The Micro–Macro Link in Social Networks

Christoph Stadtfeld

Abstract

Important questions in the social sciences are concerned with the link between micro-level behavior and aggregate macro-level outcomes. This essay proposes that studies of the micro–macro link in social systems can utilize conceptual representations and analytical strategies from the field of social networks. In particular, statistical network models and research strategies from agent-based network modeling can be combined to investigate dynamics and the emergence of structure. An empirical case study illustrates how stochastic actor-oriented models can be applied as empirically calibrated agent-based simulations. The fruitfulness of this approach is demonstrated by a Schelling-inspired case study on the emergence of segregation in social networks. It is shown that even individuals without homophilous preferences may find themselves in segregated structures due to the complex interaction of different network mechanisms. The example thereby illustrates how social networks can serve as a conceptual and analytical framework to study the micro–macro link in dynamic, interdependent, and multi-mechanistic social systems.

INTRODUCTION

The observation that societies are more than the sum of their parts, and that complex phenomena can emerge from the actions of many interdependent social actors is a central motif of Sociology, ranging from Émile Durkheim's work (Sawyer, 2002) to recent developments in the field of analytical sociology (Hedström & Bearman, 2009). Many aspects of complex social systems can be well represented by social networks in which the dynamically changing relations between social units give rise to processes and structural outcomes that cannot merely be described by an aggregation of the units' desires, beliefs, and actions. Complex dependence between individual and relational observations as found in social networks (Lusher, Johan, & Garry, 2013; Robins, 2015) can, in fact, constrain the set of action

Emerging Trends in the Social and Behavioral Sciences.
Robert A. Scott and Marlis Buchmann (General Editors) with Stephen Kosslyn (Consulting Editor).
 ISBN 978-1-118-90077-2.

opportunities of social actors, and social networks can affect their desires and beliefs, for example, through processes of social influence or knowledge diffusion (Friedkin, 1998). Social networks have been used to represent societally relevant macro-level outcomes such as sub-groups, social distances, network segregation along attributes, or hierarchies (Robins, 2015). At the same time, the behavior of individual actors in a network can be well described with sociological, economic, and social-psychological micro-level theories (Kadushin, 2012; Robins, 2015). I propose that the link between those two levels, the micro-level of individual desires, beliefs, and actions and the macro-level of complex network phenomena, can be explored by applying newly developed statistical and computational techniques from the field of social network analysis.

Section titled "A Micro–Macro Framework for Social Networks" explains a conceptual and analytical framework for the study of micro–macro links in social networks. It starts with Coleman's micro–macro model and links it to the dynamic, interdependent, and multi-mechanistic nature of social networks. The discussed analytical strategy builds upon the seminal work of Snijders and Steglich (2015) who propose the study of micro–macro links in social networks through empirically calibrated simulation models. Section titled "Schelling's Model of Segregation as A Multi-Mechanistic Network Model – An Illustration" exemplarily shows how the full Coleman cycle can be explored with a combination of novel statistical and computational network analysis techniques. I will illustrate how individuals without preferences for homophily may find themselves embedded in homogeneous clusters of similar nodes. This case study is related to Schelling's model on neighborhood segregation (Schelling, 1978), but uses the formulation of a multi-mechanistic network process in which the dynamic relation between three interdependent mechanisms—homophily, reciprocity, and transitivity—explains the emergent macro-level outcome of network segregation. Section titled "Network Representations and Outlook" broadens the scope of the paper by discussing how advanced network representations could be utilized to address more complex micro–macro problems and concludes with a discussion of promising future research directions.

A MICRO–MACRO FRAMEWORK FOR SOCIAL NETWORKS

Social Network Dynamics in Coleman's Model

Coleman's (1990) model can serve as a starting point in an attempt to develop a conceptual framework for the study of the micro–macro link in social networks (Figure 1). The analytical goal is to explain how social

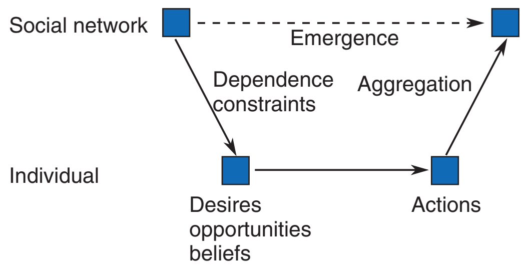

Figure 1 A social network perspective on Coleman's micro–macro model.

networks change through time and how macro-level phenomena emerge (the dashed arrow). This is achieved by investigating the underlying individual micro-level dynamics (the three solid arrows). First, by understanding how macro-level structures affect individuals' desires, beliefs, and opportunities (Hedström, 2005) and, in particular, how dependence and opportunity constraints can limit and structure the set of possible behavioral actions. Second, by understanding how individuals' actions are based on their desires, beliefs, and opportunities, for example, when they decide to create or modify interpersonal relations, or when their behavior is related to their current network position. Third, by understanding how the multi-mechanistic and interdependent actions of many individuals aggregate and thereby shape social networks on the macro level.

While Coleman's framework is conceptually appealing, it is hard to study on the whole. Empirical network studies, behavioral research studies in small settings, and studies of theoretically motivated models are exemplary approaches that have been utilized to examine parts of it. In observational network studies, it is possible to examine how individuals' actions—like the creation and dissolution of network ties (the lower-right box)—are associated with their structural network position (the upper-left box). The desires, opportunities, and beliefs of individuals (the lower-left box) are important in constructing meaningful theoretical frameworks but they often remain unobserved. Detailed behavioral studies, for example, situated in experimental lab settings, can aim at understanding the causal link between individuals' desires, opportunities, and constraints and their relational and individual actions (the lower solid arrow). Owing to the typically limited scale of experimental studies it is, however, hard to represent network dependence and network constraints. Theoretical studies can, for example, by using mathematical formulations or simulation frameworks, aim at establishing the link between the actions of many interdependent individuals and aggregate macro-level observations. However, due to the complexity of network processes is difficult to calibrate the theoretical empirically.

The Dynamic, Interdependent, and Multi-Mechanistic Nature of Social Networks

Social networks are *dynamic* systems that are constructed and changed by the social actions of a potentially large number of actors. They formally consist of two types of entities. First, one or more sets of nodes, representing social actors (e.g., individuals or organizations) or nonsocial entities (e.g., social foci, social settings, affiliations, or the internal state of social actors). Second, one or more sets of relations that connect pairs of nodes (e.g., kinship between individuals, collaboration between organizations, or individuals' affiliation with a specific social setting). Social networks are flexible in how they represent social actors and can express their behavior, desires, or beliefs either as node attributes or as network affiliations.

Social networks are a way to describe *dependence* between individuals' relation and actions explicitly and to investigate how dependence between social actors can enable emergent phenomena. The study of dependence is indeed at the core of social network analysis (Robins, 2015). Within a dyad (a pair of nodes) dependence may arise because of mutual exchange processes (Emerson, 1976). Dependence between more than two nodes can originate from transitive processes in which two nodes are more likely to connect if they link to the same third node. Transitivity can be explained, for example, by cognitive balance mechanisms (Heider, 1958). Dependence that involves more than three nodes can, for example, be related to degree popularity mechanisms (Merton, 1968) or to in-group cohesion and intergroup conflict (Tajfel & Turner, 1979). Social network researchers have discussed the translations of a variety of theoretically motivated micro-level mechanisms into mathematical representations of network dependence (Lusher *et al.,* 2013; Robins, 2015; Snijders, 2017).

Importantly, none of these dependence mechanisms in social networks operates in isolation, but typically, multiple mechanisms operate simultaneously within one network and jointly affect the actions of social actors. This *multi-mechanistic nature* of social network processes is one possible explanation of complex emergent phenomena (as illustrated in section titled Schelling's Model of Segregation as A Multi-Mechanistic Network Model – An Illustration). State-of-the-art statistical network models have sophisticated ways of expressing dependence in multi-mechanistic systems (Robins, 2015). Some of these models have been developed to be fit to dynamic data explicitly (Snijders, 2017; Stadtfeld, Hollway, & Block, 2017), however, also network models that are applied to cross-sectional data typically assume that the static network observations emerge from dynamic network processes (Lusher *et al.*, 2013).

Integrating Two Approaches

Social networks research so far mostly takes one of two approaches to studying the link between the micro and the macro level. The first approach aims at inferring micro-level models from empirically observed (macro-level) network data. The most prominent methods in the field are exponential random graph models and stochastic actor-oriented models (SAOMs) (Lusher *et al.*, 2013; Snijders, 2017). Block, Stadtfeld, and Snijders (2016) discuss their similarities and differences. The second approach aims at understanding how theoretically grounded micro-level mechanism that describe actors' (or agents') behaviors, strategies, and actions lead to the emergent macro-level phenomena through agent-based simulation models (Bianchi & Squazzoni, 2015). A related research area is work by computational scientists and physicists who explain widely observed network level structures with straightforward micro-level models (e.g., small world patterns, Watts & Strogatz, 1998).

Statistical network models tend to be more complex than agent-based models in terms of the number of parameters and mechanisms that are considered simultaneously. At the same time, they often have more rigorous assumptions than agent-based models. For example, micro-level interpretations of exponential random graph models and SAOMs tend to think of agents as myopic and assume that individuals with equivalent attributes and network position will follow the same behavioral patterns. Agent-based network models, in comparison, often aim at expressing strategic (forward-looking) behavior and actor heterogeneity. A promising approach to integrating the two research traditions is to develop computational network simulation models that are empirically calibrated (as discussed by Hedström & Åberg, 2005) while acknowledging the dynamic, interdependent, and multi-mechanistic nature of social networks. Such models could capitalize on solutions to problems discovered in the statistical network literature that relate to near-degeneracy of simulation models (Snijders, Pattison, Robins, & Handcock, 2006), and extend findings on the multi-mechanistic nature of social networks explored in a variety of empirical studies. At the same time, empirically calibrated models can be extended to express, for example, strategic considerations and actor heterogeneity. The proposed combination of statistical and computational models is in line with paradigms discussed in the field analytical sociology (Coleman, 1990; Hedström & Bearman, 2009). The application of such models could open new insights into the emergence of macro-level phenomena in complex social systems.

SCHELLING'S MODEL OF SEGREGATION AS A MULTI-MECHANISTIC NETWORK MODEL – AN ILLUSTRATION

I illustrate how to investigate the micro–macro link with a straightforward example that is inspired by Thomas Schelling's foundational model of residential segregation (Schelling, 1978). In one formulation of Schelling's model, agents (imagined as coins of two colors) are placed on the 64 squares of a checkerboard, but move their position if they are unsatisfied with the composition of their neighborhood. The neighborhood of an agent *i* is defined by the coins positioned on the (max. eight) squares that are adjacent to its current square. Coins are satisfied with their position if the ratio of neighbors of the other color is below a threshold θ. If nodes collectively act according to these rules, they will typically find themselves in neighborhoods in which the ratio of differently colored nodes is eventually much lower than θ—the segregation that emerges on the macro-level thus that cannot merely be explained with the individuals' preferences. I translate Schelling's model into a multi-mechanistic network model in which the size and the structure of each agents' neighborhood is modeled with endogenous network mechanisms. Other than in Schelling's original formulation I allow that some of the actors have no preference for homophily at all—their emerging neighborhoods will be of specific interest.

In a first analytical step, I fit a SAOM (Snijders, 2017) to data of friendship relations collected among school children. The resulting micro-level model is cross-sectional rather than longitudinal, thus describes the underlying actor-oriented processes under the assumption that the empirically observed network is drawn from the model's stationary distribution (Snijders & Steglich, 2015).

In a second analytical step, I use the micro-level model as an agent-based simulation model (Snijders & Steglich, 2015) to investigate the emergence of *network segregation*. In the following, I use the term homophily only for the micro-level preferences of individual actors, while network segregation refers to the (macro-level) ratio of network relations that connect nodes of the same attribute. By randomly varying the preferences of actor types within the agent-based simulation, I illustrate how individuals' position in a network depends on the preferences of others. In particular, I show that even actors who have no preference for homophily will find themselves positioned in networks where the majority of their network neighbors is of their type. This outcome will be observed because actors are assumed to have additional preferences—they prefer maintaining ties that are embedded intransitive and reciprocal structures. This illustrates the importance of considering the multi-mechanistic nature of social networks.

Inferring Micro-Mechanisms from Empirical Data

The empirical starting point is a single friendship network collected in the "Wired into Each Other" study by Károly Takács and colleagues (Pál, Stadtfeld, Grow, & Takács, 2016; Vörös & Snijders, 2017). It is shown in Figure 2.

The data are fit to a cross-sectional SAOM. These models conceive of network structure as drawn from a stationary distribution of an underlying network process in which individuals (the "actors") create and dissolve network ties according to a set of shared preferences. The model that I fit is specified with four parameters—a relatively small number compared to many empirical network studies. The first parameter is concerned with the number of times that individuals have to others. It indicates that individuals with many friendship ties will be more likely to drop one rather than creating an additional tie. This "outdegree" effect can be linked to the fact that network ties are often costly to maintain. It is important to include in SAOM specifications and is often understood as the model intercept (Snijders, 2017). The second parameter expresses that individuals will be more likely to create and maintain mutual network ties rather than one-sided relationships. The "reciprocity" mechanism is a fundamental mechanism in social networks (Emerson, 1976). The third parameter is concerned with

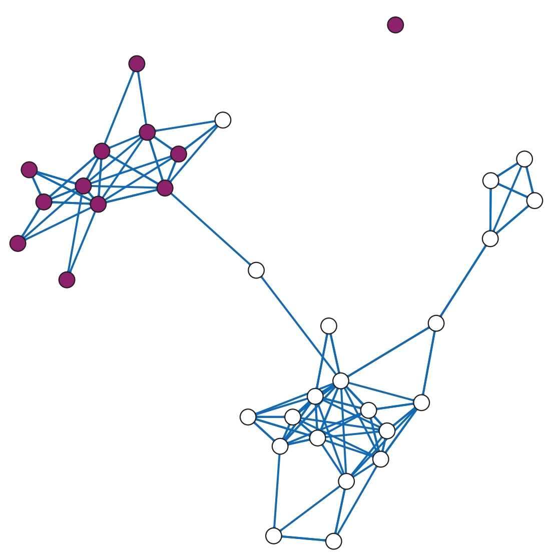

Figure 2 An empirically observed friendship network with a high proportion of in-group (same-gender) relations.

individuals' preference to be embedded intransitive structures, meaning that if individuals A–B are friends and B–C are friends then A and C will have a higher tendency to be friends as well. This "transitivity" mechanism in social networks is again considered important in many contexts and can be linked to some of the most prominent sociological and social-psychological theories within social networks research (Heider, 1958; Feld, 1981; Granovetter, 1973). Transitivity is operationalized in terms of "geometrically weighted edge-wise shared partners" (Snijders *et al.*, 2006), indicating that individuals have a preference to maintain ties in transitive structures, but the number of shared friends (the individuals B in the example above) has a sub-linear effect on the tendency of A and C to connect. The fourth parameter models the preference to form ties to individuals with the same attribute—gender in the empirical example. "Homophily" is considered an important social force in many social networks as well (McPherson, Smith-Lovin, & Cook, 2001). A "rate parameter" (Snijders, 2017) is not estimated in cross-sectional SAOMs as the model is a stationary distribution and the rate is infinite in theory (and set to a very high value in practice). Modern specifications of SAOMs typically include a number of additional effects that, for example, also consider additional attributes, degree-related effects, different triadic effects, or interactions between different mechanisms (Block, 2018; Snijders, 2017).

Estimation results are shown in Figure 3. The outdegree parameter is negative, indicating that the overall network density is low, while reciprocity, transitivity, and gender homophily have a positive effect on the creation and maintenance of friendship ties. The fit of the model is good in terms of the structures that are explicitly included—the micro model generates networks with the correct density, reciprocity, transitivity, and level of gender segregation. The fit in terms of other macro-level statistics, such as degree distributions, or specific types of triads will be unsatisfying, but can be corrected by considering additional network mechanisms. The straightforward model specification is, however, purposeful in this illustration, as it is comparable to Schelling's model of residential segregation. Both

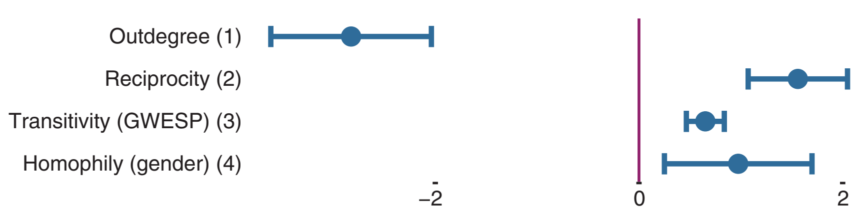

Figure 3 Results from the stochastic actor-oriented model with a straightforward four-parameter specification. Point estimates and 95% confidence intervals are shown.

models express preferences for similarity in neighborhoods and personal networks, respectively. The network models explicitly consider individuals' preferences to maintain a positive number of ties (i.e., having neighbors at all in Schelling's view), that are reciprocal and embedded in transitive structures. The three mechanisms together define and structure individuals' personal networks—their neighborhoods. These endogenous network mechanisms serve a similar purpose to the exogenous space constraints on Schelling's checkerboard that enforce the formation of neighborhoods in the first place.

Studying Macro-Structures from Micro-Models

In the next step, the empirically estimated model is utilized as an agent-based simulation model. However, I vary the percentage of nodes with homophily preferences—this extension deviates from the assumption of the SAOM that nodes with the same attributes and network positions will express the same behavior. To be able to generate different preference compositions with meaningful subsets, the model is applied to a larger network of 200 nodes (100 males, 100 females), rather than simulating networks as small as the empirical network in Figure 2 (33 nodes). However, in principle, the findings can be replicated with a network of the original size. The estimated parameters from Figure 3 remain unchanged. Only for the nodes *without* homophily preference, the homophily parameter is set to zero so that only outdegree, reciprocity, and transitivity matter for these individuals' relational actions.

Figure 4 shows prototypical networks simulated from the empirical model. The percentage of nodes with a preference for gender homophily is 10% (20

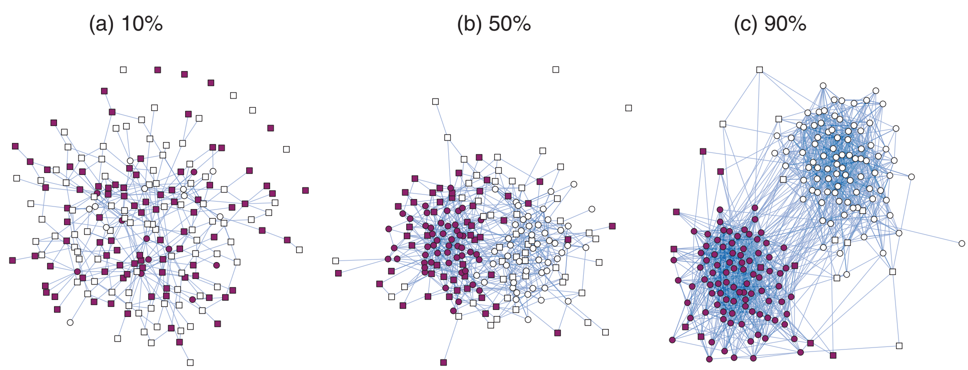

Figure 4 Networks simulated from the empirically calibrated micro-model on a set of 200 nodes. The percentage of nodes with preference for gender homophily is 10% (20 nodes), 50% (100 nodes), and 90% (180 nodes).

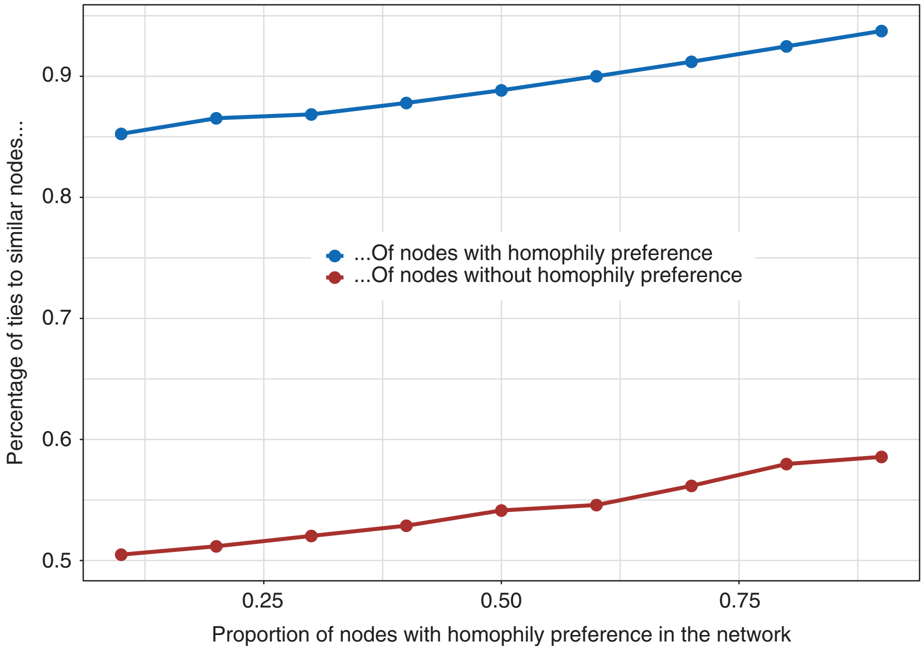

Figure 5 The more nodes with a homophily preference in the network (x-axis), the larger is the share of ties to nodes of the same type (y-axis). This holds both for the nodes with a homophily preference (blue line) and the nodes without homophily preference (red line). Values were estimated from 200 simulations each.

nodes), 50% (100 nodes), and 90% (180 nodes) in the three panels. Nodes with homophily preference are indicated as circles, those without as squares. It is evident that the more nodes with homophily preference are in the network, the higher is the level of network segregation. The last of the three networks is indeed highly segregated and it appears that also nodes without homophily preferences (the squares) are mostly linked to nodes of their own color.

I now investigate the level of homogeneity in the personal networks of homophilous and non-homophilous nodes. Results are shown in Figure 5. The more homophilous nodes are in the network, the more homogeneous will their personal networks be—this is the case both for homophilous (blue line) and non-homophilous nodes (red line). The reason for this phenomenon of unintended individual consequences lies in the multi-mechanistic social network process. All individuals strive for reciprocal and transitive relations. For a small minority of non-homophilous nodes, these needs will be easiest to satisfy when they "accept" reciprocal connections to others of the same color or embed themselves in dense clusters with homophilous nodes of the same color. The level of homogeneity in individuals' personal networks thus does not only depend on their own preferences, but also on the preference of others in the network. This effect also operates in the reverse direction: The more non-homophilous nodes are in the networks, the more diverse will the networks of homophilous nodes be.

The study illustrates how the level of network segregation is partly explained by the amplifying effect of transitivity on homophily (Stadtfeld & Pentland, 2015). The complex interaction of these fundamental micro-level network processes has been investigated in empirical network studies (Block, 2018; Stadtfeld & Pentland, 2015; Goodreau, Kitts, & Morris, 2009), but to my knowledge not in agent-based simulation studies.

NETWORK REPRESENTATIONS AND OUTLOOK

I believe that the combination of statistical and computational network analysis techniques can open new insights into the dynamic, interdependent, and multi-mechanistic nature of social networks. Many societal phenomena can be expressed with social networks, and recently proposed network representations have the potential to importantly extend the scope of micro–macro network studies in the social sciences.

Recent publications have emphasized how multivariate, two-mode, and weighted network representations can be linked to detailed network mechanisms. Multivariate and weighted networks can be used to express the co-evolution between positive and negative relationships (Labianca & Brass, 2006; Pál *et al.*, 2016), different strength of network ties (Elmer, Boda, & Stadtfeld, 2017), or the associations between networks of different types (Boda, 2018; Lazega & Pattison, 1999). Two-mode network can describe the affiliations of social actors to nonsocial entities. Such representations are very powerful, as they allow to explicitly model actors' preferences, beliefs, activities, social foci, internal structures, or affiliation with social settings (Snijders, Lomi, & Torlo, 2013; Stadtfeld, Mascia, Pallotti, & Lomi, 2016). Statistical network models have further been developed to express the coevolution of individual outcomes and network change (Niezink & Snijders, 2017; Steglich, Snijders, & Michael, 2010). Thereby, they can connect to agent-based simulation studies that explore processes of polarization or social influence (Mäs, Flache, Takács, & Jehn, 2013).

In this essay, I discussed how the conceptual micro–macro model of Coleman can be utilized in the study of social networks that are characterized by their dynamic, interdependent, and multi-mechanistic nature. I proposed to integrate recent advances in statistical network models and agent-based simulations. The application of this approach was illustrated in a straightforward case study on the emergence of segregation in social networks. Other macro-level outcomes can be explored similarly. For example, how individual behavior relates to the emergence of sub-groups, hierarchical status systems, social distances, or to the polarization of political opinions. This essay provides a conceptual framework to approach such questions on the micro–macro links in social networks.

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