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Editorial

Introduction to multilevel social networks☆

Social network research focuses on the study of social systems by conceptualizing their internal structure in terms of sets of complex dependencies among social agents in the form of dyadic social ties. Typically, models for social networks incorporate additional features such as actor attributes. Models for social networks may also be extended in various ways by considering, for example, multiplex or bipartite representations.

However, incorrect inferences can be drawn from social network analysis if the system is conceptualized in an overly simplistic way. This can happen if crucial elements of social structure are ignored when the data are collected, or are mis-specified in the model used for the analysis. As social network researchers, we know this well, because we avoid individualistic analysis of attributes when social structure is relevant. In one of the foundational articles of contemporary social network analysis, Harrison White and co-authors warned against relying on social classification as the sole basis for understanding social structure: "...largely categorical descriptions of social structure have no solid theoretical grounding; ... network concepts may provide the only way to construct a theory of social structure" (White et al., 1976, p.732). Network researchers (but not all social scientists) have learnt that lesson well.

Yet, having imbibed White's warning, we all-too-often content ourselves with a relatively simple network representation, without thinking through whether our conceptualization is sufficient for the purpose of our research. We face important theoretical choices here, and of course it is not feasible to control for every possible factor. Social systems may have important dynamic, temporal and geospatial elements, and if we regard these as central to the processes we are studying, then they need to be incorporated into our conceptualization of the social system and hence into the type of data we collect. Recent special issues of *Social Networks* have concentrated on network research involving dynamic and spatial factors.

Social systems can also contain hierarchy. In his classic paper on the "architecture of complexity," Herbert Simon (1962) offered a compelling analysis of the evolutionary mechanisms responsible of producing the hierarchical structure so frequently observed in social and natural systems. The hierarchical structure of actual social systems typically takes on a multilevel form – with multiple hierarchical layers each establishing the decision premises for the immediately lower layer (March and Simon, 1958). Such multilevel structure is intrinsic to social systems, not simply emergent, and so may need explicit representation. This is most obvious in formal organizations that are typically designed as multilevel systems with individuals nested within teams, functions, or divisions (Lomi and Larsen, 2001; Zappa and Lomi, 2015). For this reason, modeling teams within organizations is not the same as modeling social groups in less structured social settings (Freeman, 1992; Marsden and Campbell, 1984). Despite calls for network analysis to take into account the multilevel nature of organizations (e.g., Brass et al., 2004), most organizational network analysis to date has concentrated on a single level (for counterexamples, see Moliterno and Mohony (2011)). Perhaps it is not by accident that most papers included in this special issue are situated in formal organizational settings.

As Snijders recently observed (2015, in press): "Social network analysis is fundamentally a multilevel affair with its focus on relations rather than attributes, thereby already combining the actor level and the dyadic level.". *Multilevel networks*, however, have a precise definition. They are conceptualized as distinct types of nodes defined at different multiple levels (e.g., individuals and groups) with ties possible between all nodes, both within and across levels (e.g. distinct types of dyadic ties at the individual- and the group-level, as well as individual-group affiliations). This type of data structure was studied by Wasserman and Iacobucci a quarter of a century ago (Iacobucci and Wasserman, 1990; Wasserman and Iacobucci, 1991), but that field was then left fallow. In her theory of group stability, Carley (1991) was among the first to reintroduce multilevel network concepts explicitly in the analysis of group processes within organizations.

Despite these early signals of interest in multilevel networks, it was not until the last decade that Lazega and colleagues developed these ideas in the context of their empirical interest in collaborative relations among cancer researchers affiliated to different research laboratories (Lazega et al., 2008). They demonstrated that the social system of collaboration in this particular organizational field could not be properly understood without accounting for two levels of agency: that of the individual researchers, and that of the research laboratories in which they are contained. Inspired by this research, Wang et al. (2013) generalized the Lazega et al. data structure and proposed an exponential random graph model specification to study the social structure. Collectively, the papers contained in this special issue demonstrate the reach and influence that these

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multilevel ideas have in a variety of fields of substantive interest including, for example, interorganizational relations, international relations, and public administration.

It is important not to confuse a multilevel network conceptualization with standard multilevel analytic approaches. In the standard (two-level) statistical formulation of multilevel models, an individual is nested within groups, with individual outcomes studied by apportioning variance across both levels, as the individual and group level random effects are assumed to be uncorrelated, and also independent of one another within levels. This gives rise to familiar hierarchical linear modeling methods (e.g., Snijders and Bosker, 2012). In a multilevel network, on the other hand, there may be complex affiliations in the form of a bipartite network across levels; interdependence – not independence – is explicitly assumed within levels. Multilevel Exponential Random Graph Models (MERGMs) can, for example, be applied to investigate the tie structure of a multilevel network, as opposed to individual (node-based) outcomes. It is also important not to confuse the joint multilevel model-based analysis of several distinct networks, (where the term "Multilevel" is often used as a synonym for "Hierarchical Linear Modeling"), with models for a multilevel network (Snijders, 2015, in press; Zappa and Lomi, 2015; Wang et al., 2012). One example of the multilevel analysis of networks is the analysis of ego-net data with a multilevel model, as demonstrated by Snijders et al., 1995. A second example of a multilevel analysis of networks is that of Lubbers and Snijders (2007) in their re-analysis of 102 student networks in school classes. They began by fitting a separate ERGM to the friendship network in each school class. They then carried out a meta-analysis of the ERGM parameter estimates for each class by combining them in a multilevel model framework. The resulting parameter estimates in the fixed part of the multilevel model allow an overall assessment of friendship network structure in school classes in their data, and via the random effects it is also possible to make inferences about friendship tie structure in specific classes in their sample. Multilevel network analysis, on the other hand, is the analysis of a specific multilevel network, directed to the study of a multilevel network data structure, with ties between nodes at more than one level, and often also ties between levels. Examples are given above. Additional examples and applications of multilevel network analyses may be found in a forthcoming volume of collected studies (Lazega and Snijders, 2016, in press).

It is similarly important to avoid confusing multilevel and multiplex – or simply multiple – networks (Lazega and Pattison, 1999; Lomi and Pattison, 2006). The ambiguity inherent in this distinction may be traced back to Boorman and White (1976) who clearly recognized the importance of examining "multiple" networks simultaneously, while – at the same time – reconstructing roles as a "distinct level" (p. 1385) of analysis obtained via aggregation and composition of multiple networks (Boorman and White, 1976, p. 1385). This representation suggests a *multilevel* relation between *multiple networks* and roles. Wasserman and Iacobucci (1991), and – more recently – Snijders et al. (2013), and (2016, this issue) provide examples of how multiplexity may arise from a combination of 1-Mode and 2-Mode networks. Hence, an additional condition is required to distinguish between multilevel and multiplex networks.[1] More specifically, a network is multilevel not only if it contains different kinds of relations, but also if the node set contains entities defined at different levels: for example, actors and movies, scientists and research laboratories, organizational members and organizational units or project teams, business firms and industries, organizations and societal sectors, or nations and international treaties. This definition of multilevel networks and its various illustrations admits the possibility of non-exclusive – or multiple membership of lower level nodes to higher level nodes. Moreover, the extent to which ties between higher level nodes in a multilevel network are only an aggregation of ties between the lower level nodes that are contained in the higher level nodes, involves a number of unresolved empirical and theoretical issues that multilevel network analysis may help to address.

In the relatively short space of time since its inception, the multilevel network framework has proven to be a flexible approach that may be applied usefully to a variety of different social systems. One of the most interesting extensions is to an association of a social and a non-social structure proposed by Bodin and Tengö (2012) who conceptualize a social-ecological system as a multilevel network. What we have observed is that, rather than multilevel network studies being relatively rare, many researchers already have collected data of this type, but have not previously conceptualized the network as multilevel, or have not previously had the analytical tools available for a full examination of the multilevel network structure.

1. Papers in the special issue

In the eight papers selected for this special edition, a variety of methods and models are applied to a range of cross-sectional and longitudinal multilevel datasets. Methodological approaches represented in the special issue include Multilevel Exponential Random Graph Models (MERGMs), Stochastic Actor Oriented Models (SAOMs) and Multiple Membership, Multiple Classification models (MMMC models). MERGMs focus on dependence structures within and across structural levels. SAOMs emphasize the co-evolutionary link between single-level and multilevel networks. MMMC models focus on the contribution of various kinds of network ties on the variability of outcomes that are lower level node attributes. Each paper pursues distinct analytical objectives in the context of original data that the authors have collected to address a variety of domain-specific empirical problems. We think that, collectively, these papers demonstrate the flexibility, generality and usefulness of the conceptualization and analysis of multilevel networks.

Using original data on collaborative relations among health care organizations operating within a regional community, Tranmer et al. (2016) extend the Multiple Membership Multiple Classification (MMMC) model, recently proposed by Tranmer et al. (2014), to the analysis of the sources of variation in the performance of organizational sub-units embedded in a cross-sectional multilevel network.

Hollway and Koskinen (2016) adopt multilevel ERGMs to show how various micro-mechanisms of multilevel clustering shape the global network structure of fishery systems emerging from the accumulation of bilateral and multilateral relations among nations. The analysis reveals that states' bilateral ties tend to be embedded in their shared membership in multilateral fisheries agreements.

Zappa and Robins (2016) specify and estimate a MERGM to study organizational learning, and more specifically to examine how interpersonal knowledge transfer is sustained by the organizational structure of work-flow ties among organizational sub-units. The results suggest that boundary-spanning in knowledge transfer among individuals occurs most commonly in association with inter-unit work-flow ties.

Brennecke and Rank (2016) pursue similar analytical objectives in the context of data they have collected on advice seeking and

[1] An additional layer of terminology, as it were, is added by the more recent literature attempting to unify disparate terminologies under the general rubric of *multilayered networks* (see, e.g., Kivelä et al., 2014, and in particular see Table 1, page 4). In multilayer network terms, for example, multiplex networks are "multilayer networks with diagonal coupling" (See Kivelä et al., 2014, section 2.5. and Appendix).

giving relations among 434 knowledge workers and 218 project teams belonging to seven divisions of a high-tech firm in Germany. They identify specific mechanisms giving rise to cross-level interdependence within organizations.

Brailly et al. (2016) apply a MERGM to a network study of a trade fair for television programs in Eastern Europe. They explain that when investigating the performance of a market one needs to recognize the dual positioning of individuals and organizations in that context. They explain, via this empirical example, that while each level (individual, organizational) has its own specific processes, they are also partly nested.

Slaughter and Koehly (2016) explain how a hierarchical Bayesian approach can be used to develop and extend existing Exponential Random Graph Models (ERGMs), and their applications, to multilevel network data. They apply their approaches to real data – a sample of 14 networks where each network reflects the pattern of friendship relations among members of a particular person's social support network, as well as to simulated data. They conclude that hypotheses regarding the role of network-level covariates on structural patterning within networks can be easily specified and tested within the proposed models.

Using the Lazega et al. (2008) data on network relations among French cancer elite researchers affiliated to various research laboratories, Wang et al. (2016) propose Social Selection Models for multilevel networks that integrate existing Exponential Random Graph Models (ERGMs) for multilevel networks (Wang et al., 2013), and earlier models for social selection (Robins et al., 2001).

Finally, Stadtfeld et al. (2016) extend existing Stochastic Actor Oriented Models (SAOMs) for the co-evolution of one-mode and two-mode networks (Snijders et al., 2013; Lomi and Stadtfeld, 2014) to examine how social influence and social selection mechanisms jointly shape the dynamics of (internal) organizational and (external) network change.

We believe that, collectively, the papers included in the special issue on models for multilevel networks provide new scope and direction for social network research. We hope that this special issue will encourage other researchers to consider whether and how a multilevel conceptualization might be applicable to their network data. We hope to see a further growth in multilevel network analysis through the development of innovative theory, interesting data collection strategies, and compelling empirical applications.

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