Short Take

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Statistical Methods and Software for the Multilevel Social Relations Model

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Abstract

The multilevel social relations model (SRM) is a commonly used statistical method for the analysis of social networks. In this article and accompanying supplemental materials, we demonstrate the estimation and interpretation of the SRM using Stat-JR software. Multiple software templates permit the analysis of different response types, including binary, counts, and continuous responses.

In recent decades, social scientists have devoted considerable attention to research on social networks (Borgatti et al. 2009; Burt et al. 2013). Among the various applications of social network analysis, there is sustained

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interest in the predictors of ties (or the weights of ties) between nodes in a social network. Compared to conventional regression models, however, the structural components of relational data pose challenges for the analysis of dyadic data. A variety of statistical modeling approaches have been developed to account for these structural dependencies (Snijders 2011). For many research questions and analyses, the multilevel modeling parameterization of the social relations model (SRM) may be a promising alternative (Snijders and Kenny 1999). However, applications of the multilevel SRM have been limited, partly because of the lack of available software to implement the models. We address that challenge by presenting software templates that permit a point-and-click interface for specifying SRM models in Stat-JR software (Charlton et al. 2016). These templates are available as Supplemental Files on the Open Science Framework, along with a tutorial that describes how to implement and interpret the models (https://osf.io/jkz5t). The tutorial includes case studies and analyses of several example data sets, which parallel the kinds of network data that are commonly encountered in social science research (Fowler 2006; Hoff 2018; Kennedy et al. 2013; Koster and Aven 2018; Koster and Leckie 2014; Krackhardt 1999).

Originally developed by social psychologists (Kenny and La Voie 1984), the SRM partitions the variance of directed network ties into actor-level effects, partner-level effects, and dyadic effects. For example, there may be something about actor *i* that results in relatively greater or lesser ties to others in the network, and this variation is captured by an actor-level effect. Similarly, partner *j* may, in general, be the recipient of greater or lesser ties compared to others in the network, and this variation is reflected in the partner-level effect. Meanwhile, after accounting for the propensities of the respective actors and partners, there may be tendencies within dyads to form stronger (or weaker) ties, and this variation is evident in the dyadic effects. Covariances among these effects are also estimated, allowing researchers to assess both “generalized reciprocity” and “dyadic reciprocity.” The former correlation reflects the extent to which individuals covary in their propensities for directing and receiving ties. For instance, perhaps individuals who provide assistance to many others in the network also receive greater amounts of assistance, yielding a positive generalized reciprocity correlation.[1] Dyadic reciprocity, by contrast, assesses the extent to which ties from *i* to *j* are reciprocated by ties from *j* to *i* over and above that predicted by their respective actor and partner effects. Therefore, the reciprocity correlations provide statistically principled ways of investigating research questions that interest social and ecological scientists (Koster et al. 2015).

Although the SRM was initially parameterized as an analysis of variance (ANOVA) model, the multilevel parameterization has several advantages. Notably, the multilevel SRM can rather seamlessly incorporate covariates as predictors of ties. In an ANOVA context, by contrast, it is relatively cumbersome to model the effects of covariates on the dyadic response variable (Lüdtke et al. 2013). In addition, there is often substantive interest in modeling not only the dyads from a single network but rather a collection of networks (Snijders 2016; Sweet et al. 2013). For example, researchers may have data on the social networks of members of many different teams or groups (Joshi 2014; Koster and Aven 2018). In the context of an SRM, it is relatively straightforward to include an additional random effect that reflects variation in the network density among these teams or groups. It is not problematic if these groups vary in size, and the multilevel parameterization also permits the incorporation of network-level covariates (i.e., attributes of the groups) that potentially account for observed heterogeneity in network density.

Whereas there are multiple software alternatives for the ANOVA parameterization (Back and Kenny 2010), there are comparatively few tools available for estimating a multilevel SRM. One option is the *amen* package in R (Hoff 2018), which permits estimation of models for dyadic ties that are measured as binary, counts, ordinal, or continuous responses. A key limitation of the *amen* package, however, is that SRM models can currently be estimated for only a single network or group. That is, the package cannot accommodate data sets composed of multiple group networks. Other alternatives include flexible modeling packages such as BUGS (Koster and Leckie 2014; Lüdtke et al. 2013) and Stan (Jorgensen et al. 2018; Koster 2018). A downside of these packages, however, is that they require researchers to be familiar with their respective coding languages. To our knowledge, the Stat-JR templates that accompany this article are the only precompiled options for estimating a multilevel SRM with group-level random effects.[2] Also, when working with these templates, it is potentially helpful that they use the same point-and-click interface, allowing researchers to choose the data structure and link function that matches their data.

As a trade-off for the convenience of the Stat-JR templates, it is important to note that they are currently useful primarily for cross-sectional data sets with a single response variable. Longitudinal and multiplex network data are increasingly common (Hoff 2018), but the templates would need to be modified to accommodate such data within an SRM framework. In addition, the templates are appropriate only for directed network ties, not symmetric data. With symmetric data, the assignment of nodes to roles *i* and j is arbitrary, and the random effects for these nodes should have a common variance, not the respective actor-level and partner-level variances that are estimated by the SRM.[3] Another important consideration of the SRM is that dyads are assumed to be conditionally independent. In other words, the ties between nodes i and j are assumed to be unaffected by their relationships to other nodes or communities of nodes in the network. This assumption may frequently be untenable, and numerous statistical approaches have been advanced that model the triadic dependencies and block structures within social networks (Minhas et al. 2019; Snijders 2011).[4] In many cases, these models include and expand on elements of the SRM, suggesting that the models described here provide a valuable foundation for further research and advances in modeling social networks.

In conclusion, the structural dependencies that characterize network data are widely recognized. In practice, however, there are divergent responses to these dependencies. Some researchers seem to regard node-level and dyadic effects as background considerations that need to be modeled primarily to provide appropriate estimates of a small number of predictor variables. Our perspective, by contrast, is that there is much to be gained by elucidating the structural dependencies and by using the variances and correlations of the SRM for novel inferences about relational data. The statistical methods and software to model these parameters provide valuable tools that, in turn, can spur new theorizing about the sources of variation in social networks.

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Supplemental Material

Supplemental files are available at https://osf.io/jkz5t/

Notes

1. Note that the social relations model (SRM) assumes that individuals (or nodes more generally) appear as both the source and recipient of network ties, and the model is not appropriate when directed dyadic ties are intrinsically

unidirectional, such as evaluations of performance by multiple judges or auditors (Aven et al. Forthcoming; Leckie and Baird 2011).

2. For binary ties, the *p2* model is conceptually similar to the SRM (Zijlstra 2017). There is an R package, *dyads*, that allows estimation of the *p2* model, but this package evidently permits only analyses of single networks, not data sets composed of dyadic data from multiple groups.
3. Note that the SRM is appropriate only for dyadic outcome variables, not analyses in which network connections are used to calculate node-level measures, such as centrality or constraint (Burt 1992; Freeman 1978). This applies whether the node-level network measures are the outcome variable (e.g., Aven 2015) or a predictor variable (Ahuja 2000; Aven and Hillmann 2018; Shipilov and Li 2008).
4. Among anthropologists and other social scientists, a common alternative for analyzing cross-sectional social networks has been exponential random graph modeling or ERGM (An 2016; Nolin 2010). Statisticians, however, have raised concerns about the appropriateness of ERGMs in some applied contexts (Schweinberger 2011; Shalizi and Rinaldo 2013; see Minhas et al. [2019] for additional discussion).

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