside the Group Process community. As networks research has exploded into thousands of papers across many disciplines, and the formal tools of network analysis have proven powerful in countless domains, the extension of *social ties* to any kind of relational data has often led to uncritical application of theories, slowing theoretical integration. Having once been a major part of the development of social network theory and analysis, the Group Process community has lost its prominent role as much networks research moved to scales beyond small groups. However, Group Process remains a valuable domain for thinking about how the basic process elements of social networks research – role relations, interpersonal sentiments, behavioral interaction, and opportunity structures – interrelate more generally. For example, Lawler's theory of relational cohesion (Thye, Yoon, & Lawler, 2002) combines all four elements: An exogenous network exists as a prior condition (implemented as an opportunity structure in the laboratory), interaction occurs in some ties on that network, and then emotions develop as a result of that interaction, resulting in further commitment and objectification of those ties as perceived relationships. Molm's work similarly examines opportunity structures, interactions, and sentiments in clear experiments. For example, Molm, Collett, and Schaefer (2007) experimentally manipulate "forms of exchange" (which are effectively exogenous constraints on timing of exchange opportunities in the set of participants) to consider the impact on sentiments toward exchange partners.

Just as new data sources and methodological advances of CSS allow us to investigate the fine-grained structural and temporal dependencies of the social world at various spatial and temporal scales, research on social exchange is increasingly focusing on temporal dynamics and history dependence in both experimental (Kuwabara & Sheldon, 2012; Molm, Whitham, & Melamed, 2012; Schaefer, 2012) and observational (Kitts et al., 2013; Willer, Sharkey, & Frey, 2012) work. This sensitivity to interdependent dynamics sets the stage for fruitful dialog with the broader community in social networks and CSS, which can also develop large-scale experiments in online spaces (Centola, 2010, 2011) Here I have aimed to at least temporarily suspend our use of the vacuous concept *social ties*, and instead resume our attention to the interplay of role relations, interpersonal sentiments, behavioral interaction, and opportunity structures, which have for decades formed a tractable foundation for work in the Group Process tradition.

NOTES

1. Whether network centrality is a source of power or weakness depends on our definition of ties, as information conduits (Bonacich, 1987) or exchange opportunities in a negatively connected exchange network (Cook, Emerson, Gillmore, & Yamagishi, 1983). This issue is orthogonal to my focus here.

2. Of course, some relationships (advisor-advisee, patron-client, teacher-student) are directed. Given that friendship is likely understood by survey respondents as a mutual relationship, an alternative approach is to regard the disagreement as reflecting measurement error. Discrepant friendship self-reports might indicate

unbalanced sentiments within a dyad (not the same thing as a one-directional relationship), but more likely it could indicate different construal of the survey question, different use of the label "friend" (vs. lover, brother, colleague, neighbor, teammate), context effects on the salience of alters during the survey, or truncation effects due to a cap on the number of alters in a name generator. One solution (e.g., South & Haynie, 2004) is to interpret the non-tie as error and reciprocate the relationship. Another solution (e.g., Goodreau, Kitts, & Morris, 2009; Schaefer, Simpkins, Vest, & Price, 2011; Young, 2011) is to study only corroborated *mutual* friendship reports.

3. We can hardly interpret dyadic disagreements in behavior self-reports as directed sentiments, as disagreements could be due to different construal of words like *often* and *play*, differences in recall of social encounters, or differences in popularity that affect the alter's salience.

4. Modeling research has shown that such patterns can be explained parsimoniously by dynamics at the dyad level (Faust, 2007; Kitts, 2006; Macy, Kitts, Flache & Benard, 2003), without the strong information conditions required for structural balancing processes to operate in triads. However, the assumption that ties are explicitly *negative* (not merely less-positive) is essential.

5. It is important to note that the GSS is an ego-network study, which measures a small sample of Ego's discussion partners, with non-ties (to the rest of the population, including other respondents and their alters) undefined. Thus, researchers typically focus on characteristics of the alters in the observed sample, such as their demographic composition. In rare exceptions, researchers (e.g., McPherson, Smith-Lovin, & Brashears, 2006; cf. Paik & Sanchagrin, 2013) have applied the interpretation from complete-network studies to GSS ego-network data, assuming that the entire population of unmentioned potential alters are *non*-ties (unavailable for discussing important matters) because they are not mentioned on the name generator.

6. This may be a reason why so many empirical applications of sociological exchange theory have been macro-level studies of organizations or states, where there are more concrete and observable indicators of non-ties as prohibited interaction (Webster & Whitmeyer, 2001).

7. We could also refer to this brand loyalty as "commitment" in the exchange relation (Lawler, Thye, & Yoon, 2006), and for most purposes it makes sense to regard this increasing development of an exclusive exchange relation between A and B as an endogenous process, rather than as an exogenous constraint.

8. Measures of proximity (bluetooth, infrared radiation, localization by GPS, wifi, or cell tower) have high false-positive rates for detecting social interaction because people are often colocated without interacting. Meetings on shared electronic calendars produce many false positives and false negatives (Lovett et al., 2010), as people use calendars as reminders or to-do lists, often miss meetings on their calendar, attend meetings without RSVPing, or otherwise do not fit the locations listed on their calendars. Even accurate measures of colocation do not necessarily capture social interaction. Thus, these methods need to be combined with some other filter or hand-coded to identify which links represent realized social interaction. For example, Wyatt et al. (2008, 2011) combined physical colocation with automatic detection of conversations in audio recordings to identify interaction with a higher level of accuracy.

9. Audiences seem driven to interpret phone or face-to-face conversations as directed relations, just as they are driven to interpret friendship nominations on a survey as directed relationships. Although it may be meaningful to interpret conversations in some sense as directed (one person speaks first, one person dials the phone or approaches the other to initiate a conversation, and of course each utterance is directed from one party to the other), conversations themselves are generally undirected. Both parties speak and listen.

10. An approach that blurs the distinction I am making here is a fine-grained network panel approach. For example, Almquist and Butts (2013) observe a set of political blogs with snapshots of the network of links at 484 time points. Where ties are composed of time-stamped interaction events (such as phone calls or e-mails) aggregated over a time interval, reducing the interval width will make the resulting networks sparser until their observable structure disappears altogether. By contrast, some ties (web hyperlinks, marriages, corporate board overlaps) are temporally continuous so the network can be captured by an instantaneous snapshot at any time. In that case, increasing the number of snapshots by shortening the interval width will enhance the resolution of panel data, allowing us to observe the changes in the network as the length of time intervals becomes short. The appropriateness of the panel versus event-based approach then depends importantly on the assumption of temporal continuity.

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