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Cross-sectional and Longitudinal Applications for Studying Intra- and Intergroup Behavior

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Abstract

Social scientists increasingly recognize the potential of social network analysis, which enriches the explanation of human behavior by explicitly taking its social structure into account. In particular for the science of groups, social network analysis has reached a point of analytic refinement that makes it a valuable tool for investigating some of the central mechanisms that underlie intra- and intergroup behavior. The present paper highlights the general relevance of this analytic approach and describes the background, generation, and application of cross-sectional as well as longitudinal network statistics that are of specific interest to group researchers. In doing so, we aim to provide a general introduction for researchers new to this method, while demonstrating the potential and limitations of social network analysis for different areas in this field.

Keywords: social network analysis, group research, intragroup behavior, intergroup behavior

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Recent conceptual, empirical, and technical advancements have facilitated a growing interest in social network analysis (SNA). This empirical approach structures ties between network members through certain interdependencies and assumes that these interdependencies explain something about the network members (Borgatti, Mehra, Brass, & Labianca, 2009). While ties can be based on affiliations (kinship, friendship), similarities (co-membership, co-occurrence), interactions (cooperation, communication) or the flow of resources (information, material), network members include all kinds of ‘subjects’ such as individuals, institutions, cities, or even concepts in semantic networks.[1] In the narrower sense, a social network contains a quantity of members, who send ties and can receive ties (see left side of Figure 1). This information creates the mutual interdependencies that researchers need in order to calculate the majority of network parameters. If our information is limited to someone’s connections to other network members and does not include, in turn, their interconnections, then this would represent a so-called ego-network (see right side of Figure 1). An ego-centered network is still valuable for some research analyses, such as the investigation of an individuals’ general embeddedness, but it is less comprehensive and thereby lacks many analytic possibilities with regard to the investigation of structural patterns.

Insert Figure 1 about here

Complementing well-established social-psychological research methods, SNA allows us to study the naturally existing social structure. This social structure evolves based on internal mechanisms (e.g., homophily; McPherson, Smith-Lovin, & Cook, 2001) as well as external mechanisms (e.g., proximity; Prediado, Snijders, Burk, Stattin, & Kerr, 2011). The resulting social network will, in turn, socialize attitudes, beliefs, and behavior via norms that spread among individuals across their interrelating ties (Brechwald & Prinstein, 2011).

Therefore, considering this social structure and its dynamic is a beneficial perspective for understanding, predicting, and explaining human behavior.

In particular for the field of group research, SNA represents a valuable methodological tool for studying the social structure that channels and the processes that underlie intra- and intergroup relations. Its psychometric properties enable scientists (a) to consider more objective information, which relies on a comprehensive amount of relational data that is produced by different sources; (b) to specify complex patterns of supra-dyadic relationships covering indirect, transitive, and intermediate connections; (c) to capture the social influence processes operating within the interdependencies of a network; (d) to identify latent social-psychological entities such as peer groups or cliques by means of graph theory and matrix algebra; and (e) to examine the structure of, and investigate effects across, different levels including the individual, the group, and the entire social network. In this paper, we will explain these unique methodological features in more detail and illustrate how SNA could enrich different areas of group research including social identity, conformity, leadership, group decision making, group performance, group socialization, intergroup contact, and in-group versus out-group behavior.

The basic idea of the social network perspective—that behavior is a function of both individual dispositions as well as the social structure human beings are embedded within—is, in fact, far from new. To our knowledge, the first social network study was conducted in the year 1880-1881 (see Delitsch, 1900; for a recent reanalysis see Heidler, Gamper, Herz, & Eßer, 2014). Driven by the idea: “Tell me who you interact with, and I will tell you who you are, […]” (pp. 150-151, our translation from German[2]), Delitsch’s pioneering work utilized relational data in order to explain the friendship formation among 53 students of a German school class with the help of different network parameters. Later, Moreno (1934) furthered the scientific applicability of SNA by demonstrating its potential to explain external behavior; in this case, a spike in the number of runaways at a boarding school for girls in New York. Thereafter, it took about 30 years until sociologists started to use SNA systematically, and another 20 to 30 years before this approach became established in other research fields.

Nowadays, SNA is of substantial importance in psychology, as evidenced from a literature review that we conducted recently (as of January 2014). In PsycINFO, we searched for articles with “social network analy$” as a keyword and found a continuous increase in the five-yearly number of published network papers from 10 (from 1970-74) to 2430 (from 2010-2014). This rising interest in and application of social network research is based on the advanced technological and statistical possibilities over the last years. While Delitsch (1900) needed 20 years from data assessment to publication, the application of complex algorithms to a huge amount of relational data or the detailed visualization of large network graphs is a matter of seconds today. These improved methodological opportunities also stimulate conceptual and empirical advancements in the field of SNA, such as the recent innovation offered by SIENA that allows researchers to study network-behavior dynamics (see section on longitudinal applications), which in turn attract more scientific attention.

SNA has now reached a level of conceptual and statistical refinement that makes it an appealing method for all research fields that aim to explain behavior in general and social behavior within and between groups in particular. We believe that the time has come to explicitly bridge this empirical approach to the broad field of group research. Hence, in the present paper, we seek to point out how different topics in group research can be enriched by a social network perspective. For this purpose, we organize this paper around the introduction of a large variety of well-established network parameters and procedures—broadly classified into cross-sectional and longitudinal network applications—that are of specific interest to this field. After a general introduction of cross-sectional and longitudinal network applications, we will provide a brief explanation of different network statistics including procedural information about how they are generated and demonstrate their application to illustrative topics in group research. This overview of network applications is not exhaustive, but rather a selection that aims to highlight the immense potential of SNA to shed light on open research questions within the science of groups.

Cross-sectional Applications

In general, cross-sectional forms of SNA are useful in order to study precisely the social structure of networks. In this regard, the main questions concern: (a) who is directly or indirectly connected to whom; (b) which latent substructures are detectable; and (c) how does social influence spread among the interrelated network members within the overall social network? In order to address these research objectives, network analysts have to be clear about the network boundary. Having a well-defined boundary does not only specify the elements for the data assessment, but also ensures that we capture the actual population, to which we want to generalize our findings. Network boundaries can occur naturally (e.g., school class, neighborhood, business companies) or need to be defined by the researcher (e.g., a specific subgroup of interest). Whenever possible, researchers should consider more than one network (e.g., studying many school classes that form separate social networks) to test the robustness and increase the external validity of their revealed network effects. These comparisons within and across different social networks represent possible study designs for inter- and intragroup researchers. However, it should be noted that the network boundary does not have to be the group boundary. The identification of substructures—either by means of SNA (e.g., peer groups within a school class) or external attributes (e.g., gender, ethnic background)—also allows intergroup comparisons within one social network, which are of specific interest to small-group researchers.

Once group researchers have specified the network boundary, different forms of data allow the elicitation of social networks. These include questionnaires, observations, or archival analysis that assesses some kind of interdependency information. The most common and economical method is a brief and simple questionnaire that asks all network members to nominate other network members with respect to one or more forms of connection (e.g., friendship). Usually with the help of a roster that lists all network members, participants nominate each other either on an open-ended list (e.g., “Who are your friends?”) or by applying a limited nomination procedure (e.g., “Who are your 5 best friends?”). Inevitably, an unlimited number of nominations creates more data, but especially in smaller networks, such as a school class, a limited nomination procedure is sufficient in most cases and does not result in a significant lack of information (Friederickson & Furnham, 1998). Depending on the nature of assessed ties, network information can capture very different types of connections. While most research focuses on friendship or other positive interdependencies like cooperation, there is an increasing interest in studying negative forms of connections such as dislike or bullying behavior (Huitsing et al., 2012). These connections can be assessed on a binary level (tie is present or absent), ordinal level (tie is negative, neutral, or positive), or interval level scaling format (tie is evaluated on an equidistant scale), but binary connections represent the most common scaling format in SNA and are the required input data for the majority of network statistics.

After all network data had been collected, the information is entered in statistical programs as directed or undirected graphs. Whereas directed graphs specify the relation between network members and can distinguish whether A nominates B, B nominates A, or whether A and B are reciprocally connected (cf., Figure 1), undirected graphs only indicate the existence or absence of a connection between two members. As a matter of course, directed graphs contain not only more, but also more valuable information that is of specific interest for many research questions. However, it may be worth symmetrizing data to undirected graphs in some cases. For example, undirected graphs increase the likelihood of an overall connectedness and thereby facilitate the estimation of some network parameters (e.g., closeness, explained below). From the variety of established statistical programs for the cross-sectional analysis of social networks, we recommend the R package sna (Butts, 2008) and the UCINET Software (Borgatti, Everett, & Freeman, 2002), which both allow the calculation of all network parameters and procedures presented below. Helpful software tools to visualize social networks are NetDraw (Borgatti, 2002) for small to medium large networks and Pajek for larger networks (Batagelj & Mrvar, 1998). More detailed conceptual and practical information about cross-sectional SNA can be found in the seminal book by Wasserman and Faust (1994) as well as in the instructive manual by Hanneman and Riddle (2005).

A major benefit of SNA is its multi-modal structure that includes different, hierarchically nested levels. These can typically be categorized as micro-, meso-, and macro-level or, in network terms, as individual, group, and network level, which structure the following presentation of cross-sectional network statistics and their application to relevant issues in group research.

Individual Level

N-step ego networks. This information specifically addresses an individual's connections in the network, with n specifying the number of linking steps from ego. That is, a *1-step ego network* illuminates ego's direct connections (cf., right side of Figure 1), while a *2-step ego network* illuminates ego's direct and extended connections by additionally determining the connections of ego's connections.

The detailed identification of ego's embeddedness within the social network provides researchers with helpful data for studying intergroup contact, in particular extended contact, which refers to the amount of out-group contact that someone's in-group friends have (Wright, Aron, McLaughlin-Volpe, & Ropp, 1997). The assessment of extended contact may be inaccurate when relying on self-reports, which require to report the out-group contact of in-group friends, because individuals are likely to lack knowledge concerning their in-group friends' out-group contact or to be prone to different types of biases. However, initial studies demonstrate that network data can enrich the assessment of extended contact, either with 2-step ego networks (Munniksma, Stark, Verkyten, Flache, & Veenstra, 2013) or with a combination of network and self-reported contact data in 1-step ego networks (Wölfer, Schmid, Lolliot, & Hewstone, in prep.). More specifically, the latter study used SNA to compute reciprocal friendship patterns between classmates of the same in-group (i.e., A likes B and B likes A). This more objective assessment of contact advances standard self-reports that merely consider an individual's unidirectional perspective. Then, within each 1-step ego network, the authors averaged the degree of out-group contact that these identified in-group friends specified to have, which precisely meets the above mentioned definition of extended contact. These first research efforts represent a promising starting point that facilitates the examination of extended intergroup contact as well as its relation to further aspects in group research such as intergroup prejudice or discrimination.

Network centrality. Within the scope of group research, another application of SNA on the individual level concerns the analysis of network centrality or the social status of network members. The most important centrality parameters are the *degree* (Freeman, 1979), *Bonacich's centrality measure* (Bonacich, 1987), *closeness* (Freeman, 1979), and *betweenness* (Freeman, 1977), each of which captures a very specific aspect of social status.

The degree quantifies a network member's number of connections or in directed graphs the number of incoming ties (indegree) and outgoing ties (outdegree). In Figure 1, individuals are sized by their indegree, which indicates that the network members #5, #10, #22, and #23 are the socially most central network members in this regard.[3] An extension of the degree parameter represents Bonacich's centrality measure. Although member #6 and #15 have the same indegree, with two connections each, they are not equally important within the social network of Figure 1, because the direct connections of #6 (i.e., #10 & #18) are, in turn, more strongly connected to other network members than are the direct connections of #15 (i.e., #11 & #17). Bonacich's centrality measure takes these indirect relations into account by considering the number of someone's connections and the number of connections from those to whom someone is connected. Another conceptually different centrality parameter represents closeness that indicates spatial centrality within the social network. The closeness parameter specifies the sum of geodesic distance, which is the total number of least necessary steps from a network member to all other network members. Network members with a high closeness score, like #14 in Figure 1, are—independently of the number of connections—important to the extent that they have good reachability for and to every member of the social network. Finally, sometimes network members are important, although they are neither strongly connected, nor central, but many members depend on them to make connections to others, like member #13 in Figure 1. This idea is reflected with the betweenness parameter that indicates someone's linking role within the social network or the extent to which the social structure changes, if this network member is removed from the network. Even though these parameters differ conceptually, they tend to have a moderate to strong empirical overlap (Valente, Coronges, Lakon, & Costenbader, 2008). Therefore, in order to avoid conceptual redundancies or statistical multicollinearity, it is advisable to concentrate on one network centrality parameter, which is best suited to operationalize the respective research question.

The detailed examination of network centrality with a broad variety of different parameters allows intragroup researchers to generate useful variables that can further our understanding of social influence processes and the consequential behavior within groups. For example, in research on decision making in groups, ties can be structured via the extent to which group members exchange information. The corresponding centrality in these networks specifies the amount of information that an individual possess, which was found to positively predict this member's influence on the group decision (Kameda, Ohtsubo, & Takezawa, 1997). Moreover, centrality in friendship networks specifies popularity, which facilitates the examination and intervention of school harassment. In more detail, friendship centrality allows the researcher to identify salient network members, who—depending on their degree of prosocial behavior—exert either positive influence by reducing prejudice (cf., Paluck, 2011) or negative influence by victimizing less powerful peers (cf., Wölfer & Scheithauer, in press). Furthermore, centrality in advice networks provides valuable information for studying the antecedents and consequences of leadership behavior. More specifically, individuals who are active in giving and receiving advice, were perceived as charismatic leaders, whose presence is, in turn, positively associated with the overall group performance (Balkundi, Kilduff, & Hanison, 2011). Besides pursuing these valuable lines of research, further applications are possible, in which group researchers could make use of network centrality measures in order to explore different aspects of intragroup behavior. Given the fact that network centrality parameters precisely capture the social influence of individuals, it is plausible that this information assists, for example, the examination of processes related to minority and majority influence.

Group Level

Beyond the individual level, network members appear together in clusters with stronger in-group than out-group connections and consequently form the next mode: the group level. This latent social structure can be identified exclusively by means of SNA, which, comparable to a cluster analysis, determines the strongest connections within the social network. In the course of this analysis, researchers can also identify isolates, who do not belong to any group. Figure 1 colors network members by their group membership and reveals a network composition of four groups (yellow, red, blue, black), three dyads (orange, green, purple), and two isolates (white).

Social groups can be extracted in many different ways, but two common methods are the *social cognitive mapping* (SCM; Cairns, Cairns, Neckerman, Gest, & Gariépy, 1988) for data produced with a group nomination technique and the *hierarchical clique clustering approach* (HCCA; Everett & Borgatti, 1998) for data produced with an individual nomination technique. With the SCM approach, participants are asked to name all groups (i.e., students who frequently spend time with each other) within their social network including those of which they are a member as well as those they do not belong to. For example, Amy can nominate the group 'Sarah, Michele, and Amy' as well as the group 'Sean, Michael, and Jack'. For the subsequent group extraction, data are aggregated into a co-occurrence matrix that plots all network members against each other. The cells of this matrix summarize the frequency with which two individuals were named as belonging to the same group, while the diagonal specifies an individual's number of nominations to any group. The next step intercorrelates all columns of this matrix, so that each cell of the resulting correlation matrix indicates the co-occurrence correspondence between two network members. Thereafter, network members with significantly intercorrelated co-occurrence are grouped together. And finally, in order to identify non-overlapping groups, confirmatory factor analysis determines the best-fitting structure of discrete clusters. More detailed procedural information on this approach can be found in Cairns and colleagues (1988) as well as in Gest, Farmer, Cairns, and Xie (2003).

The HCCA is based on the analytic unit of a clique, which is defined as the maximum number of network members who have all possible ties present among each other (Luce & Perry, 1949). That is, if A is connected to both B and C, which are in turn connected among each other, then A, B, and C would constitute a clique. Conceptualizing cliques as the maximal complete subgraph is very precise, but allows for multi-group membership, so that the HCCA is used in order to produce non-overlapping groups. This approach utilizes a Co-

Membership Matrix, wherein network members are plotted against each other and every cell presents the number of times that two network members are in the same clique. With this matrix, non-overlapping groups are produced based on the criterion of creating a maximally large group of network members that were all co-members within a previous clique. Hence one can think of this procedure as a meta-clique approach, in which co-membership is used for group extraction in the same way as ties are used for clique extraction.

Social network statistics on the group level are appealing to both intra- and intergroup researchers. The group structure per se already contains important information and the presented methods that extract these latent social entities equip researchers to objectively identify and subsequently analyze this structure of interest. Extracting the group structure has already been used in previous intra- and intergroup research. Poteat (2007), for example, identified peer groups in order to investigate homophobic attitudes and behavior on this contextual level and revealed a strong group socializing effect. That is, being a member of a homophobic peer group positively predicted individuals future degree of homophobia, while controlling for individuals' own homophobic attitudes and behavior. Moreover, the group structure also advanced research on in-group versus out-group behavior, because it allows researchers to analyze how and why individuals favor their own group over other groups (Tarrant, 2002). At the same time, information regarding the group structure promises to enrich yet unexplored areas in this regard including the development of social identity (cf., Tajfel & Turner, 1979), normative conformity (cf., Deutsch & Gerard, 1955), or information exchange and decision making in groups (cf., Stasser & Titus, 1985). For example in the last mentioned research area, social network data equip researchers to examine the flow of information with regard to the role of group members' motivations (cf., Faulmüller, Mojzisch, Kerschreiter, & Schulz-Hardt, 2012) or to disentangle individual- and group-level factors that are responsible for the process of group decision making (cf., Faulmüller, Kerschreiter, Mojzisch, & Schulz-Hardt, 2010).

Network Level

The final level, the network or graph level refers to the macro mode and describes the overall structure of the social network. The purpose of graph-level parameters is twofold: On the one hand, they serve as important control variables for researchers, who analyze connections across different social networks and, on the other hand, they allow researchers to examine the contextual routes along which social influence spreads. Besides the most important graph-level parameters, such as *density*, *reciprocity,* and *centralization*, the *E-I index* (Krackhardt & Stern, 1988) is of specific value for group researchers.

Density reflects the overall connectedness within a network by relating the number of existing ties to the number of theoretically possible ties between all network members. Reciprocity specifies the number of mutual relationships by measuring the extent of bidirectional connections. Centralization indicates the variance of centrality within a social network by determining the difference in the network members' number of connections (i.e., the degree). And finally, the E-I Index captures the contextual network connectedness between two groups by subtracting the number of out-group ties from the number of in-group ties and dividing this difference by the total number of ties.

These parameters enable researchers to study important areas of group research. For example, the conceptualization of groups as information-processing systems that derive decisions based on the extent to which their members share cognitions or preferences (Mojzisch, Kerschreiter, Faulmüller, Vogelgesang, & Schulz-Hardt, 2014; Tindale & Kameda, 2000) implies that graph-level parameters in information networks serve as useful measures. In particular, density and reciprocity allow researchers to capture this overall sharedness and the way it structures the spread of social influence. Moreover, centralization has the potential to inform research about hierarchies within groups and the consequential intragroup behavior, as it distinguishes equally-powered networks from networks that are unequal with regard to the centrality of their network members. Finally, the E-I index can enrich intergroup contact research by examining the overall degree of integration or segregation between network members of different ethnic backgrounds or religious beliefs. Generating this index across different networks allows researchers, in turn, to predict the score of this index with the help of characteristics of the network members (e.g., acculturation strategies, intergroup anxiety, or norms), which helps to shed light on the promoting factors for intergroup integration.

Longitudinal Applications

Most social networks are highly flexible systems and the static snapshot at a given moment will gradually change over time. Empirical information concerning the longitudinal evolution of social networks adds to our knowledge of their dynamic structure and the groups they constitute or contain. In this respect, the *stochastic actor-based model* (Snijders, 2001) represents a powerful and frequently used statistical approach for longitudinal SNA.

This model includes several assumptions, which are central to the understanding of this approach and the interpretation of its estimates. We aim to frame their description as briefly and non-mathematically as possible (for more details see Snijders, 2001; Snijders, van de Bunt, and Steglich, 2010). First, the network change in the stochastic actor-based model is based on a Markov process. This assumption implies that the future network state can be predicted solely as a function of the current network state. Second, changes in the network are made by the network members. This is considered to be a purposeful process, in which individuals strive to maximize their satisfaction with the local network neighborhood. As a result, the actor-based network change is explainable by the attributes and network positions of individuals. Third, the network change takes place continuously between two measurement points. Hence the gradual change is decomposable into smallest possible units of analysis. These so-called ministeps represent a network members' opportunity to establish, dissolve, or maintain a (non-)relationship. Finally, ministeps never happen simultaneously, but constitute a sequence of chronological elements that allow one network member at a time no more than one opportunity for a tie change. Building on these assumptions, the stochastic actor-based model explains the network dynamics with the help of the evaluation function, which estimates the tendency of individuals to create or maintain network ties in their local network neighborhood.[4]

As in cross-sectional applications of SNA, researchers need a well-defined network boundary for examining social networks over time and, whenever possible, should aim to consider many different networks in order to increase the generalizability of their research. With the stochastic actor-based model, it is possible to jointly analyze the dynamic of many different social networks in two ways: Either researchers define structural zeros to indicate the impossibility of ties between members of different social networks or, in a statistically more sophisticated way, they apply multilevel SNA (Snijder & Baerveldt, 2003). The latter approach allows the sequential examination of the micro-level (within-network analyses) and macro-level (between-network analysis). While the micro-level separately determines the estimates across different social networks, the macro-level uses this information for the purpose of separating the error variance from the true variance of the population.

For longitudinal SNA, researchers need at least two waves that assess the social network of the same individuals within the same network boundary, although, as usual in longitudinal research, the statistical possibilities and analytic power increase with the number of measurement points. The predominant method that is used to elicit longitudinal networks represents the nomination technique of participants by means of questionnaires. This is most likely related to the fact that the stochastic actor-based model requires network members to actively make decisions about the network change, which excludes all ‘subjects’ that are incapable of cognitive processes (e.g., cities or concepts) and all assessment methods used in those cases (e.g., observations or archival analysis). However, among cognitively capable network members, longitudinal network researchers can study all kinds of interdependencies including friendship ties (Snijders et al., 2010), cooperative ties (Lomi, Snijders, Steglich, & Torló, 2011), or conflictual ties (Huitsing et al., 2012), while using a scaling format of binary level.

Social network dynamics can be analyzed in directed and undirected graphs, even though the former allows the researcher to model more effects. This modeling process is implemented in the Simulation Investigation for Empirical Network Analysis (SIENA), which is either embedded within StOCNET (Snijders, Steglich, Schweinberger, & Huisman, 2007) or within the R environment (Ripley, Snijders, Boda, Vörös, & Preciado, 2013). Both of these referenced SIENA manuals include helpful and understandable instructions that clarify the issues of data preparation, software handling, statistical modeling, and interpretation of effects. An advantage of SIENA is the statistically sound integration of individual characteristics, which allow researchers to investigate the longitudinal interplay between social networks and the attributes, attitudes, or behavior of their members. As described in the next two subsections, individual characteristics can be modeled as predictors (network dynamics) or as additional outcome variable (network-behavior dynamics).

Network Dynamics

In its basic form, SIENA focuses on *network dynamics*, which examine the extent to which individual characteristics affect the network formation. Analogous to the procedure of generalized linear models, the network dynamic is determined probabilistically with a linear combination of different effects specified with the evaluation function (explained above). More specifically, one can compare this statistic to a multinomial logistic regression, which estimates the probability that a specific network member will form or maintain a relation to another specific member. Consequently, the respective effects are interpreted as log-odds ratios and, after an exponentiation, as odds ratios. For example, a reciprocity effect with an estimate of 1.5 represents the initial log-odds ratio, which—applied to the exponential function with base e, also known as Euler's number (e^x)—indicates that network members are $e^{1.5}$ = 4.5 times more likely to form or maintain a reciprocated tie compared to an unreciprocated tie. The upper half of Table 1 describes and illustrates the most important SIENA effects for modeling network dynamics.[5]

Insert Table 1 about here

Network dynamic effects are of two kinds covering structural network effects and covariate effects. While structural network effects capture endogenous network mechanisms, covariate effects estimate the network dynamics based on exogenous factors that describe the network members (e.g., group membership). Structural network effects can be further subdivided into overall network effects (density and reciprocity), network closure effects (transitive triplet and balance), triadic effects (three-cycle and betweenness), and degree-related effects (in-degree popularity and out-degree popularity), whereas covariate effects distinguish attribute effects (covariate alter and covariate ego) from similarity effects (covariate similarity). Beyond these main effects, SIENA enables modeling several interaction terms that either combine different information (covariate ego X covariate alter interaction) or test moderating effects (in-degree popularity X covariate ego interaction). From this variety of available effects, the model specification should be based on the theoretical background and the research question of interest. However, effects that need to be included in every SIENA modeling procedure are density and reciprocity as well as at least one network closure effect (cf., Ripley et al., 2013).

Along these lines, SIENA offers several possible applications for studying the network dynamics within and between groups. When researchers consider the network as the group, intragroup processes of interest concern, for example, the formation of friendships (Snijder & Baerveldt, 2003) or the evaluation of group-based interventions that target the social network structure (Wölfer & Scheithauer, in press). All of these and related phenomena can be studied longitudinally based on individual characteristics of the network members, especially with degree-related and covariate effects. In more detail, Wölfer and Scheithauer (in press) used the covariate alter effect to model the bullying behavior of network members and examined its longitudinal effect on the network formation while conducting a school-based bullying prevention program. This evaluation took account of the complexity of peer network processes involved in bullying and revealed the hypothesized effect of bullies' reduced popularity, reflected in their network centrality. That is, in contrast to the waiting-control group, bullies in the intervention group, experienced a decrease in their social influence due to the program-related change of attitudes, norms, and behavior. When researchers consider multiple groups within networks, intergroup processes and particularly the effect of a group status—defined by ethnic background, religious belief, or peer-group membership—become a possible subject of analysis. More specifically, covariate effects allow the researcher to specify the group membership for testing its influence on an individual's network position over time and thereby test whether certain groups become integrated or banished to the fringe of the network. The corresponding covariate similarity effects, or so-called same effects in the case of dichotomous variables, allow testing the preference for homophily versus intergroup contact.

Network-Behavior Dynamics

The original focus of network dynamics (Snijders, 2001) became quickly enriched by the consideration of *network-behavior dynamics* (Steglich, Snijders, & Pearson, 2010;

Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). Behavioral dynamics additionally examine the extent to which the network formation affects individual characteristics. The reason for studying the longitudinal network dynamics together with the changing attributes of their members is grounded in the fact that the network-behavior dynamic is a mutually dependent and coevolving development. This extended stochastic actor-based model allows disentangling selection effects (network dynamics) from socialization effects (behavioral dynamics) and consequently reaches a point of analytic refinement that comes close to the explanation of causal mechanisms.

Analogous to network dynamics, behavioral dynamics happen in the smallest possible units (i.e., ministeps) and only one at a time. Their estimation similarly relies on an evaluation function, which determines the tendency of network members to increase or maintain their score on a behavioral scale. Again, this evaluation function specifies a linear combination of different effects, which can be interpreted similarly to the effects in a multinomial logistic regression. The lower half of Table 1 presents the most important behavioral dynamic effects. These effects can be classified into behavioral tendencies (linear and quadratic shape) and influence effects that are based either on the local network neighborhood (average similarity and average alter) or the overall network position (in-degree and out-degree). In addition, it is possible to include covariate effects for explaining the behavioral dependent variable based on attributes of the network members. In this regard, main effects specify the impact of a covariate on behavioral dynamics, whereas interaction effects allow the examination of moderating effects in influence processes. In any case, it is recommended to include the linear shape effect and, if the behavioral dependent variable is continuous, also the quadratic shape effect (cf., Ripley et al., 2013).

Studying network-behavior dynamics is primarily suitable for gaining a better understanding of the longitudinal mechanisms of group socialization. This research objective is analyzable by modeling the above-described influence effects that emanate from one's local network neighborhood. Recent studies in the field of aggressive behavior used this powerful approach to study peer influence processes in youth. For example, Rulison, Gest, and Loken (2013) revealed a socialization effect among adolescents with regard to physically aggressive behavior, indicating that individuals' aggressive behavior is shaped by the aggressive behavior of the peers to whom they are connected. Moreover, Molano, Jones, Brown, and Aber (2013) discovered that social cognitions seem to moderate this socialization effect to the extent that children with high levels of hostile attributional bias are more susceptible to aggressive behavior of their peers. Besides these initial investigations, this network approach has the potential to enrich further issues of group research by examining, for example, the effects of members' network position on the behavioral dependent variable. That is to say, the effects of leadership roles can be studied by examining the development of central members, who occupy such a leadership position within their network, with regard to their psychosocial constitution or well-being. Moreover, researchers can also study individuals' intergroup attitudes depending on the intergroup contact possibilities of their network position.

Discussion

In the present paper, we introduced the social network approach to group researchers and highlighted its applicability to their specific scientific interests and objectives. In doing so, we did not focus on a single procedure, but rather presented a broad family of statistics covering cross-sectional and longitudinal social network methods. These statistics include both recent advancements that are completely novel (e.g., network-behavior dynamics) as well as already established procedures that are still innovative for the field of group research (e.g., n-step ego networks). We contend that SNA offers the potential to enrich traditional methods of group research, but it is also—as it is true for every method—characterized by some limitations of which researchers need to be aware.

The Potential of Social Network Analysis

While SNA has already started to make important contributions to group research across different areas (e.g., Balkundi et al., 2011; Molano et al., 2013; Munniksma et al., 2013; Poteat, 2007; Snijder & Baerveldt, 2003; Tindale, & Kameda, 2000), it is still a relatively rare approach in this field. This is surprising given its conceptual suitability for studying intra- and intergroup relations, its unique psychometric properties, and its broad applicability to different research questions within the science of groups. In this paper, we demonstrated the methodological scope of SNA, the consideration of which enables group researchers to adequately consider contextual and environmental factors, which—in addition to the already applied techniques of this field—would advance scientific knowledge concerning behavior within and between groups. This applies especially to research questions that have not yet received much analytic consideration from a social network perspective; these include, but are not limited to, the development of social identity, leadership-coworker interaction, use of and susceptibility to social influence, the formation and dissolution of overall intergroup relations, as well as the longitudinal effect of group membership on behavior and vice versa.

Another appealing aspect of SNA concerns its potential to build bridges to other disciplines that investigate groups from a different scientific perspective. The main idea of studying the interdependencies and dynamics of a social structure allows researchers to address many classic problems; not only in psychology, but also in sociology, politics, education, engineering, economics, or linguistics. Moreover, even though network researchers in social science pursue somewhat different goals than network researchers in natural sciences (cf. Borgatti et al., 2009), the general applicability of SNA even includes the fields of biology, zoology, or physics. This fact creates substantive opportunities for scientific interactions or collaborations across different disciplines to further advance the science of groups.

Furthermore, the methodological field of SNA is not only characterized by instructive handbooks—for cross-sectional applications see Wasserman and Faust (1994) or Hanneman and Riddle (2005); for longitudinal applications see the most recent SIENA manual by Ripley and colleagues (2013)—but also by inexpensive software programs. These are obtainable either for a reasonable price (UCINET, NetDraw) or even for free (SIENA, RSIENA, Pajek), which allows researchers to become acquainted with the network approach, independently of their available resources.

Finally, besides the existing potential, we anticipate further statistical advancements. Many of the currently available techniques resulted from successful efforts that fine-tuned a method to a specific research question. Given the pioneering role of SNA in most fields, different research interests will most likely yield additional improvements that, in turn, inspire conceptual and theoretical advancements. To illustrate the rapid development in this field, Veenstra and colleagues (2013) recently summarized many empirical innovations of network-behavior dynamics, although this method is only ten years old. In sum, we believe that this is just the beginning of a promising line of research that improves almost day by day.

Limitations

SNA represents a powerful analytic approach, but analyses have to go beyond mere descriptions of the social structure. That is, analyzing network formation (e.g., friendship patterns) becomes much more informative once researchers integrate external information, especially attributes that describe the network members (e.g., their ethnic background), in a conceptually reasonable and statistically sound way. In fact, this point is not necessarily a limitation, but rather an important aspect that needs to be considered when utilizing SNA. Fortunately, as shown throughout this paper, SNA offers many ways to consider external information and its successful analytic consideration should be a major challenge.

A second limitation regards the sampling problem. In contrast to conventional sampling procedures, individuals in social networks are not sampled independently, but result from and are exposed to the interdependencies within a certain network boundary. Strictly speaking, each social network, independently of its size, represents only one unit of analysis. Therefore, whenever possible, researchers should aim to study many different social networks simultaneously in order to generalize the observed effects of the network members within a specific boundary.

Moreover, at least in its cross-sectional form, SNA is based on algorithms and mathematical operations, which do not allow researchers to derive essential information for statistical inference (e.g., standard errors or confidence intervals) from the network data alone. That is, cross-sectional social network parameters are, in their basic form, like the outcome variable in experiments, of descriptive nature and need to be combined with subsequent inferential statistics in order to test scientific hypotheses. Given the multi-modal structure of networks (individuals nested in groups nested in networks), an ideal form of integrating cross-sectional social network data involves the use of multilevel analysis (cf., Wölfer, Cortina, & Baumert, 2012).

While statistical inference is possible when studying longitudinal network dynamics, SIENA is also not free of limitations, which arise from its underlying assumptions. The Markov assumption that excludes certain types of information as explanatory elements for the network formation is critical. However, it is possible to overcome this limitation by including covariate effects, which contain relevant information that is not derivable from its previous state (e.g., the time since when there was a specific connection between two network members). Moreover, the assumption that network members control their network ties and are consequently sufficiently informed about the network is challenged by research that suggests structural knowledge deficits of network members (cf., Janicik & Larrick, 2005). That is, individuals gather information about the relationships among others around them, which unavoidably becomes less complete with increasing size and complexity of their social network. Although Snijders and colleagues (2010) correctly relativize this limitation by highlighting that this assumption requires network members to be primarily informed about their 2-step ego network, it still needs to be considered when researchers plan to study or interpret network(-behavior) dynamics.

Conclusion

SNA does not, of course, provide the answer to every empirical problem, but it does offer a powerful family of statistical parameters and procedures that can enrich many fields of research, in particular the science of groups. An optimistic view into the future includes the scenario that group researchers will not only utilize, but also tailor, technical aspects of SNA to their very specific research questions. In any case, we look forward to future studies in this field that shed light on open research questions or deepen our understanding of group phenomena from this additional analytic perspective.

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Footnotes

[1]In line with the scope of this journal, our conceptualization of network members will focus on individuals.

[2]Original quote: „Sage mir, mit wem Du umgehst, so will ich Dir sagen, wer Du bist, […].“

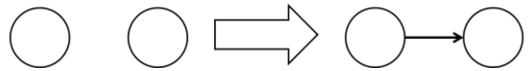
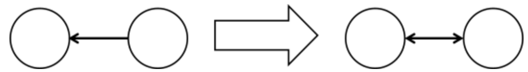
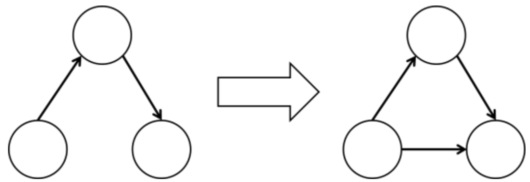
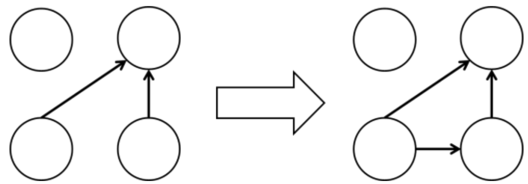
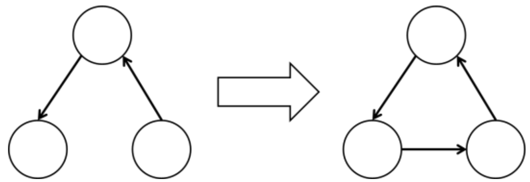
[3]Technically speaking, researchers do not need SNA to generate this parameter, but can simply count the number of connections by utilizing other statistical programs. However, many network statistics build on the degree, for which it is important to be familiar with this concept.

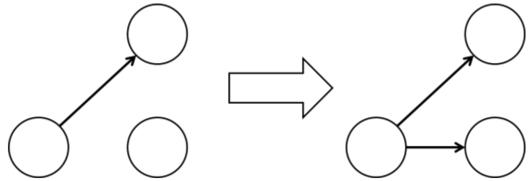
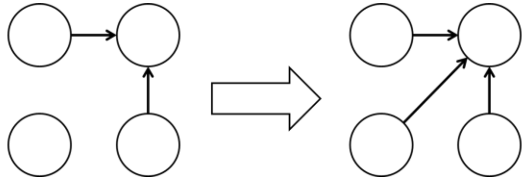
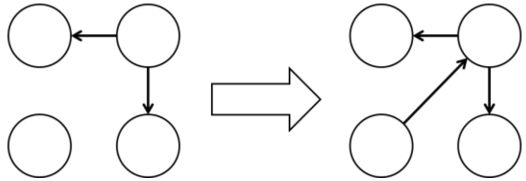
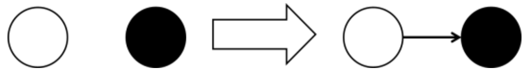
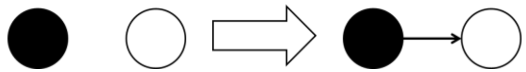
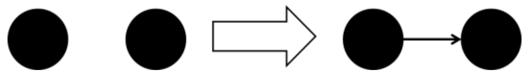
[4]The evaluation function is the main element for modeling network change and the focus of this section on longitudinal applications. However, if researchers are further interested in unraveling the tendency to create and maintain ties, the creation or endowment functions can also be modeled. While the creation function examines the preference for establishing new ties, the endowment function examines the aversion for breakoff ties or the preference for maintaining ties, respectively.

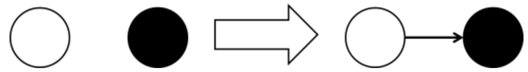
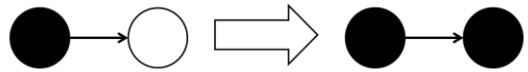
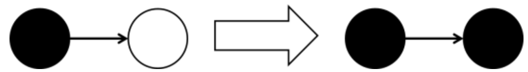
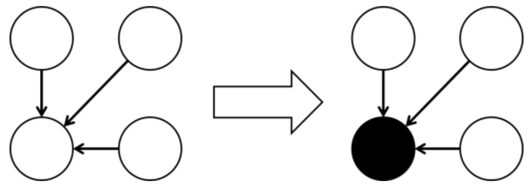
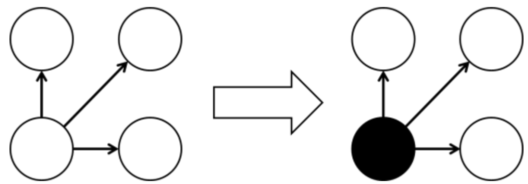
[5]For an exhaustive list of available effects see the respective SIENA manuals (cf., Ripley et al., 2013; Snijders et al., 2007).

Tables

Table 1: Selection of SIENA effects for modeling network dynamics and behavioral dynamics

Effect	Description	Illustration
Network Dynamics		
Outdegree (Density)	Preference for ties to a random network member (measure of the basic intercept)	
Reciprocity	Preference for ties that respond to an existing unidirectional connection (measure of mutuality)	
Transitive triplets	Preference for ties to network members that are the friends of my friends (measure of network closure)	
Balance	Preference for ties to network members with a similar ego network of existent and non-existent ties (measure of structural equilibrium)	
Three-cycles	Preference for ties that form unidirectional cycles (measure of non-hierarchy or generalized exchange)	

Betweenness	Preference for ties to network members, which are unconnected to each other (measure of a members linking role)	
In-degree popularity	Preference for ties to network members with many incoming ties (measure of status attraction)	
Out-degree popularity	Preference for ties to network members with many outgoing ties (measure of activity attraction)	
Covariate alter	Preference for ties to network members high on the respective covariate (measure of covariate popularity)	
Covariate ego	Preference for ties from network members high on the respective covariate (measure of covariate activity)	
Covariate similarity	Preference for ties to network members with similar values on the respective covariate (measure of homophily)	

Behavior dynamics		
Linear / quadratic shape	Preference to high values / extremes on the behavioral dependent variable (measures of distributional feature)	
Average similarity	Preference for behavioral similarity to connected network members (measure of assimilation)	
Average alter	Preference for high values on the behavioral dependent variable, if connected network members have correspondingly high values (measure of contagion)	
In-degree	Preference of network members with many incoming ties for high values on behavioral dependent variable (measure of status effect)	
Out-degree	Preference of network members with many outgoing ties for high values on behavioral dependent variable (measure of activity effect)	

Note: Black nodes indicate high scores on the covariate or behavioral dependent variable, respectively.

Figure Captions

Figure 1. Left: Complete social network; Right: Ego network of network member #22; nodes represent individuals whose size is proportional to their indegree and whose color denotes by their peer-group membership (white nodes are isolates with no peer group); lines represent relationships that are connected by double-headed arrows in case of mutual relationships

Figures

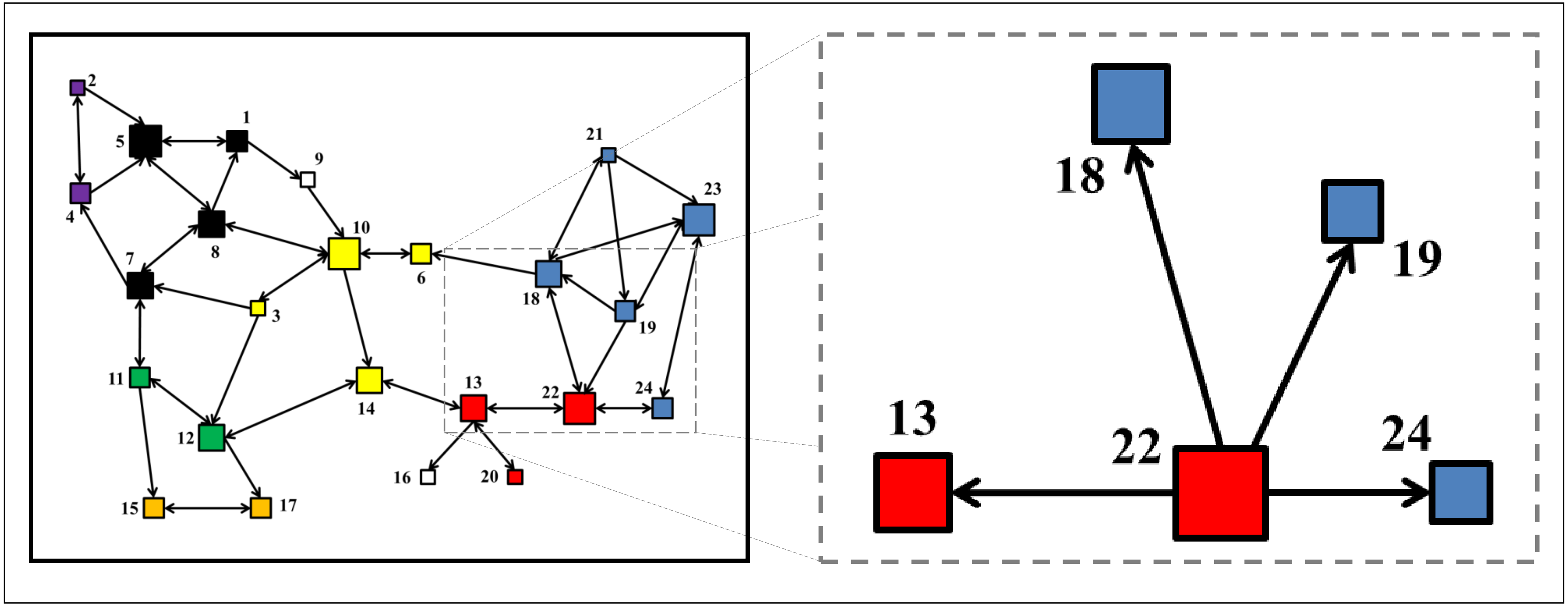


Figure 1