Building a Team Leadership Index Through Computational Methods

Kui Xie, Gennaro Di Tosto, and Lin Lu
xie.359@osu.edu, ditosto.1@osu.edu, lu.962@osu.edu
The Ohio State University

Abstract: To help monitoring and controlling the latent social dynamics associated with leadership, we test a methodological approach that makes use of computational techniques to mine the content of online communications and analyze group structure to identify students who behave as leaders. The results allow us to quantify each individual's contribution and summarize their engagement in the form of a leadership index. The proposed methodology is fully automated and has the potential to be easily replicable. The summary offered by the leadership index is intended as actionable information that can guide just-in-time interventions to help sustain student engagement.

Introduction

As pedagogical models for supporting online collaborative learning, structured tasks and peer-moderated online discussions have shown unique benefits (Rovai, 2007). Students often assume leadership roles to facilitate discussions. They can positively affect the dynamics in their groups by engaging with participants, raising questions and advancing problem solving (Zha & Ottendorfer, 2011). The social dynamics in peer-moderated online discussions are complex. For example, student leaders can be appointed officially by the instructor (e.g., Xie, Yu, & Bradshaw, 2014) or can emerge through group interactions (e.g., Wickham & Walther, 2007).

However, because students in online educational settings are often physically isolated, these complex processes are often latent and not explicitly observed (Xie, Lu, Cheng, & Izmirli, 2017). This makes the assessment of leadership in online group learning critical yet challenging. While some literature has portrayed team leadership as a set of personal traits (e.g., beliefs, attitude, self-efficacy, and identity), this study focuses on how leadership is manifested through engagement, communication and interaction. In online learning settings, learners exercise their leadership by initiating conversations, setting group goals, moderating discussions, managing conflicts, monitoring project progress, and evaluating team products (Chang & Lee, 2013). In addition, leadership is often distributed among group members and evolves through members' active participation in group processes (Spillane, 2005). Even when some specific learners are formally assigned a leading role, others may also play informal leadership roles. This shared and distributed perspective directs us to look for the locus of leadership through learners' behavior and interaction, rather than their individual mental perceptions.

Research on leadership, though, has relied heavily on students' self-reporting (e.g., Chang & Lee, 2013) or on other qualitative approaches (e.g., Gressick & Derry, 2010) which have methodological and practical limitations (Greene, 2015). Data tracked in technology-based learning systems afford powerful new analytical approaches to uncover the complex processes of group learning interactions (e.g., Xie, Miller, & Alison, 2013; Baker & Inventado, 2014). We propose the adoption of a computational approach, based on natural language processing (NLP) and social network analysis (SNA), for the detection of leadership in peer-moderated online collaborative learning.

Study aim

We aim to develop a quantifiable index of team leadership through the mining of corpus data and log data recorded in an online discussion system. Therefore, we situate the definition of leadership in the context of peer-moderated online discussions, specifically referring to the individual contributions made online and their effect on group structure. Starting from the analysis of the messages logged into the digital forum of an online course, we developed and tested computational techniques capable of identifying patterns of interactions associated with messages that display elements of leadership.

Our objective was twofold: to design a methodology easy to automate and deploy in multiple contexts and to combine our analysis into a single outcome index, capable of reflecting a quantitative summary of students' leadership behavior and providing actionable knowledge for group instructors to sustain students' engagement. The following research questions guided the design of this study: (a) To what extent can data mining extract linguistic features to detect leadership in order to minimize human intervention? (b) To what extent can social network analysis model leadership at an individual level? (c) To what extent does our computational approach provide evidence of emergent leadership?

Context

Participants were 57 students (gender: males 11, females 46; age: min 19, max 53, median 29) from four sections of a mixed-level course at a university in the Southeastern United States. A majority of participants were majoring in education-related disciplines, and their distribution by academic level was: freshmen 4 (7.0%), sophomores 6 (10.5%), juniors 18 (31.6%), and seniors 29 (50.9%). They reported their ethnicity as follows: White 31 (54.4%), African-American 21 (36.8%), and Other 5 (8.8%).

This 16-week course was offered entirely online and presented students with discussion topics drawn from issues related to technology integration in K-12 education. The four sections were taught by the same instructor and followed identical learning procedures. Student-led weekly discussions were the major class activities. In each discussion session, up to two students were appointed as moderators. They designed discussion questions around the topic of the module, while the rest of the class followed instructions designed by the appointed moderators and participated in asynchronous online discussions. Every student was given an opportunity to lead a discussion session during the semester. The instructor facilitated the first week discussion; students led the remaining ones.

Methods

To address our research questions, we analyzed student online discussions recorded in the university learning management system (LMS). The metadata and text content from 4,083 forum posts constituted the starting input. Data analysis involved two steps, each with its own computational technique.

The first analytical step sought to identify and enumerate interactions that exemplify leadership behavior by processing students' posting content. To that end, we adopted supervised learning techniques based on natural language processing (NLP) to classify posts in two categories: leader messages and generic discussion messages. Leader messages have the function of moderating interactions, facilitating discussion, or eliciting participation from others. They were identified in one of two ways: (1) automatically, assuming that online contributions made by appointed moderators contain leadership elements (term-based condition); (2) manually, by three researchers, who independently reviewed a random sample of posts and labeled them as either leader or generic messages using their best judgement until unanimity in the coding was obtained (label-based condition). As a result, two balanced datasets were generated, and we refer to them respectively as term-based coding and label-based coding. These datasets were then used to train two binary classifier models, a Logistic Regression model (LR) and an Adaptive Boosting model (AdaBoost), which were applied to probabilistically predict the likelihood of each of the remaining posts to belong to the class of leader messages.

The second analytical step studied leadership as a personal characteristic displayed by students in their interactions. With leader messages resulting from the previous step as input, we used social network analysis (SNA) to quantify the influence students had when communicating with their peers and to define their structural relationship. The influence of actors in a social network is a function of the number of connections they have, i.e. their centrality—with eigenvector centrality being a widely-adopted version of this measure and Katz centrality (Katz, 1953) an established variation particularly suited to our domain, characterized by asymmetric networks with a relatively small number of nodes. Our leadership index, a measure useful in ranking students' contribution to peer-moderation, is therefore built on Katz centrality values in weighted directed networks connecting the senders and the recipients of the forum posts identified as leader messages.

Findings

The NLP modules processed a feature vector matrix containing 1,305 posts of appointed moderators and regular participants with 3,592 unique words as features. The datasets were split into a training set (90% of the entire data) and a testing set (remaining 10%). Ten-fold cross-validation was applied to both LR and AdaBoost models. Accuracy, precision, recall, and F1-measure were measured to evaluate the performance of training and testing steps across the *term-based* and *label-based coding* conditions (see Table 1).

Table 1: Comparison of coding conditions in the categorization of students' forum posts

	Term-based coding		Label-based coding	
	Logistic Regression	*AdaBoost*	*Logistic Regression*	*AdaBoost*

Cross-Validation	Accuracy	0.702	0.568	0.799	0.688
	Precision	0.677	0.613	0.808	0.808
	Recall	0.750	0.585	0.750	0.583
	F1-Measure	0.712	0.599	0.778	0.678
Testing	Accuracy	0.671	0.718	0.860	0.797
	Precision	0.747	0.762	0.912	0.857
	Recall	0.635	0.686	0.838	0.727
	F1-Measure	0.686	0.722	0.873	0.787

The *label-based condition* outperformed the *term-based condition* across both LR and AdaBoost, indicating that a set of *leader* messages in the first dataset contains more unique linguistic patterns associated with leadership than those in the latter dataset. These results are well within our expectations, since manual coding required intensive labor. More interesting for our purposes, though, the promising performances in the *term-based coding* condition justify our assumption that an exogenous factor, such as the mechanism of peer-moderation adopted in our online course, affects student behavior in a consistent way.

Social network analysis (SNA) was subsequently used to identify individuals who were central to the network structure and to compare their engagement with that of appointed moderators. Senders' and recipients' information was used to visualize the leadership patterns for each weekly discussion as recorded by the LMS. The probabilistic output of the LR model developed in the previous step was applied to weight the edges in the graph, converting communication networks into leadership networks. Our results highlight that appointed moderators, although influential, are not always the most central nodes. As demonstrated in all networks derived from logged interactions, other students emerge as leaders, and SNA can help bring them into focus: they are the emergent leaders our approach aims to identify.

To test the validity of the computational approach, we compared classifications determined through the term-based and label-based coding conditions. We found a positive correlation between the average leadership index obtained by each student in these coding conditions: r = .776, t (50) = 8.704, p < .05, which indicates that the two conditions are able to capture similar relationships among students. However, term-based coding, which does not require the intensive manual coding of the label-based condition, can provide automatic and real-time feedback and is therefore preferable. We also looked at correlations between leadership index and engagement measures derived from the trace data aggregated at the week level. Table 2 provides the descriptive statistics and the correlation coefficients. In general, students' leadership index was significantly correlated with their engagement measures. These results align with findings from the literature, which suggest that team leaders often exercise their influence through active interactions and communications (Xie, Yu, & Bradshaw, 2014).

Table 2: Descriptive Statistics of Weekly Engagement and Correlations (N=365)

	Mean	*Std. Dev.*	*Min*	*Max*	*Correlations with Leadership Index*
Leadership index	1.125	. 135	1	2.082	
Number of posts	9.542	6.413	1	50	.639*
Number of replies	8.933	6.175	0	42	.623*
Length of posts (character)	5816.121	4152.379	350	27332	.425*
Topics started	.610	1.183	0	8	.215*
Topics read	22.421	17.516	2	115	.420*
Length of logins (second)	20134.24	16122.25	3189	144997	.535*
Times of logins	90.236	67.634	8	430	.098

The leadership index also allowed us to study emergent leadership over time, observing how students responded to being appointed moderators and clustering students based on their recorded patterns of leadership to further highlight specific profiles. Using the *leadership index* scored during the week they were appointed peer-moderators as reference point, students were grouped in five clusters, according to the gap-statistics (Tibshirani, Walther, & Hastie, 2001). Patterns in the response to the mechanism of moderation appointment are clearly visible: some students were only affected while acting as official moderators (cluster 2); others appeared to carry over that behavior after their turn (cluster 4), while cluster 3 displayed leadership before and up to moderation week, but disengaged from activities after; clusters 1 and 5 represent students with consistently low and consistently high leadership. This shows how leadership is a social and developmental process and students develop their leadership in a variety of ways (Emery, Daniloski, & Hamby, 2011).

Conclusions

This study examined student participation in structured tasks and peer-moderated online discussions as recorded by one course LMS and proposed a novel measure to detect leadership in group learning. Our findings underscore the dynamic nature of leadership behavior, the result of both an explicit mechanism of appointment to moderating roles and social dynamics emerging from student interactions. The derived *leadership index* is the output of a methodology designed to minimize human intervention. Analyzing different linguistic patterns in the context of peer-moderated collaborative learning, the resulting classification performs comparably to one produced by three researchers manually coding samples from the dataset, a conclusion that highlights the reproducibility of this kind of study in the broader framework of learning analytics.

The *leadership index* is also intended as actionable information, suitable to be incorporated in learning management systems to enhance their reporting and analytical features. A simple but timely signal of the degree to which a student engages in online discussions could constitute the basis for interventions aimed at helping teachers to retain and sustain student participation. Our presentation will discuss directions for future research and the implications of this approach for the fields of learning analytics and online education more broadly.

References

Baker, R. S., & Inventado, P. S. (2014). Educational Data Mining and Learning Analytics. In J. A. Larusson & B. White (Eds.), *Learning Analytics* (pp. 61–75). New York, NY: Springer New York.

Chang, W. L., & Lee, C. Y. (2013). Virtual team e-leadership: The effects of leadership style and conflict management mode on the online learning performance of students in a business-planning course. *British Journal of Educational Technology, 44*(6), 986-999.

Emery, C., Daniloski, K., & Hamby, A. (2011). The reciprocal effects of self-view as a leader and leadership emergence. *Small Group Research*, *42*(2), 199-224.

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist*, *50*(1), 14-30.

Gressick, J., & Derry, S. J. (2010). Distributed leadership in online groups. *International Journal of Computer-Supported Collaborative Learning*, *5*(2), 211-236.

Katz, L. (1953). A new status index derived from sociometric analysis. *Psychometrika*, *18*(1), 39–43.

Spillane, J. P. (2005, June). Distributed leadership. In *The educational forum* (Vol. 69, No. 2, pp. 143-150). Taylor & Francis Group.

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *63*(2), 411–423.

Wickham, K. R., & Walther, J. B. (2007). Perceived behaviors of emergent and assigned leaders in virtual groups. *International Journal of e-Collaboration, 3*(1), 1-17.

Xie, K., Lu, L., Cheng, S.L., & Izmirli, S. (2017) The interactions between facilitator identity, conflictual presence, and social presence in online collaborative learning. *Distance Education. 38*(2), 230-244.

Xie, K., Miller, N.C., & Allison, J.R. (2013). Toward a social conflict evolution model: Examining the adverse power of conflictual social interaction in online learning. *Computers and Education, 63*, 404-415.

Xie, K., Yu, C., & Bradshaw, A.C. (2014). Impacts of role assignment and participation in asynchronous discussions in college-level online classes. *The Internet and Higher Education, 20*, 10-19.

Zha, S., & Ottendorfer, C. L. (2011). Effects of peer-led online asynchronous discussion on undergraduate students' cognitive achievement. *American Journal of Distance Education*, *25*(4), 238-253.

