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Impact of methods for reducing respondent burden on personal network structural measures

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Abstract

We examine methods for reducing respondent burden in evaluating alter–alter ties on a set of network structural measures. The data consist of two sets, each containing 45 alters from respondent free lists: the first contains 447 personal networks, and the second 554. Respondents evaluated the communication between 990 alter pairs. The methods were (1) dropping alters from the end of the free-list, (2) randomly dropping alters, (3) randomly dropping links, and (4) predicting ties based on transitivity. For some measures network structure is captured with samples of less than 20 alters; other measures are less consistent. Researchers should be aware of the need to sample a minimum number of alters to capture structural variation.

Keywords: Personal networks; Structure; Respondent burden

1. Introduction

Increasingly researchers who study personal networks are interested in collecting the data to calculate *structural variables*. By structural variables we mean measures that rely on the pattern of relationships within a network. These measures include network density (the most commonly applied structural measure for personal networks), centrality (degree, closeness and betweenness), centralization (degree, closeness and betweenness), components, core/periphery and isolates. These are in contrast to *compositional variables* that summarize the characteristics of alters within the personal network; such as the proportion of the network that are women, smokers, or family, the average age or the average intensity of the relationship between the respondent and their alters.

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Of course the problem with collecting data on personal network structure is the issue of respondent burden. An adjacency matrix for a personal network requires the respondent to assess some portion of the ties between their alters. This task grows geometrically as the number of alters increases. If we make the assumption that the best assessment of personal network structure can be achieved by having the respondent evaluate all possible alter–alter tie evaluations, a network of 10 alters requires 45 evaluations and a network of 50 alters requires 1225 evaluations.

We have two goals for this paper. First is to determine which method for reducing respondent burden best approximates the structural measures from the unabbreviated network. Second, using this method, what is the minimum number of alters necessary to approximate the unabbreviated network. We approach this problem empirically using two datasets.

2. Background

Unlike whole networks where the data for an adjacency matrix are either collected from network members through survey, observation or secondary data, personal network structural data are collected from respondents by asking them about the ties between their alters. Whole network data collection is therefore high on researcher burden, and low on respondent burden as the task of collecting tie data is distributed across network members who the researcher must observe or interview individually. In contrast, personal network data collection is low on researcher burden and high on respondent burden as the respondent provides the researcher with all information on the ties among their various alters. This is a key difference. The problems associated with sampling and missing data in whole network analysis stem from the inability of researchers to interview or observe network members. For personal networks, alters and ties are missing because respondents either did not recall them or were not asked about them in such a way as to fully capture the network structure. Both approaches result in adjacency matrices, and certain sampling issues affect these matrices similarly. Therefore, much of the literature on sampling and missing data in whole networks is relevant to personal network research.

Friedkin (1981) showed that the simplest network structural measure, network density, was sensitive to network size—as networks grow in size, density declines. He demonstrated the importance of normalizing social network metrics when comparing networks of varying size. Taken another way, he confirmed that if something less than the entire network were measured, the most fundamental structural measures would be affected. Galaskiewicz (1991) tested the effects of different sampling techniques on point centrality in whole networks. As one would expect, he found that the more ties sampled, the lower the error on the estimate of point centrality, regardless of network size. Anderson et al. (1999) considered network size and density as exogenous conditions of network data collection and examined how size and sparseness affected other network metrics (degree centralization, betweenness centralization, H–F hierarchy, Krackhardt hierarchy, connectedness and efficiency). They found that network metrics are affected by size and density, but that the pattern of the effect is not the same for different metrics. They proposed a test to determine if the observed values of the metrics were significantly different from what would be expected from the distribution given a specific network size and density. Frank (2002) measured the effect of different sampling strategies on network centrality. Using random graph models he showed that sampling vertices versus edges and the use of snowball sampling will result in different probabilities of selection for nodes with different centralities. A similar approach was used by Hoon Lee et al. (2006). Costenbader and Valente (2003) used a bootstrapping method to test the effect of non-response on eleven centrality measures. By successively dropping nodes then correlating the resulting centrality scores with the original, they found differences in the