Advancing Social Influence Models in Learning Analytics

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ABSTRACT: Our goal is to contribute to the *Learning Analytics & Knowledge* conference workshop on *Using Network Science in Learning Analytics* by advancing the use of a particularly important, but not widely used network science technique: modeling influence. Influence, the process through which individuals affect one another, has long been a key construct in social network analysis, but these models are uncommon in learning analytics-driven uses of network approaches. In this paper, we review prior educational research using influence models, provide an example from our recent work, and articulate some future directions for the use of influence models. We conclude with a description of how this work can contribute to the conference workshop and a call to consider how influence can complement selection and other network techniques used in learning analytics research.

Keywords: social network analysis, social influence, social capital, exposure effects, social media

1 INTRODUCTION

Network analysis is a complex methodological and theoretical lens through which a range of learning-related constructs can be examined. This complexity extends to learning analytics-driven uses of the network concept. This complexity has numerous effects. First, studying networks can be both compelling and challenging. This is particularly true for the networks learning-analytics scholars study, such as networks evidenced through conversation threads in online courses (e.g., Chen et al., 2019). These online networks may differ in fundamental ways from face-to-face networks for which network analysis has more often been used, such as advice-seeking networks among teachers in the same school building (Frank et al., 2004). These differences mean that although some established methods can be used, others must be modified, and, in some cases, new techniques must be developed. Consequently, another key product of the complexity of network analysis is that associated methods are likewise complex. That is, a range of methodologies that can be—and have been—used to analyze networks. This is especially true in the new terrain of data accumulated by educational technologies and learning analytics platforms, as well as digital-trace data and metadata from social media platforms.

This proposal will contribute to the *Learning Analytics & Knowledge* conference workshop on *Using Network Science in Learning Analytics* by advancing the use of a particularly important, but not-widely-used network analytic technique: modeling *social influence*. Influence has long been a key construct in social network analysis (Frank, 1998).

For instance, sociologists developing the social influence approach used statistical models to understand how *social capital* (i.e., resources inherent to and available through relationships) exerted its power (Bourdieu, 1980). In short, influence may be thought of in terms of how individuals affect one another (Frank, 1998).

Although social influence may seem to be an essential characteristic of network studies, a review of research on social network analysis in learning analytics reveals a strong preference for another type of network process: *social selection*. Selection models aim to understand who interacts—and potentially forms relationships—with whom (Fincham et al., 2018). These selection processes are contemporarily estimated using powerful extensions of inferential statistical techniques such as logistic regressions, Exponential Random Graph Models (ERGMs; e.g., Gašević et al., 2019).

Social influence is distinct from—but also complements—social selection; these processes likely exist in a reciprocal relationship (Frank & Fahrbach, 1999). Furthermore, much of the existing social network analysis literature draws from descriptive statistical and visual approaches to understand networks. Each of these methodologies contributes its own distinct understanding to the phenomenon of social networks. However, social influence is currently under-represented in the current buffet of methods.

Our central argument here is that influence models are especially valuable because they allow researchers to interrogate what is intuitively important about networks. That is, it may seem self-evident that social networks can influence actions, behavior, and learning. However, measuring these phenomena can be difficult without the aid of the rather advanced statistical techniques of influence models.

To advance the understanding and adoption of influence models in learning analytics, we offer four pieces in this proposal. First, we provide a review of prior research in education on the use of influence models to understand networks. Second, we illustrate the use of influence models in the context of a recent study that explored influence in the context of an informal, technology-based online community of science educators. Third, we constructively critique our past research and suggest ideas for future work, whether these are our own efforts or those of other learning analytics researchers. We specifically highlight influence models for the effect of relationships in a network, which we consider to be a core yet missing element of network analysis. Fourth, and finally, we conclude with a description of how we see this work as contributing to the aims of the workshop.

2 PRIOR RESEARCH INVOLVING INFLUENCE MODELS

The prior research that has utilized influence models has primarily done so in the context of studies of the face-to-face networks of educators, teacher leaders, and administrators. For example, Frank et al. (2004) examined how the use of innovative digital technologies, namely the use of computers for five specific educational goals and activities, were adopted by teachers throughout a district when teachers identified as leaders among their peers adopted and productively used the tool. They collected network data from all of the teachers in the district by asking them to *nominate* up to ten individuals who they go to for help. Then, they determined how much of the variability in teachers' use of computer technologies depended upon who they said they went to for help over the preceding year.

Counter to prevailing trends in educational technology research that has focused upon individual characteristics (often psychological), Frank et al. found that more variance in computer use was explained by social capital measures—who teachers went to for help—than more traditional, psychologically-focused measures of teachers' value for computers. The authors interpreted that it was through social capital (and social relationships) that teachers were exposed to expertise in a meaningful, context: a relationship with a trusted peer.

Another, more recent, example was reported by Horn et al. (2020), who focused on the nature and effects of the discussions that teachers had in workgroups. Extending their own and others' work that examined not just *that* influence took place (e.g., Coburn et al., 2010), Horn et al. examined how influenced was a function of the depth of the conversations that took place among teachers when exposure to expertise might occur. In other words, whereas Frank et al. (2004) assumed that when teachers nominated others (i.e., those who they turned to for help) this help is provided, Horn et al. modeled the kinds of substantive discussions that took place among those with differing expertise. This latter study found that those teachers who regularly participated in rich discussions about (mathematical) content were more likely to teachers' developing greater expertise.

These prior studies and other research (e.g., Cannata et al., 2010, Frank et al., 2020; Reddy et al., 2017; Sun et al., 2014) demonstrate that social influence can account for a great deal of the variance in key outcomes. Our contention is that these examples, which sometimes frame influence in terms of "exposure" (to expertise; Frank et al., 2004) effects, prompt questions for learning analytics research, too. For instance, relevant questions may include whether social interactions that take place in digital contexts for educational purposes (e.g., for teachers or learners participating in online learning communities) really matter. If so, how do these interactions matter (e.g., social influence)? In the next section, we describe a recent study in which we attempted to understand whether, and how, involvement in a social-media-based community for science educators influenced participants' sustained involvement over time.

3 AN ILLUSTRATION: INFLUENCE WITHIN #NGSSCHAT

To illustrate a recent effort to model social influence, here we describe a project focusing on science educators' adoption of the Next Generation Science Standards (NGSS). Specifically, educators have connected and interacted through a synchronous Twitter chat (#NGSSchat) to form a social-media-based professional network used to discuss topics related to the current science standards (i.e., the NGSS) in the United States (Rosenberg et al., 2020). In this study, we used public data mining methods to access more than 7,000 #NGSSchat posts, by around 250 participants, to one of approximately 50 one-hour synchronous "chats" that took place over two years, from 2014-2016. During these chats, participants discussed topics ranging from how to effectively communicate with parents about the new science standards to interpreting and discussing the research that contributed to the new standards.

Our goals in studying #NGSSchat were to (a) describe the depth of conversations that took place, (b) understand who was selecting to interact with whom, and (c) determine to what extent someone's future participation in the network was a function of with whom they interacted. The first and second goals were important for determining whether this social media-based network fostered meaningful conversations. That is, we wanted to know whether #NGSSchat discussions were "balanced" in terms of an egalitarian mix of posts going between researchers and teachers (i.e., not merely from researchers *to* teachers) and detailed (i.e., not predominantly superficial posts). The third goal specifically pertains to influence. If #NGSSchat operated like the face-to-face networks described in the previous section, then we would hypothesize that some type of social influence was likely taking place. Furthermore, we would surmise that this social influence bolsters the Twitter #NGSSchat network in the eyes of science educators who might understandably be skeptical about the value of this community.

To model influence, we examined how participation in #NGSSchat across an entire year could explain the rate of participation in the following year. We used a general linear model (with a Poisson outcome distribution because the dependent variable was a count) to predict sustained participation. We operationalized sustained participation as the number of original tweets each individual sent to #NGSSchat in one academic year (2015) as a product term representing involvement in each of the types of conversations. This term was intended to capture not only how many conversations an individual participated in, but also how some conversations may matter more when sent by central individuals. Accordingly, calculating these terms involved determining the number of times every other individual interacted with each individual and then multiplying that number by a centrality measure (in-degree centrality). Thus, these terms were intended to account for participating in conversations in which one received replies from individuals central to the network. Finally, we summed these multiplied terms to create a total value, or *exposure* (to influential others) term, for each individual. Thus, our model was relatively simple: we predicted the number of posts individuals sent in the subsequent year on the basis of *an exposure term* reflecting their involvement in conversations with central (and therefore potentially influential) individuals. We also included a predictor term to take into account individuals' professional roles.

Our analysis showed that the degree of individuals' exposure to conversations (accounting for the centrality of conversation participants) was associated with greater sustained participation. Specifically, for every one-*SD* increase in the number of conversations in which an individual participated, individuals were likely to post 9-15 additional tweets (in log-odds units, β's = 1.43 – 1.83, $p < .001$) in the next year, accounting for individuals' professional roles. From this, we inferred that if involvement in transactional conversations can support individuals to feel like they belong, conversation exposure might be what causes individuals to choose to continue to participate in the network. In sum, our analysis of Twitter #NGSSchat showed that involvement in conversations (similar to Horn et al. [2020]) predicted later participation.

4 FUTURE DIRECTIONS FOR MODELING INFLUENCE

Throughout this paper, we have described how influence matters for key outcomes: learning, implementing new teaching practices and making progress toward educational improvement efforts. However, one critique of our illustration we wish to raise is related to whether our outcome (i.e., sustained participation) is actually important. We consider this critique as a worthy outcome for the same reasons that we think studying social influence in digital contexts is important: It can allow us to determine whether and how #NGSSchat interactions matter. In this way, studying an outcome endemic to the network, rather than one external to it (e.g., whether teachers implemented what they learned or discussed through #NGSSchat, as determined through an observational measure) leaves open the question of the role of #NGSSchat in the implementation of the new science standards.

The previously described study on #NGSSchat (Rosenberg et al., 2020) was not alone in utilizing an imperfect outcome, and other studies have also linked teachers' networks to the implementation of their classroom practice (Frank et al., 2020). Therefore, a key future direction for modeling influence will be to explore whether and how educators' and learners' participation in myriad networks impacts their learning, actions, and capabilities. The more interesting question is not *whether* networks impact these and other outcomes, but, rather, *which* outcomes networks affect, and *how* they do so. For example, given the lack of focus in social media research on new teachers' needs, we might investigate how new teachers' participation in informal online networks affects their teaching practice.

Another future direction concerns the makeup of exposure terms that are so critical to influence models. Network analysts face numerous decisions regarding how to construct these. For instance, exposure terms can be based on the number of interactions or whether or not individuals interacted. Moreover, the effects of interactions from different individuals can be calculated in different ways: some influence processes are cumulative, such as, for example, when individuals are exposed to expertise from varied individuals, whereas for others the average influence is more salient. Finally, the time period over which exposure is evaluated is critical, and, distinct from descriptive analyses, there must be a time period over which exposure takes place—and, so, multiple measures are needed. Similarly, there are nuances to sort out related to influence as the learning analytics field has begun to address in the context of tie formation—or selection (Fincham et al., 2018).

5 CONTRIBUTIONS TO THE WORKSHOP AND CONCLUSION

Because the *Using Network Science in Learning Analytics* workshop is intended to identify common challenges faced by network science scholars and to surface these challenges in a way that supports the advancement of this field, our presentation will address several of the detailed workshop themes, particularly causality, the linkage between micro- and macro-processes, and linkages across time. Our contribution is to broaden the kinds of network science techniques learning analytics scholars use. Social influence is a model for network processes that differ from selection models that predict tie formation and network structure (e.g., Fincham et al., 2018), and is quite different from descriptive analyses that compute individual- and network-wide statistics, or simply present network visualizations. Several specific ways that this work will add to the workshop is to prompt discussions of (a) what kinds of questions are suited to the use of influence models, (b) how influence is similar to and different from other approaches, especially selection model effects through ERGMs, and (c) what the relative absence of influence models in the literature suggests about potential gaps in the growing body of learning analytics research that utilizes network science techniques—and what addressing those gaps might yield.

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