Deconstructing the Evolution of Collaborative Learning Networks

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ABSTRACT: As social interaction becomes an integral component in online learning environments, analyzing the dynamic evolution of peer learning networks is necessary to better understand and support learners in these contexts. This study investigates a unique network of collaborative artifact composition within a college-level online course, focused on the co-evolution of this network and student engagement at the individual level. Using stochastic actor-oriented models (SAOM), I find that students tend to form cohesive subgroups but not to produce "super stars" in collaboration activities. Moreover, collaboration exerts peer influence on individual course engagement, but there is no evidence of engagement-based selection of collaborators. These identified trends can help the instructor(s) refine their course design and implement appropriate intervention to foster more effective learning communities.

Keywords: Social Learning Analytics; Connectivism; Learning Networks; Collaborative Composition; SuiteC; SAOM

1 BACKGROUND

Learning theories from earlier social constructivism to more recent connectivism have highlighted the role of social interaction in human learning (Siemens, 2005; Vygotsky, 1978). In these theories, learning occurs when people as nodes of knowledge make connections and knowledge flows within the interpersonal network. Empirically, research that employs social network analysis to examine online peer interaction partially justifies the theory of connectivism (e.g. Cho, Gay, Davidson, & Ingraffea, 2007; Dawson, 2008; Joksimović et al., 2016; Wang & Noe, 2010). However, most of these studies analyze the final network generated throughout the course period without attending to the dynamics of information flow and network changes, which is a central theme of connectivism. As such, analyzing the evolution of learning networks will add new insights to the understanding of peer interaction.

Towards this end, a handful of recent studies have leveraged statistical models of network dynamics to understand the temporal dependencies of learning network structures (Joksimović et al., 2016; Poquet, Dowell, Brooks, & Dawson, 2018; Stepanyan, Borau, & Ullrich, 2010; Zhang, Skryabin, & Song, 2016). Across these studies, reciprocity, individual performance and performance-based homophily consistently contribute to the formation of learning ties, while hierarchical structures including triad closure, preferential attachment and Simmelian ties are not always present. These studies are largely concentrated on discussion forums in MOOCs and may not generalize to other learning networks. To fill this void, the current study delves into the dynamics of artifact composition networks in formal higher education settings. It also traces the co-evolution of network structures and individual learning behavior, thus differentiating the underlying processes of influence and selection (Lewis, Gonzalez, & Kaufman, 2012) in peer learning environments.

2 FRAMING OF THE STUDY

This study takes advantage of SuiteC, a specially designed set of student-centered learning tools embedded within the Canvas learning management system (LMS). Partially informed by connectivism, this toolkit facilitates sharing, discussing and remixing student-contributed artifacts via three interconnected apps: Asset Library is a repository of such artifacts (a.k.a. assets) with rich social networking functions; Whiteboards is a platform for real-time collaboration on remixing assets; Engagement Index introduces a leaderboard to create a gamified vibe. (Jayaprakash, Scott, & Kerschen, 2017).

SuiteC enables more closely connected learning experience than traditional online learning environments. It is then meaningful to investigate how learning networks develop within this augmented system. As an exploratory step, this study delves into the learning network formed through collaborative composition in the Whiteboards (referred to as “whiteboard network”). This network differs substantially from a discussion network because the former engages learners in a process of working together towards a certain target while the latter involves direct and short communication between learners (Liu, Chen, & Tai, 2017).

In this context, I propose the following research questions:

1. What are the network structural properties (e.g. reciprocity, homophily) that characterize students’ collaboration in the Whiteboards over time?

2. Do collaborators exhibit similar levels of course engagement over time, or do students tend to collaborate with peers who have similar levels of engagement?

3 DATA AND METHODS

3.1 Dataset

The dataset comes from a fully online course offered to residential students of a four-year university in the US. The course was offered in Spring 2016 and lasted for 14 weeks. Each week students were required to share assets and interact with peer assets around the topic of that week. They were also required to collaborate on composing one or more whiteboards that feature the same topic.

All the actions within SuiteC apps were recorded, with a total count of 658,967. These actions were taken by 114 users and involved 1,366 whiteboards and 6,672 assets.

3.2 Modeling Strategy

Stochastic actor-based models (SAOM) were used to study the co-evolution of the whiteboard network and course engagement. This model family basically assumes that changes of network ties result from micro-level decisions of individual actors (nodes) decisions that maximize their current network function. When time-variant individual behaviors come into play, individual actors decide their behaviors by maximizing their behavior function. In the context of SuiteC, these assumptions seem reasonable and not very restrictive.

The whiteboard network was defined as a non-directed network among individual students, which resembles a co-authorship network. Engagement was originally defined for each learner as her total number of actions. For modeling purposes, the data were further transformed in two manners. First, the 14 weeks were divided into 4 periods based on the topic structure and a network was constructed for each period. Second, engagement values were first calculated within each period and then converted to a categorical variable with five levels.

To model the dynamic interplay between collaborative composition and engagement, network and behavior functions were used. The network function modeled local structures and attributes that contributed to the presence of a collaboration tie over time, including density (base effect), triangle, nodal degree, individual engagement and dyadic engagement similarity (Ripley, Snijders, Boda, Vörös, & Preciado, 2018). The behavior function, by contrast, modeled factors that influence observed behavior (engagement), including linear and quadratic terms of engagement and the average engagement similarity between a focal student and her collaborators.

4 RESULTS

Table 1 reports summary statistics of the whiteboard network across the four periods. Network density ranges from 0.02 to 0.04; it slightly moves up from period 1 to 2 before dropping heavily and then recovering through periods 3 and 4. On average, each student collaborates with two to three other students on composing whiteboards during each period. The Jaccard coefficients of the three transitions (not reported) are all above 0.3, a recommended threshold for applying SAOM.

Table 1: Summary statistics of the whiteboard network across four periods.

Period	1	2	3	4
Density	0.035	0.042	0.021	0.028
Average degree	2.843	3.422	1.735	2.313
Number of ties	118	142	72	96

Table 2 reports the estimated effects of function terms. Model 1 solely takes into account the evolution of whiteboard network (RQ 1), while Model 2 adds its interplay with course engagement (RQ 1 and RQ 2). In terms of network structures, the triangle effect is significantly positive whether engagement is incorporated or not, meaning that, if two students have both collaborated with the same third student, they are more likely to work together. By contrast, the significantly negative degree effect suggests that a student who already has multiple collaborators is less likely to collaborate with more peers. These effects combined suggest a tendency to form cohesive subgroups and to participate equally.

In Model 2, the engagement and engagement similarity effects on the whiteboard network are not significant. In other words, refusing any difference in the likelihood of pairwise collaboration for different combinations of engagement levels. By contrast, the average similarity effect on engagement is strongly positive. In other words, students tend to engage as much as their peers with whom they have collaborated. These results provide evidence for peer influence but against peer selection, i.e. students being assimilated to their collaborators, instead of similar students being attracted to work together.

Table 2: Estimated effects of the network function and the behavior function.

Effect	Model (1)	(2)
Whiteboard network		
Rate		
Period 1	3.539*** (0.602)	3.323*** (0.628)
Period 2	2.836*** (0.530)	2.982*** (0.566)
Period 3	1.532*** (0.289)	1.584*** (0.298)
Structural		
Density	-1.577*** (0.260)	-1.556 (0.268)
Triangle	1.782*** (0.244)	1.801*** (0.237)
Degree	-0.209*** (0.074)	-0.227*** (0.077)
Covariate		
Engagement		0.222 (0.149)
Similarity of engagement		1.190 (1.370)
Engagement		
Rate		
Period 1		3.807*** (0.834)
Period 2		34.168*** (11.202)
Period 3		10.427** (4.490)
Behavior		
Engagement linear		-0.100*** (0.032)
Engagement quadratic		0.109*** (0.029)
Network		
Average similarity of engagement		1.945*** (0.705)

Note: Standard errors reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5 DISCUSSIONS

This paper reveals that cohesive subgrouping and equal participation are characterizing structures of students' collaborative composition network. It also finds that while students' general course engagement is influenced by their whiteboard collaborators, students who engage in the course environment to a similar extent are no more likely to collaborate on whiteboards than if they are different. These findings have implications both for social learning analytics researchers and for online learning practitioners. For one thing, research efforts should delve into the dynamic interplay between structures of learning networks and low-level learner behaviors in networked learning environments. Also, the artifact composition network exhibits more desirable structures than discussion networks, so online instructors may consider collaborative tasks more often when they intend to leverage the benefits of social interactions to foster student learning.

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