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Networks containing negative ties

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ABSTRACT

Social network analysts have often collected data on negative relations such as dislike, avoidance, and conflict. Most often, the ties are analyzed in such a way that the fact that they are negative is of no consequence. For example, they have often been used in blockmodeling analyses where many different kinds of ties are used together and all ties are treated the same, regardless of meaning. However, sometimes we may wish to apply other network analysis concepts, such as centrality or cohesive subgroups. The question arises whether all extant techniques are applicable to negative tie data. In this paper, we consider in a systematic way which standard techniques are applicable to negative ties and what changes in interpretation have to be made because of the nature of the ties. We also introduce some new techniques specifically designed for negative ties. Finally we show how one of these techniques for centrality can be extended to networks with both positive and negative ties to give a new centrality measure (PN centrality) that is applicable to directed valued data with both positive and negative ties.

1. Introduction

Many classic network datasets include both positive and negative relations. For example, among the standard datasets included in UCINET (Borgatti et al., 2002), the Sampson monastery data, Bank Wiring Room and Read's highland tribes all have negative relations. Negative relations are fundamental to certain theoretical approaches in network analysis, such as balance theory (Heider, 1946; Cartwright and Harary, 1956), and the related clusterability theory (Davis, 1967). In addition, negative relations have been a standard part of blockmodeling (Lorrain and White, 1971; Breiger et al., 1975; Everett and Borgatti, 1995) and semigroup work (Boyd, 1990). Furthermore, there is a considerable psychological literature on negative ties (Taylor, 1991) and conflict (Tajfel and Turner, 1979). Recently, negative interactions like bullying and social exclusion have been the subject of extensive research (DeWall, 2013).

We note that our interest is specifically in relations that are in themselves negative, rather than positive relations that may have negative consequences. For example, positive relations may enable the flow of useful ideas and emotional support, but may also transmit disease and misinformation. Thus, this paper is not intended as a contribution to the 'dark side of social capital' literature (Portes and Sensenbrenner, 1993; Gargiulo and Benassi, 2000). Rather, we are concerned with directly negative relations, such as the antagonistic "hina" relation reported by Read (1954), the conflict relation in the "bank wiring room" data reported by Roethlisberger and Dickson (1939), and the judgments of dislike and disesteem among monks reported by Sampson (1969). All of these represent negative sentiments or behaviors toward other actors in the network.

The question we address in this paper is how to analyze negative tie data. One reason for concern is that negative relations tend to form different structures than positive relations do. For example, in positive tie networks we almost always see high levels of transitivity – e.g., the friends of friends are often friends. But in negative tie networks we see very low levels of transitivity: enemies of enemies do not tend to be enemies. As a result, they tend not to have any clustering. Even more fundamentally, negative tie networks tend to be very sparse, making it difficult to fit tie-level models, and typically resulting in highly disconnected networks, making it impossible to apply certain network analysis methods.

A deeper reason for concern about negative tie networks is that social processes that occur in positive tie networks may not occur in negative tie networks. For example, in a friendship network, we expect the ties to serve as a backcloth along which traffic may flow (Atkin, 1977). So if there is a directed path from A to B to C to D, we expect that over time and with some probability something (e.g.,

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information) could diffuse from A to D. Much of the machinery of network analysis, especially centrality, is based on this expectation (Borgatti, 2005). But, under what circumstances can we expect flows beyond the dyad in a negative tie network? Suppose A dislikes B, and provides B with some embarrassing news about B's mother. If B dislikes C, can we really expect B to pass the original message along to C?

In this paper we present a general assessment of which network analytic concepts and techniques apply to negative relations, and how interpretations need to be adjusted when they are applied to negative ties. We also introduce new concepts and measures specifically designed for negative ties.

In so doing we hope to provide tools that will help network researchers understand networks of negative ties or at least provide them with tools that will enable them to test empirical hypothesis about such networks. For example at the node level if we had robust negative tie centrality measures we could examine whether people with high or low centrality are ignored or preferred in who is chosen for promotion in an organizational trust network. At the network level if we had measures that accommodate both positive and negative ties we could see the effect of negative ties on the centralities of all the actors in the network and hence determine how detrimental (or not) negative ties are. We may be able to detect potential victims or groups of victims in a bullying network and hence plan an intervention at an early stage which provides support and so prevents an escalation. We do not specifically aim to demonstrate the full potential of the methods we propose here, but hope to start to build a collection of tools that will aid empirical analysis.

2. Standard methods

There is one class of standard network concepts that clearly applies to negative data without modification of any kind. This is the set of positional or role equivalence concepts, such as structural equivalence (Lorrain and White, 1971), automorphic equivalence and regular equivalence (White and Reitz, 1983; Everett and Borgatti, 1995), all of which are indifferent to the type of relation they are applied to. For example, if nodes A and B are structurally equivalent in a directed negative-tie network, it means that A and B send negative ties to the same third parties, and receive negative ties from the same parties. Structurally equivalent nodes are typically expected to have similar outcomes with respect to structural processes, and this applies to negative ties as well. Structurally equivalent nodes are also seen as occupying similar positions or playing the same roles in a network, and again this will be the same for negative ties. The same applies to other equivalences.

In principle, statistical techniques such as QAP correlation (Hubert and Schultz, 1976) and regression (Dekker et al., 2007) can be applied to both positive and negative directed tie data, although the specific models we fit may be different, and not just in a mirror-image way. For example, sameness of language might be positively related to positive ties, but would not necessarily be negatively related to negative ties – after all, sometimes negative ties arise precisely because people are able to communicate with each other. In practice, the sparseness of negative tie data can sometimes cause problems with estimation. Similar considerations apply to exponential random graph models (ERGM). The overall framework is perfectly applicable to negative data but the models that actually fit are likely to be different. Moreover, it may be that many of the configurations (both directed and undirected) currently available in ERGM software packages are less relevant for negative ties, and new configurations should be developed.

The situation with centrality measures is a bit more complicated. Perhaps the most translatable centrality measure is simple degree (Freeman, 1979). In certain respects, degree makes perfect sense for negative ties. For example, if the directed relation is "dislikes", then the actors with high indegree can be described as the most disliked in the network – wholly parallel to the case of a "likes" network, where indegree indicates popularity. Similarly, in the context of social capital, high degree in a positive-tie network represents an asset in an actor's social ledger (Labianca and Brass, 2006), while high degree in a negative-tie network represents a liability. The difference in interpretation between degree in positive and negative tie networks parallels the difference in the interpretation of the ties themselves, which causes us no difficulties. Bonacich and Lloyd (2004) extend eigenvector centrality to networks of negative ties resulting in a status measure. We explore their ideas more fully later in this paper.

On the other hand, one way that we commonly interpret degree centrality is in terms of risk of exposure to something flowing through a network (Borgatti, 1995). For example, suppose a virus enters a group at a random node and is transmitted at random to an adjacent node, and so on. The probability of a random walk reaching a particular node after a given number of hops is a function of the degree of that node. Hence, in a positive-tie network, degree centrality provides an index of exposure. However, as noted earlier, in a negative-tie network we do not normally expect things to flow along paths of length greater than one, in which case degree centrality will not function as an index of exposure.

Similar considerations apply to other degree-related concepts, such as graph density and degree-based graph centralization.[1] For example, for positive ties, increased density would suggest a group with greater social cohesion. For negative ties, we would generally expect the opposite. However, there are cases where the parallel is less exact. For example, if in the negative-tie case all ties involve just a few individuals (i.e., high graph centralization or a core/periphery structure), the overall effect on the network could be an increase in cohesion as the majority of the group bonds over the common enemy.

Whereas degree centrality can be interpretable in settings where flows do not make sense, betweenness centrality is difficult to interpret in the absence of flows. As Freeman (1979) defines it, a node's betweenness is essentially the number of times that the node is along the shortest path between two others. Where there are multiple shortest paths between two nodes, the focal node's betweenness score is incremented by the proportion of those shortest paths that it is along. As discussed in Borgatti (2005), the formula for betweenness centrality gives the expected number of times that something flowing through a network (either directed or undirected) will reach a particular node, given that it travels only on shortest paths and chooses at random between equally short paths. It is difficult to see how this measure could be interpreted in the absence of some kind of a flow process. This is especially true for flow betweenness (Freeman et al., 1991), which is built on the concept of maximum flow through a system of pipes whose capacities are given by the strengths of ties. Most variants of betweenness centrality depend on the notion of flow, and as such are generally inappropriate for negative-tie networks.

Closeness centralities (Freeman, 1979; Valente and Foreman, 1998; Stephenson and Zelen, 1989) are also difficult to interpret in the absence of flows. All closeness centralities summarize the length of paths (or, more generally, directed walks) that link a node to the rest of the network. The longer these paths, the greater the amount it takes for things to flow between the nodes, and the greater the probability of a failure to flow. Therefore, nodes separated from the network as a whole by longer paths are

[1] Our remarks here and in subsequent paragraphs apply equally to directed and undirected graphs.