An assessment of social network data trustworthiness

Neil Yetz, M.P.H., M.S. candidate

Colorado State University

Thesis Proposal

“One of the most potent ideas in in the social sciences is the notion that individuals are embedded in thick webs of social relations and interactions” (Borgatti et al, 2009). Social science as a field could not exist without social relations. This idea relates directly to the social ecological model (Bronfenbrenner, 1977). The social ecological model is arguably the most heavily utilized model in public health and social science. The social ecological model emphasizes the integration of the social environment and an individual predicting determinant of health. We can approach this integration of social systems and the individual via social network analysis (SNA). Social networks analysis helps to define and measure the connections among people, organizations, and/or other individual units (Valente, 2010). More specifically, SNA is the process of understanding social structures through networks and graph theory through quantitative approaches (Butts, 2008).

The concept of social networks has been around since the time of Plato in Socrates, when they analyzed the influences of social classes on people (Borgatti, 2009). Milgram (1967) used social network methodology to determine everyone connected via six degrees of separation. Despite Social network methodology, utilization SNA prior to the 21st century was scarce. The scarcity is due to the overall complexity of social networks. In fact, analyzing large scale social networks in early scientific studies was nearly impossible. Acquiring social network data is a timely task to both acquire and analyze.

In recent years, the number of studies with social network methodologies have increased exponentially. Advances in statistical programming have provided social science researchers the ability to include strong social network components within their research studies (Luke, 2015). Several cutting-edge social network analyses methodology require intensive processing power to be performed. Advanced Bayesian modeling techniques such as Exponential Random Graphing Models (ERGM) and *S*imulation Investigation for Empirical Network Analysis (SIENA) models (Ripley et al., 2018; Snijders, 2005) are examples of modeling techniques that require heavy processing power. These techniques are now feasible thanks to advances in advanced statistical programming languages (i.e. R, UCINET & Python).

Social network data collection has also become more feasible over time. Social network sites such as Facebook and Twitter have provided a path for large quantities of social network data. Online social networks (OSN) are often collected via an application programing interface (API) provided by OSN providers. These OSN websites automatically collect a wealth of data from their users (Abdesslem, Parris & Henderson, 2012).

However, modern utilization of SNA goes well beyond the of social networking websites. Research implementing social network methods include identifying characteristics of terrorist networks (Ressler, 2006), obesity (Cohen-Cole & Fletcher, 2008) and adolescent drug use (Valente, 2003). Survey research with a social network component consists of questionnaires that ask about relationships among a specified target group (Serrat, 2017). The questionnaires focused on identifying a network requires careful thought about their methods. There are two common approaches to collecting social network data in survey research:

1. *Social Cognitive Mapping:* Originally developed by Cairns and colleagues (1997), this method shows survey responders a list of names of individuals within the network. Roster methods require the use of a stem question such as, “To whom do you report to at work?” or “Please select individuals you have a friendship with…”. However, the roster method may only be utilized in networks where the set of potential alters in known. (Butts, 2008). Roster methods are exclusive to a closed network and do not allow the option of anyone entering or leaving the network.
2. *Name Generator/Nomination method:* This method gives participants to name anyone or several individuals within a network. The name that may be generated are limitless. A common prompt a participant may see is, “Please indicate five individuals that you would seek advice from within your office…”. Several limitations exist with this method including, false negatives due to subject forgetting or fatigue (Butts, 2008). Errors especially occur in instances where the ego has many connections (Brewer, 2000).

Both methodologies can create enormous datasets. Datasets that are hard to sift through without a systematic and methodical approach. Additionally, using these methods to collect data requires a large assumption: That respondents can properly assess their own networks. This assumption is especially important depending on the population being assessed. For example, are adolescents able to properly assess their friendships with their peers?

Social network analysis has shown to have a useful place in community interventions. Based on the real-world implications SNA has, researchers need to be held accountable that the data they collect for analytical purposes are valid and trustworthy. Without assessing the trustworthiness of collected data, there is no understanding how valid our conclusions are. In short, there needs to be systematic checks to determine the quality and trustworthiness of the data that has been collected.

There Cole and colleagues (2011) have proposed latent variable approaches to validating social network data. However, a standardized process to validate collected social network data remains unclear.

Fields focused on testing and measurement incorporate a numerous number of methods to ensure validity and reliability exist within the measures they use. Social network data is a measure of relationships and bonds and there is no excuse to ensure the quality. Furthermore, data quality measures exist in many other fields. This thesis project proclaims the assumption that social network data needs to be validated via standardized methods.

The validation of network data comes with its challenges. When social network data is collected, it

There are a variety of methods for collecting friendships and bonds.

Despite these differing methods, the way social network data is processed is quite similar. Social network data may be represented in terms of an edge list or adjacency table. However, despite the standardized way of representing social network data, there is no standard process in existence to ensure the quality of social network data.

Social science’s dependability on reporting of standardized validity and reliability measures helps to ensure the credentials of the field. Social Network Analysis, an expanding part of the social science field does not follow these same rules. It is naïve to assume that the network data collected by researchers is valid and appropriate for analyses. Even more so, populations of interested may differ in the validity of network data collected. For example, research on adolescent survey self-report is mixed and no analogous studies exist on their ability to self-report social network data. Therefore, because there is no standardized methodology to evaluating social network data, the legitimacy of the field is at risk.

Past research has been performed the validation of the sociometric properties of social networks (Dunn & Westbrook, 2011). Often sociometric techniques are focused on comparing observed network properties to that of randomly generated network.

I propose creating a standardized method for validating social network data. My proposal serves as a set of analogous measures to those used in psychometric testing and measurement. Several analogous measures will be tested such as reliability, trustworthiness, and validity levels.

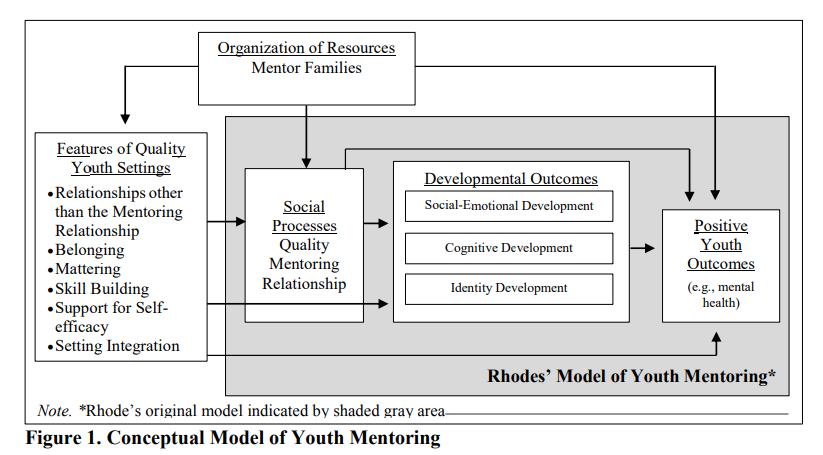
At the end of the project, a series of “checks” will be created to create an understanding of the validity of social network data. This is an essential step to determine the true effects of the network on health outcomes.

Due to the quantitative properties of SNA, a series of quantitative terms are used to represent relationships between people and systems. When these terms are used, we are establishing a mathematical representation of the network as a whole or the individual components of the network. Individual units in the network are referred to as nodes. In SNA, we study the connection and relationships between nodes (Marin & Wellman, 2008). The connecting points representing edges within a network are known as edges.

**Data Collection**

Data for this thesis project were collected via Campus Connections (CC), a youth mentorship service-learning program at Colorado State University (CSU). Campus Connections trains undergraduate students to mentor at-risk adolescents (i.e., those deemed at risk for not 2 E reaching their full potential due to significant individual and/or environmental risk) aged 11-18 within the local community. Youth and mentors pair up one time a week for four hours per week for 12 weeks. To date, more than 1,500 mentee-mentor pairs have participated in this program to date. Past work indicates that CC is practical, feasible, and in high demand.

Campus Connections utilizes evidence-based practice to promote positive youth outcomes. Along with CC’s desire for evidence-based practice, it utilizes and extension of Rhode’s model of youth mentoring as shown in Figure 1(Rhodes, 2002, 2005).



Results from past research indicate that Campus Connections adolescent outcomes rank similarly to other youth service programs. These effects on positive youth development tends to be relatively modest with some key outcomes not being substantially improved. A unique aspect of CC is the establishment of a *Mentor Family* component. Mentor families involve nesting three to four mentor-mentee pairs into a “family group” to experience the program in unison. These mentor families consist of multiple levels of support. Level one consists of the mentor-mentee dyad. Mentors and mentees establish a closely-knit bonding experience between the mentor and mentee. Level two is the establishment of the mentor family. The mentor family component of CC is based on a

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