

## A Social Network Perspective on Peer Supported Learning in MOOCs for Educators



Shaun Kellogg, Sherry Booth, and Kevin Oliver  
North Carolina State University, United States

### Abstract

A recent phenomenon in the MOOC space has been the development of courses tailored to educators serving in K-12 settings. MOOCs, particularly as a form of educator professional development, face a number of challenges. Academics, as well as pundits from traditional and new media, have raised a number of concerns about MOOCs, including the lack of instructional and social supports. It is an assumption of this study that challenges arising from this problem of scale can be addressed by leveraging these massive numbers to develop robust online learning communities. This mixed-methods case study addresses critical gaps in the literature and issues of peer support in MOOCs through an examination of the characteristics, mechanisms, and outcomes of peer networks. Findings from this study demonstrate that even with technology as basic as a discussion forum, MOOCs can be leveraged to foster these networks and facilitate peer-supported learning. Although this study was limited to two unique cases along the wide spectrum of MOOCs, the methods applied provide other researchers with an approach for better understanding the dynamic process of peer supported learning in MOOCs.

**Keywords:** MOOC; social network analysis; online learning; communities of practice

## Introduction

MOOCs, or massively open online courses, have gained extensive media attention for their vast enrollment numbers and the alliance of prestigious universities collectively offering free courses to learners worldwide. Though MOOCs have primarily consisted of undergraduate level courses at these respective colleges, early reports on participant demographics suggests that a typical MOOC ‘student’ already holds a bachelor’s or master’s degree and is employed full- or part-time (Balch, 2013; Belanger & Thorton, 2013; Kizilcec & Piech, 2013; University of Edinburgh, 2013). For many, MOOCs are filling the role of continuous education and ongoing professional development, serving to satisfy personal intellectual curiosity or enhance the workplace skills of post-graduates.

A recent development in the MOOC space has been the growing number of courses tailored to educators serving in K-12 settings. In April, 2013, the Friday Institute for Educational Innovation at North Carolina State University, in partnership with the Alliance for Excellent Education, launched MOOC-Ed.org along with its first course aimed at supporting school technology leaders (Kleiman, Wolf, & Frye, 2013). Shortly after, Coursera announced a partnership with leading schools of education and cultural institutions, to open up a series of training and development courses for teachers worldwide (Empson, 2013). Education leaders, such as former governor of West Virginia and President of the Alliance for Excellent Education Bob Wise (2013), see MOOCs as a means for schools and districts facing slashed budgets and increasing demands to provide personalized professional development at a fraction of the cost of traditional models. MOOCs as a new model of online professional development present new opportunities and pose new challenges. MOOCs typically provide little or no instructional support beyond the prepared videos and course materials posted by professors and staff. Due to their scale, even MOOCs with active instructors make it impossible to provide the level of instructional feedback and support that would be expected in smaller face-to-face or conventional online course settings.

This problem of scale, however, presents a unique opportunity for social networking and the development of peer support networks to fill this instructional void. In a report commissioned by the Canadian government to study the implications of MOOCs for the digital economy, McAuley, Steward, Siemens, and Cormier (2010) noted that MOOCs have the potential to “model and build collaborative networks of unprecedented size that transcend time and space” and the “network ties created between people during a MOOC have the potential to continue as sustainable and relevant personal and professional connections beyond the boundaries of the course itself” (p. 35). This case study adopts a social network perspective in order to investigate peer interaction and support in two MOOCs designed for the professional development of K-12 educators (MOOC-Eds).

## The Social Network Perspective and MOOCs

It is only in the past couple of decades that network thinking has gained considerable attention in academia, as noted by Borgatti and Foster (2003) in the exponential growth of publications on “social networks.” Research in education has followed a similar trend, which McFarland, Diehl, and Rawlings (2011) attribute “not only to a growing awareness of networks brought on by the popularity of social networking sites like Facebook and Twitter, but also as a result of statistical breakthroughs and substantial increases in computing power” (p. 88). While social learning theories such as social cognitive theory and social constructivism have become an accepted part of our knowledge base for understanding the learning process (Bandura & McClelland, 1977; Grusec, 1992; Wu, Tennyson, & Hsia, 2010), educational researchers have noted the limitations of these theories in the digital age (Bell, 2011). In their theory of connectivism, Siemens (2005) has described learning as a process of network formation, with connections being key to networked learning, while Downes (2009) asserts that knowledge consists of the network of connections formed from experience and interactions with a knowing community.

The process of network formation described by Siemens, specifically the development of peer-support networks, is of primary interest to this study. In their review of the literature, Rivera, Soderstrom, and Uzzi (2010) classify these processes into three broad mechanisms: 1) assortative mechanisms, 2) relational mechanisms, and 3) proximity mechanisms. Assortative mechanisms theorize that the creation, persistence, and dissolution of ties between individuals are “outcomes that rely on the compatibility and complementarity of actors’ attributes” (p. 94). One assortative mechanism is *homophily*, or the tendency for individuals in the physical and virtual world to show a preference for interacting with others who share similar characteristics such as gender, age, ethnicity, and education level. Although this social phenomenon and its effects have been studied across a variety of offline educational settings (Burgess, Sanderson, & Umaña-Aponte, 2011; M. H. Jones, Alexander, & David, 2010; Rocca & McCroskey, 1999), our understanding in online learning settings is limited (Yuan & Gay, 2006). Stepanyan, Borau, and Ullrich (2010) examined homophily and popularity effects among students utilizing Twitter as part of an English language course at a university in Shanghai and found a preference among students to “follow” and communicate with other students with similar academic grades histories. Homophily has also been examined in the context of school reform. Penuel et al. (2010) examined the impact of a school-wide reform effort to improve teacher collaboration around literacy instruction at two elementary schools. The researchers found that in the school that had not succeeded in enacting significant reforms, there continued to be a fractured social network where subgroups were defined by homophily, while in the successful school they found “a cohesive advice network with subgroups aligned to the formal organization of the school into grade-level teams... and a coach who played a central role within the advice network” (p. 63).

Relational mechanisms emphasize the impact that the network's structure has on the formation of ties and encompasses network effects such as reciprocity, transitivity and actor prestige. For example, *reciprocity* (e.g., communications involving back-and-forth exchange) has been described as one of the defining attributes of any network, real or virtual (Aviv, Erlich, Ravid, & Trotter, 2008). However, evidence for reciprocity as a mechanism in online social spaces, that is knowledge exchanges between two parties that are mutual and perceived as fair by both parties, is mixed. Wang and Noe (2010) reported on the relationship between the norm of reciprocity and knowledge sharing in the context of communities of practice and noted that a third party rather than the original recipient often reciprocates an individual's knowledge sharing in communities of practice. Chiu et al. (2006), on the other hand, investigated knowledge sharing in an IT-oriented professional learning community in Taiwan and found that the degree to which participants' felt a norm of reciprocity was positively associated with individuals' frequency of their sharing knowledge, though not the quality of their postings. These mixed results reflect those of other studies of network interaction in online virtual communities (C.-J. Chen & Hung, 2010; Hew & Hara, 2007; C. Wang & Lai, 2006). The evidence suggests a pattern of generalized exchange, which Cropanzano and Mitchell (2005) describe as a process of "group gain":

[B]enefits are put into a single common "pot" and individuals take what they need from this common pool regardless of their particular contribution. Likewise, they contribute to this cache when they are able. Notice that the exchange is not directly transacted from individual to individual. Rather, all things are held in common. Group gain does not involve dyadic or interpersonal exchanges; rather, all things are held in common. (p. 879)

Research also suggests that actors who are more spatially proximate, that is, live or work near one another, are more likely to form social ties. These mechanisms have been found to shape social networks in both physical and online settings. Barab, MaKinster, and Scheckler (2003) noted that proximity in terms of physical location influenced whether members of work teams collaborated with each other, even when team members were spread out over geographic distances and were working together through online collaborative tools. Huang, Shen, and Contractor (2013) reported similar findings in terms of proximity among members of gaming communities, while Yuan and Gay (2006) found that proximity as well as other shared sociodemographic characteristics influenced network ties even among individuals who have only interacted through computer-mediated communication.

Finally, social network theory posits that the structure of social relations can facilitate or inhibit outcomes for individuals and has been used to explain a wide variety of phenomena in the social sciences (S. Borgatti, Mehra, Brass, & Labianca, 2009). In online learning settings such as higher education, studies have found relationships between network measures and academic outcomes like knowledge construction (Aviv,

Erlich, Ravid, & Geva, 2003; Rossi, 2010), academic performance (Cho, Gay, Davidson, & Ingraffea, 2007; Russo & Koesten, 2005), and positive dispositions toward the learning experience (Dawson, 2008; Lowes, Lin, & Wang, 2007). The process of knowledge co-construction in online learning spaces in particular has received considerable attention by network researchers in education (Aviv et al., 2003; Heo, Lim, & Kim, 2010; S. Wang & Noe, 2010; Zheng & Spires, 2012). Wang and Noe (2010) examined the relationship between knowledge construction and learners' positions at the core, core-periphery, and periphery of the network and found that the closer students are to the "core" of a network, the more active they are in the "information-sharing" and "negotiation of meaning" levels of knowledge building.

Although still in its infancy, the MOOC literature to date has explored topics as diverse as self-regulated learning (Littlejohn, 2013), user attributes and behaviors (Aiken, Lin, Schatz, & Caballero, 2013; Belanger & Thorton, 2013; Breslow et al., 2013; Deboer, Stump, Pritchard, Seaton, & Breslow, 2013), completion rates (Clow, 2013), and learning analytics (Fournier, Kop, Sitlia, & others, 2011; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2013; Sinha, 2012). A handful of studies have even addressed learning as a social process (Cabiria, 2008; Levy, 2011; Mak, Williams, & Mackness, 2010; Viswanathan, 2012). In this review, however, only one study proposed research to explore networked learning by "experimenting with social network analysis to see if it yields findings about the nature and longevity of group formation" (Breslow et al., 2013, p. 23).

The above review of the literature highlights the potential for network thinking to expand our understanding of the learning process as a social endeavor. However, there is a need for more research in the field of education, and online learning in particular, that explores mechanisms shaping network processes. In addition, studies that have examined network outcomes such as knowledge construction have drawn their data from college-level online courses where participation is tied to course grades and discussion forums are highly structured by an instructor. This study aims to address these gaps in the MOOC literature through social network analysis (SNA) and qualitative methods that explore the processes and product of peer support networks in two MOOC-Eds.

## Methodology

This study employs a mixed-method case-study design. The case study approach is well-suited for studying emerging complex social phenomenon in a natural setting in which the investigator has little or no control (Yin, 2009).

This study is framed by three primary research questions related to peer supported learning:

- RQ1. What are the patterns of peer interaction and the structure of peer networks that emerge over the course of a MOOC-Ed?
- RQ2. To what extent do participant and network attributes (e.g., homophily, reciprocity, transitivity) account for the structure of these networks?
- RQ3. To what extent do these networks result in the co-construction of new knowledge?

Yin (2009) states that an important component of case study research is the development of theoretical propositions used to guide the study. Each proposition, Yin notes, directs attention to something that should be examined within the study. One aim of this study is to find commonalities that describe educator interaction patterns within MOOCs and identify mechanisms that are predictive of social ties. Based on the theoretical framework and the above literature review, three theoretical propositions for network processes are also put forth below.

Early findings in network research have also noted tendencies for a small proportion of individuals in social networks to have a disproportionate number of social ties (Rivera et al., 2010). These types of networks are commonly referred to as scale-free networks and their degree distribution, that is, the number of ties each actor in the network has, follow a power law distribution rather than a normal curve. This skew in the number of ties has been noted by Wenger who asserts that CoPs typically consist of a small core group of active participants who participate quite frequently and assume community leadership; a small active group of members who participate regularly but not as frequently as the core group; and a large portion of members, peripheral participants, who rarely participate (Wenger et al., 2002). Findings from the literature suggest this core-periphery structure is common among large online communities, including online learning communities.

P1. The social network is likely to be characterized by a small core of highly connected individuals, with a large proportion of actors surrounding the periphery of the core.

Researchers have suggested that reciprocity is one of the defining attributes of any network, real or virtual, and that an individual forms a tie with someone who has already related to him or her, or with someone who is a promising resource and will probably reciprocate (Aviv et al., 2008). However, evidence for reciprocity, that is, knowledge exchanges between two actors that are mutual, as a mechanism in non-education related online networks is mixed. Although Hakkinen and Jarvela (2006) found evidence of reciprocity among pre-service teachers in a web-based course, Aviv et al. (2008) hypothesized that in distance learning networks, levels of reciprocity would be no greater than would be expected by chance due to limited face-to-face contact and discussions being limited in scope and time. To their surprise, they found that in all 95

internet-based networks formed in Open University of Israel courses, reciprocity was observed beyond what would be expected by chance in all networks. Thus, the following proposition is put forth:

P2. Reciprocity will have a positive effect on tie formation in MOOC-Eds.

Finally, assortative mechanisms speculate that the creation, persistence, and dissolution of social ties are all outcomes that rely on the compatibility and complementarity of actors' attributes, while proximity mechanisms suggests that actors who are closer geographically are also more likely to form a tie (Rivera et al., 2010). As detailed earlier, network researchers have provided evidence of homophily and proximity in the formation of network ties, even in academic settings where similarity is not a necessary condition for learning, and where learners have only interacted online. As new ties are more likely to form between individuals who share similar characteristics, homophily and geographical proximity are likely to play an important role, especially in a MOOC environment where participants are unlikely to know each other and are therefore unlikely to have pre-existing ties. It is expected, therefore, that there will be more ties than would be expected by chance between participants of the same gender, educational background, similar educational background, in similar educational roles (e.g., principals), and with similar years of experience.

P3: Shared personal and professional attributes (homophily) and differences in experience (heterophily) will increase the likelihood of a network tie.

## Research Context

In the spring of 2013, The Friday Institute launched the MOOC-Ed Initiative (mooc-ed.org) to explore the potential of delivering personalized, high-quality professional development to educators at scale (Kleiman et al., 2013). In collaboration with the Alliance for Excellent Education, launched this initiative with a 6-week pilot course called Planning for the Digital Learning Transition in K-12 Schools (DLT), which was offered again in September 2013. This course was designed to help school and district leaders plan and implement K-12 digital learning initiatives. A second course, Mathematics Learning Trajectories: Equipartitioning (EQP), ran in August 2013. It introduced elementary- and middle-grades educators to learning trajectories as a framework for interpreting and implementing the Common Core State Standards. Among the core design principles of MOOC-Eds are collaboration and peer-supported learning. Courses combine Google Course Builder with Vanilla Forums and Google Hangouts on Air to facilitate these learning activities.



## Data Collection

To address the above research questions, data came from two primary sources.

*MOOC-Ed registration form.* All participants complete a registration form for each MOOC-Ed course. The registration form consists of self-reported demographic data, including information related to their professional role and work setting, years of experience in education, and personal learning goals.

*MOOC-Ed discussion forums.* All peer interaction, including peer discussion, feedback, and reactions (e.g., likes), take place within the forum area of MOOC-Eds, which are powered by Vanilla Forums. To build peer support networks for network analyses, a MySQL file was downloaded for the two fall DLT and EQP courses. Separate database tables containing postings and comments were joined, or combined, to create a single network edge list (e.g., who interacted with who), which included participant IDs, timestamps, discussion text and other attributes. These data are merged with participant information from registration forms to create a single network analysis data file containing both peer interaction and participant attributes for qualitative coding and later import into SNA software. Because of the specific focus on peer supported learning, postings to or from course facilitators and staff were removed from the data set. Finally, analyses described below exclude more passive forms of interactions (i.e., read and reaction logs), and include only postings among peers.

## Data Analysis

This study employed a mixed-methods approach that uses both SNA with qualitative methods to address the proposed research questions. SNA is a research methodology that seeks to identify underlying patterns of social relations based on the way actors are connected with each other (Scott, 2000; Wasserman & Faust, 1994). Specifically, SNA involves network metrics at the global level (e.g., density, reciprocity, degree distribution) and the individual level (e.g., centrality, node degree). In this study, SNA was used to measure and visualize patterns of interaction. *NodeXL*, a freely available template for Microsoft Excel, was used to calculate basic SNA metrics and create visualizations. In addition, two specialized network techniques were employed to address the first two research questions: blockmodeling and exponential random graph models (ERGMs).

To further examine patterns of peer support, actors in the network were categorized into distinct mutually exclusive partitions using the core-periphery and regular equivalence functions of UCINET. The former used the CORR algorithm to divide the network into actors that are part of a densely connected subgroup, or “core”, from those that are part of the sparsely connected periphery (S. P. Borgatti, Everett, & Freeman, 2002). The latter employs the REGE algorithm to partition actors in the network based on the similarity of their ties to others with similar ties. On the importance of regular equivalence, Hanneman and Riddle (2005) note that “it provides a method for



identifying "roles" from the patterns of ties present in a network, rather than relying solely on the attributes of actors to define social roles." In essence, blockmodeling provides a systematic way for categorizing educators based on the ways in which they interacted with peers.

The exponential family of random graph models (ERGM; also known as  $p^*$  models) provide a statistical approach to network modeling that addresses the complex dependencies within networks. ERGMs were used to model the effects of individual and network attributes on support ties formed between participants. ERGMs predict network ties and determine the statistical likelihood of a given network structure, based on an assumed dependency structure, the attributes of the individuals (e.g., gender, popularity, location, previous ties) and prior states of the network. This study followed the procedure for constructing ERGMs described by Robins et al. (2007) and used statnet, an open-source suite of software packages for R to perform this modeling (Handcock, Hunter, Butts, Goodreau, & Morris, 2008). One common problem with model specification, known as degeneracy, is that parameter estimates can produce networks that are implausible (Snijders, 2011). To prevent model degeneracy, this study used the fixed version of the geometrically weighted terms for popularity spread (gwidegree) and transitivity (gwesp), with lambda set to one (Hunter, 2007; Robins et al., 2007). One limitation of this study is that models that incorporated parameters to assess transitivity, even geometrically weighted ones, still resulted in degeneracy and as a result this relational mechanism could not be modeled.

Finally, this study adopted the interaction analysis model (IAM) to assess the extent to which the interactions among educators resulted in the co-construction of knowledge (Gunawardena, Lowe, & Anderson, 1997). Two independent coders participated in a training session in which they were introduced to the content analysis coding scheme, and an initial codebook with examples from the literature. The session consisted of joint coding by the two coders and the lead author and involved independently coding and then discussing a subset of discussion threads selected by stratified random sampling based on length of discussion threads. All discussions were coded by the two primary coders, and in cases of disagreement, the third coder would assign a code. Discussions in which two out of three coders could not agree were excluded from the analysis. In total, 655 (40% of total) peer postings from DLT, and 232 (31%) from EQP were included in the analysis.

## Findings

### RQ 1. Patterns of Peer Support

Network level statistics provide an overall description of the social network in terms of edge counts and network density, as well as the average measures of actor centrality and reciprocity. Table 1 provides a summary of these measures. As would be expected, the number of replies to peer postings (edges) increases with the number of educators in the network (vertices). Also as expected, graph density, that is, number of unique edges out of all possible edges, decreases in MOOCs with more educators as the number of possible edges increases exponentially with number of vertices. On average, DLT participants had ties to fewer peers as evidenced by both the average edge weight and in/outdegrees.

Table 1

*Overall Network Measures for each MOOC-Ed*

Network metrics	DLT	EQP
Vertices	377	91
Unique edges	1420	361
Edges with duplicates	360	370
Total edges	1780	731
Edge weight avg.	1.29	1.69
Reciprocated vertex pair ratio	0.15	0.15
Reciprocated edge ratio	0.26	0.26
Graph density	0.01	0.06
In/outdegree avg.	4.20	5.44
In/outdegree median	2	3
Indegree range	0-57	0-30
Outdegree range	0-41	0-37

Aside from these differences, some basic patterns can be identified across both MOOC-Eds. Measures of network reciprocity, for example, are fairly similar across the two MOOC-Eds, despite the size and varied composition of educators in each network. Also, both MOOC-Eds demonstrate similar patterns in the distribution of in/outdegree. As illustrated in Figure 1, the majority of educators had support ties with three or fewer peers. There were, however, several individuals in each course with a disproportionate number of ties compared to their peers. These “core” educators will be discussed in more detail below. Finally, the edge weight measure also demonstrates that most ties between educators consisted of a single communication and a general tendency for an individual’s responses to be distributed evenly among peers.

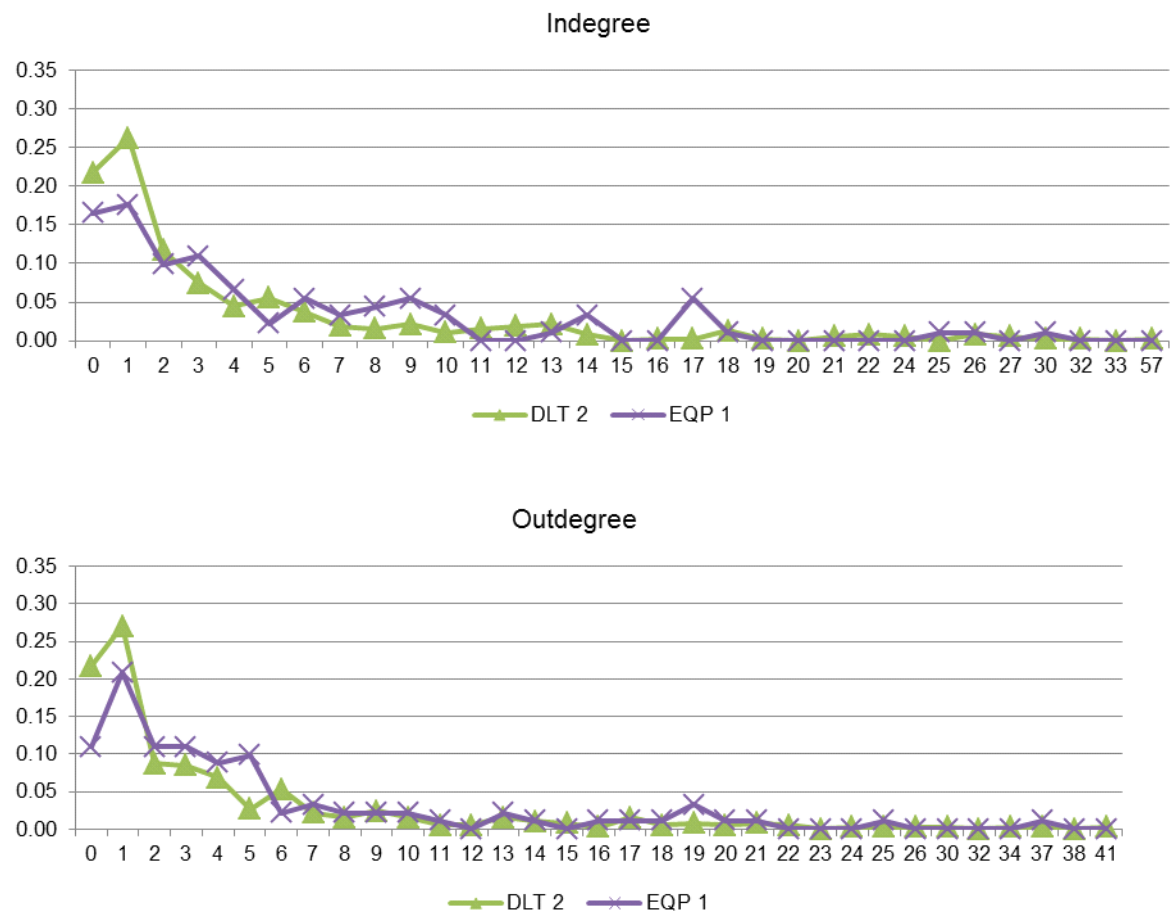


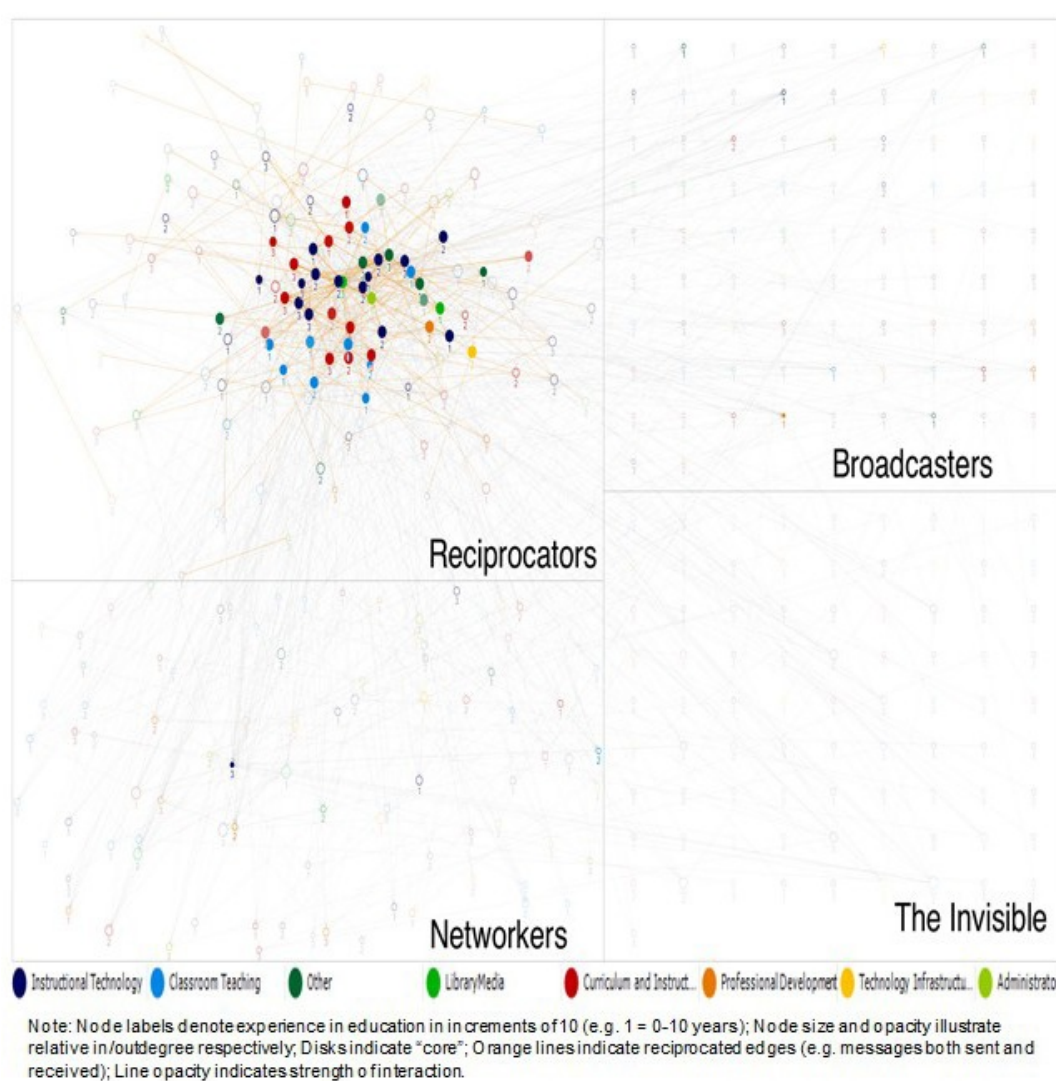
Figure 1. Proportion of outdegree distribution.

Figure 2 illustrates the combined results of these two partitions for the DTL peer support network. Solid discs represent educators identified as core to the network, while circles represent those on the periphery. In addition, all educators are blocked off into the following four simplified categories identified through blockmodel analysis: 1) Reciprocators – educators who participated in at least one mutual exchange as illustrated by the double-arrowed orange line connecting two educators, 2) Networkers – educators who were both the recipients and givers of support, though not with the same individuals, 3) Broadcasters – educators who initiated a discussion thread, but neither reciprocated with those who replied, nor posted to threads initiated by others, and 4) The Invisible – educators who responded to the postings of peers, but received no responses in return. As illustrated by the size of the block in Figure 2 and Table 2, Reciprocators made up the largest proportion of educators in both courses, and nearly all those identified as core to the network belonged to this group.

Table 2

*Percentages of Educators in CORR and REGE Partitions*

	DLT	EQP
<b>Core-Periphery</b>		
Core	13%	21%
Periphery	87%	79%
<b>Regular equivalence</b>		
Reciprocators	34%	36%
Networkers	23%	36%
Broadcasters	22%	11%
The Invisible	22%	16%



*Figure 2.* Sociogram of DLT peer-support network illustrating core-periphery and REGE partitions.

## RQ 2. Mechanisms of Peer Support

ERGM estimation results for the two MOOCs are summarized in Table 3 and show the coefficients associated with each parameter, as well as the standard error. Similar to logistic regression, which predicts a binary variable from a number of predictor variables, ERGMs predict the presence of a network tie from several parameters, with estimates indicating the importance of each to the presence of a tie (Lusher, Koskinen, & Robins, 2012). Estimated coefficients can be thus explained in terms similar to logistic regression. Positive significant coefficients indicate that the corresponding parameters in the observed network (e.g., ties between educators with the same role), controlling for all other parameters in the model, occur more than would be expected by chance, thus increasing the likelihood that a tie will occur, and vice-versa for negative coefficients. Finally, the edges term in the model is equivalent to the number of ties in the observed network and serves the equivalent function of the y-intercept in linear regression (Morris, Handcock, & Hunter, 2008).

For all models and across both courses, the comparatively large significant parameter coefficient for reciprocity indicates a strong effect and suggests that educators are considerably more likely to respond to a peer posting if they have received a prior response from that same peer. The large significant negative coefficient for popularity spread is a little less intuitive to interpret, but Lusher (2012) explains that a large, negative popularity spread, as in this case, indicates that most actors have similar levels of popularity and that the network is not centralized on indegree. Another way to interpret this is that each response an educator receives significantly decreases the probability that an educator will receive an additional response.

Table 3

*Summary of ERGM Model, Estimates and SE*

	DLT		EQP	
	Estimate	SE	Estimate	SE
Baseline (Edges)	-4.50***	0.08	-2.05***	0.16
Structural mechanisms				
Reciprocity	3.43***	0.09	1.80***	0.17
Popularity spread	-3.33***	0.09	-3.38***	0.19
Assortative mechanisms				
Role homophily	0.17**	0.06	-0.01	0.11
Role nodefactor <sup>a</sup>				
Administrator	-0.01	0.06	-0.25	0.14
Curriculum	0.08*	0.00	-0.32**	0.11
Library/Media	0.21***	0.05	--	--
Instructional tech	0.06*	0.03	--	--
Teacher educator	--	--	-0.08	0.06
Tech infrastructure	-0.07	0.07	--	--
Prof. development	0.00	0.05	-0.20*	0.11
Other	0.11**	0.04	-0.05	0.07
Homophily by grade	0.17***	0.04	0.03	0.08
Homophily by gender	0.08*	0.04	0.04	0.04
Experience difference	0.04	0.04	-0.02	0.07
Experience nodefactor <sup>b</sup>				
11-20	-0.01	0.03	0.12	0.07
More than 20	-0.04	0.03	-0.03	0.06
Desire to connect	-0.04	0.03	-0.10	0.09
Proximity mechanisms				
State or country	0.71***	0.08	0.06	0.18
Geographical region	0.05	0.06	-0.18	0.11
Group assignment	0.54***	0.05	--	--
AIC	14847		3353	

Notes. \*  $p < .05$ . \*\*  $p < .01$ . \*\*\*  $p < .001$ .

<sup>a</sup> Classroom Teaching serves as the comparison group

<sup>b</sup> Educators with 0-10 Years of Experience in Education serve as comparison group

Regarding assortative mechanisms, results for homophily by role indicate a positive significant effect in the DLT MOOC, but no effect in the EQP course. This indicates that, in general, if educators shared similar roles it increased the likelihood of a support tie in the former course but not in the latter. When homophily was examined by grade levels worked with (e.g., elementary, high school), as well as by gender, the effects were again positive and significant only in the DLT course, indicating that if two educators worked at the same school level, or shared the same gender, it also increased the likelihood of a tie. A heterophily terms was also added to examine educators' years of experience;

however, the presence of ties between educators with different years of experience found in the observed network were no more than would be expected by chance.

In addition to homophily and heterophily, this model also examined the extent to which educators' professional role, experience, or desire to connect increased the likelihood they would have a support tie with peers in the network, either on the giving or receiving end. The findings suggest that across both MOOCs, one's professional role significantly increased or decreased the likelihood they would form a support tie when compared to classroom teachers. Regarding years of experience and a desire to connect, however, no significant effects were found, suggesting that in both cases, educators with more experience or who expressed a desire to connect were more likely to be involved in a support tie.

Finally, findings for two of the three proximity mechanisms were significant in DLT, but not in EQP. In these two courses, this indicates that educators were more likely to respond to a peer if their school or work location was in the same U.S. state or country, even beyond the effect of being assigned to discussion groups by the first letter of their state or county in DLT. This did not carry over to geographical regions, however. That is, being located in the southern states of Georgia, North Carolina, and South Carolina did not increase the likelihood these educators would respond to each other's postings.

### RQ 3. Co-Construction of Knowledge

Results of the interaction analysis model provide insight into the extent to which discussion resulted in the co-construction of new knowledge. Coding classified each discussion thread into one of the following five categories according to the highest phase reached by the postings within that discussion.

Phase 1 - Sharing and comparing. Further the discussion by providing observations, opinions or examples that support or extend prior statements.

Phase 2 - Dissonance and inconsistency. Identify areas of disagreement or potential disagreement.

Phase 3 - Negotiation and co-construction. Explore common ground, clarify intent, seek agreement or integrate ideas.

Phase 4 - Testing and modification. Test ideas against prior information, research and/or data and proposed synthesis of ideas.

Phase 5 - Summary, application and metacognition. Summarize agreements, describe applications of knowledge or acknowledge changes in understanding.

The data, shown in Figure 3, display the proportions of total discussions by the highest phase reached. In both courses, that vast majority of discussions analyzed either remained at the level of sharing and comparing information, or entered a process in



which dissonance was recognized among peers and process of negotiation or construction began to take place. However, few discussions moved beyond Phase 3.

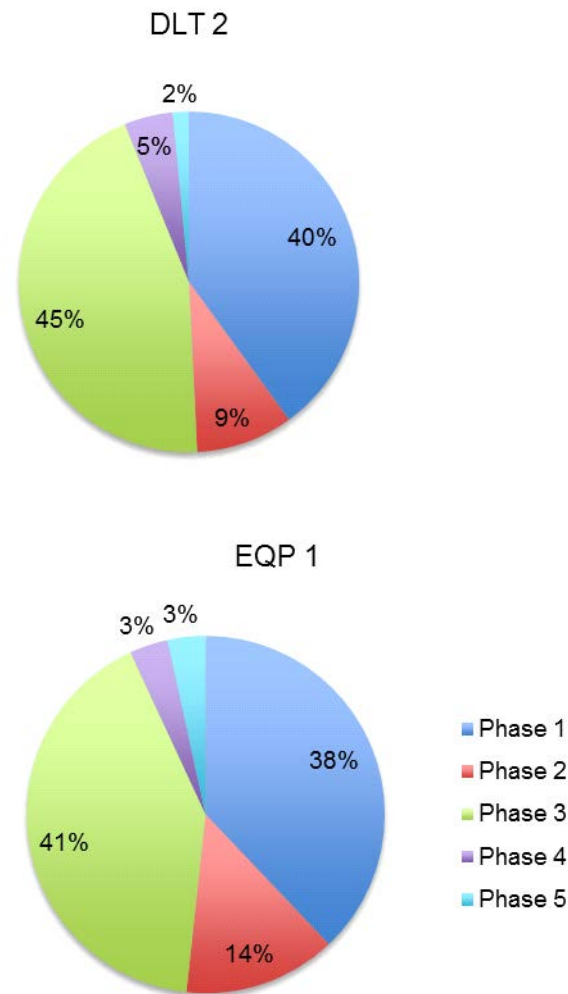


Figure 3. Highest phase of knowledge construction reached by discussion threads.

## Discussion

Wenger, Trayner, and De Laat (2011) describe social networks as “a set of relations, interactions, and connections... with affordances for learning, such as information flows, helpful linkages, joint problem solving, and knowledge creation” (p. 9). This study demonstrates that even with technology as basic as a discussion forum, MOOCs can be leveraged to foster these networks and facilitate peer-supported learning that results in the process of knowledge construction. However, mirroring emerging MOOC findings on steep declines in participation and course completion, both peer networks demonstrate similar drop-offs in the extent to which educators leveraged their peers.

Findings on patterns of peer interaction are characteristic of online social networks in general, in which core-periphery structures, power-law degree distributions, and the prevalence of weak-ties are common (Aviv, Erlich, & Ravid, 2007; Butts, 2008; C. R. Jones, Ferreday, & Hodgson, 2008). In terms of regular equivalence partitions, these results are comparable to the findings by Wasko, Teigland, and Faraj (2009) in two online professional networks of practice. The authors reported that half of the network consisted of “outsiders” who did not receive responses, and “seekers” who received responses but did not reciprocate or pay it forward. Blockmodel analysis, however, failed to fully capture the nuances in patterning of ties. For example, while Broadcasters provided no response to their peers, many received responses from a large number of peers. In contrast, The Invisible, who despite receiving no communications from their peers, consisted of many educators who provided a disproportionately large number of responses. Finally, both Reciprocators and Networkers often skewed either towards a greater indegree or outdegree, that is, they tended to receive more support than they provided, and vice-versa.

Beyond describing the patterns of peer interaction, this study examined mechanisms that shape the structure of these networks. Several theoretical propositions drawn from the literature on social networks, online learning, and social learning perspectives were examined through ERGM analysis. Across both MOOCs, significant effects were found for the relational mechanism of reciprocity, but not for a popularity effect. Of specific interest to this study was the impact of educators’ professional roles and years of experience. Drawing from the communities of practice perspective on social learning (Wenger et al., 2011; Wenger, 1999) it was anticipated that educators in similar professional roles and settings might be more likely to interact based on a shared “domain of practice”, and that less experienced educators might seek out more experienced peers for support. However, evidence for homophily and proximity were only identified in the larger DLT course, and there was no evidence of a mentoring effect in either. The lack of homophily in EQP may be the result of the MOOC-Ed’s unique content focus, creating a specific shared domain of practice while also encouraging interaction across grade levels, negating a need to seek out others in similar roles and settings. The absence of a mentoring effect in both courses, however, may stem from the lack of what Baker-Doyle and Yoon (2010) refer to as “expertise transparency”. That is, with limited information about their peers gleaned from postings or the small handful of completed participant profiles, it may be difficult to identify experts in the MOOC. In a case study of online communities for educators, Booth (2011) suggested that network size and detailed member profiles may have played a role in cultivating knowledge sharing among educators.

Finally, findings on knowledge construction demonstrated that over half of the discussions in both courses moved beyond sharing information and statements of agreement and entered a process of dissonance, negotiation and co-construction of knowledge, but seldom moved beyond this phase in which new knowledge was tested or applied. These findings echo difficulties in promoting knowledge construction online

found by several researchers (Aviv et al., 2003; Heo et al., 2010; Hou & Wu, 2011; Pena-Shaff & Nicholls, 2004). For instance, Gunawardena et al. (1997) found that interactions among conference participants as part of distance education online debate seldom moved beyond the lower phases of sharing and comparing information. Zheng and Spires (2012) found that communication between students in a graduate level education course primarily remained at the lower level Phase I stage of sharing and comparing information despite active facilitation by the instructor. It is tempting to conclude that because so few discussions reached Phase 5, there was little application of shared knowledge to the problems or issues under discussion. However, this may be the result of our interpretation of the IAM coding scheme. Practical strategies and solutions to problems or issues raised during discussion were frequently shared, but these were often coded as Phase I because they did not arise through an explicit process of negotiation and co-construction of new knowledge. Johnson et al. (2008) noted that interaction must be intentionally designed into the learning context or it is unlikely to result spontaneously. The authors of this paper contend that the same is also true for fostering knowledge construction in MOOCs.

The findings from this study also suggest several design implications for future MOOC-Eds. Kraut and Resnick (2012) have proposed numerous design claims intended to encourage contributions and exchanges in online communities, but several stand out for consideration for the design of future MOOC-Eds. Design claim 5 states that simple requests for contributions rather than lengthy or more complex ones lead to greater compliance among those who do not care strongly about contributing. In addition to the more substantive contributions such as reflective discussion prompts or detailed peer feedback, MOOC-Eds should consider providing discussion opportunities which request quick, practical information that would be of use to other educators in the community, such as requests embedded and directly relevant to content and resources provided throughout the course. Design claim 11 also states that participants are more likely to respond to the requests of others, such as with feedback on discussion postings, when they come from others who are familiar to them or more closely resemble them. One simple approach to doing so would be to request participants make public information about their professional experience and personal background gathered from the registration process via their personal profiles so peers can more easily identify each other's professional roles, work context, and experience.

Finally, beyond just facilitating the quantity of exchanges, it is important to ensure the quality of interaction is contributing value to the community. While "quality" interaction can be defined in a variety of ways, Pear and Crone-Todd (2002) point out that meaningful interaction is not just sharing opinions and information, but should stimulate the learners' intellectual curiosity. Likewise, social constructivists do not maintain that all conversation and discussion occurring anywhere anytime are meaningful for learning, but that discussion should be directly relevant to his/her real life and take place within a culture similar to an applied setting (Brown, Collins, & Duguid, 1989). In order to foster meaningful dialogue, Pear and Crone-Todd (2002)

suggest providing guidelines for interaction, while Rovai (2001) stresses the importance of setting expectations for participation, whether in a formal social context such as an online course, or an informal context such as an online community of practice. Future MOOC-Eds will likely need to better scaffold social learning processes in order to fully leverage the potential of peer-supported learning.

Although the scope of this study was naturally constrained by funding and time, these limitations present several avenues for future research. Naturally, generalizations cannot be drawn based on two MOOCs from a single department at a university. Ideally, this study would have been comprised of numerous courses across multiple platforms to compare the networks that emerged and test the robustness of ERGMs used to model peer support mechanisms. In addition, the simplified model presented in this study was designed to examine a few theoretical propositions based on available data in aggregated form. Howison, Wiggins, and Crowston (2011) note that aggregate networks fail to capture temporal dynamics, and that replies in online threaded messages are often not a valid measure of the construct of interest, in this case “peer support”. A more complete model would have included additional relations, such as posts “read” or “liked”, as well as attributes of the postings such as timing, strength, and especially content of the postings. Finally, Edwards (2010) notes a need for a more systematic integration of SNA and content analysis, for “whilst we may divorce form from content, or structure from agency for analytic purposes, it is in that ‘messiness’ of actual social networks that they are always combined...”

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# Massively Open Online Course for Educators (MOOC-Ed) network dataset

**Shaun Kellogg and Achim Edelmann**

Shaun Kellogg is a research scholar at the Friday Institute for Educational Innovation and an adjunct assistant professor in the College of Education at North Carolina State University. His research interests center on the application of learning analytics to improve of K-12 educational contexts and educator professional development. Achim Edelmann is a postdoctoral associate at the Duke Network Analysis Center. He received a PhD in sociology from the University of Cambridge. He specializes in the sociology of culture, network analysis, and social theory. His current research focuses on bridging the structure-culture link in theory and practice, and on contemporary developments in the sociology of science. Address for correspondence: Dr Shaun Kellogg, Friday Institute for Educational Innovation, North Carolina State University, 1890 Main Campus Drive, Campus Box 7249, Raleigh, NC 27606, USA. Email: sbkellogg@ncsu.edu

## Abstract

This paper presents the Massively Open Online Course for Educators (MOOC-Ed) network dataset. It entails information on two online communication networks resulting from two consecutive offerings of the MOOC called *The Digital Learning Transition in K-12 Schools* in spring and fall 2013. The courses were offered to educators from the USA and abroad. Though based on the same course, minor controlled variations were made to both MOOCs in terms of the course length, discussion prompts and group size. The dataset provides opportunities to examine how participants leverage online communication forums to support their learning. In particular, it allows modeling network mechanisms to better understand factors that facilitate or impede the exchange of information among educators.

## Dataset

This paper references the following MOOC-Ed social network analysis dataset:

Title: Massively Open Online Course for Educators (MOOC-Ed) network dataset

Location: <http://dx.doi.org/10.7910/DVN/ZZH3UB>

Creator: Shaun Kellogg, Achim Edelmann

Date: October 30, 2014

Format: Comma Separated Values

Restrictions to use (if any): CC0—“Public Domain Dedication”—Good scientific practices expect that proper credit for use of this data is given via citation.

## Introduction

As an emerging model for online learning, Massively Open Online Courses (MOOCs) present new opportunities and challenges for facilitating learning. In particular, they offer novel forms and new dimensions of social interaction that need to be integrated in our understanding of learning. Social interaction has been identified as a crucial factor in the educational process. Prominent theoretical approaches to learning such as Social Cognitive Theory or Social Constructivism more broadly argue that social interaction and dialogue are critical to successful learning (Bandura & McClelland, 1977; Glassman, 2001; Grusec, 1992; Hung & Der-Thanq, 2001; Johnson & Johnson, 2009). However, it remains an open question as to what extent and in what ways



MOOCs support interactions in educational contexts. Assessing the implications of MOOCs for the digital economy, McAuley, Stewart, Siemens and Cormier (2010) report that MOOCs have the potential to “model and build collaborative networks of unprecedented size that transcend time and space” and the “network ties created between people during a MOOC have the potential to continue as sustainable and relevant personal and professional connections beyond the boundaries of the course itself” (p 35).

The dataset described below provides detailed information on the communications taking place between learners in two such MOOCs, along with relevant characteristics of the participants such as their professional roles or their experience in education. The primary use of this dataset is to enable social network analyses (SNAs) of these communications (Rivera, Soderstrom & Uzzi, 2010). SNA provides a set of analytical tools and statistical techniques to account for patterns in how actors connect with each other (Scott, 2000; Wasserman & Faust, 1994). Although this has opened up novel ways of examining theories and questions in the social sciences more broadly, application of SNA in educational research has remained surprisingly limited despite obvious advantages.

As McFarland, Diehl and Rawlings (2011) point out, the statistical methods educational researchers have historically used to study the context of learning rest on assumptions such as statistical independence and normality that run counter to available evidence that “presents classrooms as complex interdependent social environments” (p 90). In contrast, SNA offers statistical methods to adequately account for these complex interdependencies in interaction processes. For example, exponential random graph models (Snijders, Pattison, Robins & Handcock, 2006; Wasserman & Pattison, 1996) can be used to appropriately model various social selection processes such as homophily, reciprocity and triadic closure that shape the structure of social networks (Hunter, Handcock, Butts, Goodreau & Morris, 2008).

However, Carolan (2013) notes, only few scholars have applied such techniques in research on educational processes, partly because we lack appropriate data. This is especially the case with regard to new forms of online education. Being able to apply network analytical techniques to such settings requires a particular form of empirical data. In particular, data must sufficiently capture the structure of social interactions by identifying who communicated with whom and how often. The dataset presented here is intended to help fill this gap. It was specifically created for describing communication patterns and modeling network processes in MOOCs created for educators in order to better understand factors that facilitate or impede the exchange of information and resources among participants (Kellogg, Booth & Oliver, 2014). However, it is suitable for academics and researchers interested in network processes in online learning communities more generally. For example, it allows tracing the ebb and flow of communications over time, analyzing the impact of offline proximity on online communication dynamics or the building of cohesive subgroups within the student community. This might help to improve the design of future courses for online learning.

### **Context of dataset**

In spring 2013, the Friday Institute for Educational Innovation at North Carolina State University launched the Massive Open Online Course for Educators (MOOC-Ed) Initiative. MOOC-Eds are designed specifically for professional educators and follow the guidelines for effective professional learning and a special set of design principles: multiple voices, self-directed learning, peer-supported learning and job-connected learning (Kleiman & Wolf, 2015). MOOC-Eds have similarities with and differences from both the structured learning experience of xMOOCs, and the community-oriented aspects of cMOOCs.

xMOOCs are typically online versions of traditional university course formats in which knowledge is delivered from the teacher to the students in the form of lectures, curated resources and



assignments (Haggard, 2013). Like xMOOCs, MOOC-Eds provide a curated set of resources around predefined topics in a centralized learning platform. They also provide structured activities for engaging with this content including assignments and projects.

In contrast, cMOOCs follow a “connectivist” design principle and their core pedagogical model is peer learning. They allow and actively promote communication between teachers and students in various forms. Learning takes place in communities of students and experts, and may be distributed across multiple learning platforms such as blogs, social networking sites and discussion forums. Like cMOOCs, MOOC-Eds are purposefully designed around multiple voices and the exchange of multiple perspectives among educators, students and other experts. Crucial to MOOC-Eds, thus, is the inclusion of activities and online discussion that facilitate the exchange of ideas and experiences among peers.

A typical unit in a MOOC-Ed consists of a short video introduction to the topic, followed by a set of core and supplementary resources (eg, videos from other perspectives, case studies, articles, reports, etc) with embedded opportunities for peer interaction to explore the topic further. To stimulate interaction, the two course instructors regularly engaged with participants. Group spaces within the forums were created based on participants’ locations or professional roles to enable focused discussions. The course also includes a small project and peer feedback on submitted projects.

The MOOC-ED initiative was launched with a 6-week online course called *Planning for the Digital Learning Transition in K-12 Schools*. The aim of this course was to help school and district leaders plan and implement K-12 digital learning initiatives. Specifically, the goals of this course were to help educators understand the potential of digital learning in K-12 schools; assess progress and set future goals for their school or district; and begin to develop a plan to achieve their digital learning goals. The course was divided into five units: (1) Envisioning Schools of the Future; (2) Changing the Culture of Teaching and Learning; (3) Elements of a Successful Digital Learning Transition; (4) Leading the Transitions; and (5) Crowdsourcing Feedback, Lessons and Resources.

In autumn 2013, the course was offered a second time in a slightly modified version. The course was expanded to 8 weeks to allow more time to complete assignments and the course project, and modifications were made to the forums to facilitate discussion. Specific changes include: the addition of an online “role-call” asking participants to introduce themselves to their peers at the beginning of the course, replacing low-interest discussion questions, a slight change to initial groups and simplified guidelines for providing feedback on participant projects shared in the forums. The dataset was created from the first two iterations of this course, and is described in more detail below.

### **Description of dataset**

The dataset presented here includes individual characteristics of participants who posted at least once in the online forums as well as information on the online communications between those participants. Individual characteristics were provided by participants on the course registration form. Communications were constructed by a query of the MySQL database that recorded participants’ user-logs of activity in the online forums. In particular, the initiator of a discussion thread was identified as the default recipient of all responses in that thread unless comments were explicitly directed at other comments/participants in the thread. We also identified postings that were directed at comments/participants other than the originator of the thread, based on two criteria: First, whether someone other than the originator of the thread was referenced using the forum’s “quote” feature, and second whether the comment explicitly entailed the name of participants previously commenting in the thread. To ensure the accuracy of this process, all comments identified as entailing either quotes or the names of previous commentators were visually

Unit 2/3 Discussions &gt; Group N-Z &gt; Changes in what, how, when and where students learn?

## How would you change how, when, and where students learn?

I in [Changes in what, how, when and where students learn?](#)

How would you like to see how, when, and where students learn for the students in your school or district? What great examples of this have you seen?

J

I want learning to be 24/7. I want it to be individualized for each child. I want students to understand that learning is a life-long constantly occurring process. Digital learning has the potential to allow this to happen. We have to break down the barriers of school buildings, grades, traditional calendars, traditional times for learning, even the traditional classroom. As my school begins the one to one initiative for our students, the energy and excitement about learning is contagious. Teachers are letting go of their lead in front of the classroom role and letting students take more control of their learning and teaching others. They are gradually becoming facilitators of learning instead of traditional whole group instruction teachers. The transformation is amazing to witness and opens up numerous learning possibilities for our students. The idea of students having a screen up on their desk, table or floor does not bother me as much as how they are using that tool to help them learn what they need to learn and having the appropriate skills to use technology effectively to become the best student that they can be.

N

I agree that this is a necessary move. A challenge is getting teachers to let go of that control. So many are worried about time to cover the curriculum and assessment scores. What they fail to realize is scores will go up and the will cover the curriculum in a much deeper fashion. It opens a whole new world of exploration.

B

N said:

I agree that this is a necessary move. A challenge is getting teachers to let go of that control. So many are worried about time to cover the curriculum and assessment scores. What they fail to realize is scores will go up and the will cover the curriculum in a much deeper fashion. It opens a whole new world of exploration.

N – I agree that one of the challenges will be the lose of control that some teachers feel. Some teachers fear that they will not be able to answer student questions in this move to student-centered/project based facilitator role. This actually opens a huge door for the students to "teach the teacher" which means everyone is learning at a much deeper level.

Figure 1: Reply to a discussion comment

inspected. To illustrate this process, consider the beginning of a discussion thread between I, J, N and B in Figure 1. The thread was initiated by I, which thus represents the default recipient of all comments in this thread. Accordingly, the comments by J and N are considered to be directed at I. The comment of B, however, is a direct response to the comment by N as signaled by the use of the quote-feature as well as the explicit mentioning of N's name within B's comment.

Table 1: List of node and edge attribute data for both networks

Variable name	Description
Node attributes	
UID	Unique identification number of course participants
Instructor	Identification of course facilitator (1 = instructor)
Role	Professional role (eg, teacher, librarian, administrator)
Experience	Years of experience as an educator
Grades	Works with elementary, middle, and/or high school students; note: “generalists” signals a combination of two or more grade levels
Location	US state or non-US country
Group	Initial assignment of discussion group
Gender	Male, female
Expert	Identifier of “expert panelists” invited to course to share experience through recorded Q&A; (1 = expert panelist)
Connect	Dummy whether participants listed networking/collaboration with others as one of their course goals on the registration form
Edge attributes	
Sender	Unique identifier of author of comment
Receiver	Unique identifier of identified recipient of comment
Timestamp	Time comment was posted
Parent	Primary category or topic of thread
Category	Subcategory or subtopic of thread
Thread_id	Unique identifier of a thread
Comment_id	Unique identifier of a comment

Table 2: Basic descriptive characteristics of both networks

	Network 1	Network 2
Directed	Yes	Yes
Nodes	445	492
Isolates	3	66
Density	0.98%	0.85%
Mutual dyads	212	285
Asymmetric dyads	1512	1492
In-/Outdegree	min = 0/0, max = 273/74, mean = 4.35	min = 0/0, max = 184/132, mean = 4.19
Tie-frequency	min = 0, max = 15, mean = 1.26	min = 0, max = 12, mean = 1.24
Network centralization	0.38	0.27

The data are stored in two files for each of the MOOCs: a node attribute file and a network edgelist. Both files are in csv-format, with variable names in the headers. The node attribute file contains individual characteristics of participants (nodes). The second file entails the network data in an edgelist format. Each row signifies an online communication (edge) with the corresponding “sender,” “receiver” and further attributes of the communication listed across the columns. A description of variable names, as well as basic descriptive statistics of each network, is provided in Tables 1 and 2 respectively.

### Limitations

The dataset provided is limited in several ways. First, the actual text of the online communications is not included due to the extensive cleaning that would be required to ensure participants’ anonymity. Second, the dataset includes only participants who posted publicly in the course

forums and excludes those who viewed discussions but did not post themselves, or only sent or received messages privately. Finally, due to our coding decision, comments might erroneously be treated as directed to the originator of a thread if participants did not explicitly name or quote the intended recipients.

### Statements on open data, ethics and conflict of interest

The collection, processing and analysis of this data was sponsored by Athabasca University as part of the MOOC Research Initiative and supported through funding from the Bill and Malinda Gates foundations (award number: C00009135V3). This data is hosted on the Harvard Dataverse Repository and made available under the Creative Commons CC0 Public Domain Dedication. For more information on the CC0 waiver, please visit the Creative Commons website at <http://creativecommons.org/about/cc0>. Dataverse Community Norms (<http://best-practices.dataverse.org/harvard-policies/community-norms.html>) as well as good scientific practices expect that proper credit is given via citation for use of this data.

This study and the dissemination of data and findings from this study were approved by Institutional Review Board for the Use of Human Subjects in Research at North Carolina State University (IRB Number: 3413). In addition, the MOOC-Ed Privacy and Terms of Use (<https://place.fi.ncsu.edu/mod/page/view.php?id=395>) made clear to participants that participation was completely voluntary; that personal information such as name or email address provided would not be released, sold or rented to any entities or individuals outside of the MOOC-Ed project; and that they granted the Friday Institute nonexclusive, royaltyfree, license to use, reproduce, distribute and display content they created in connection with the MOOC-Ed. There is no conflict of interest in the dissemination of data presented in this paper.

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