Design of machine learning powered visualizations to support rapid assessment of online student discussions

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Abstract: This paper reports on the design of machine learning powered analytic visualizations to support instructors in rapidly assessing student behavioral and cognitive engagement in online discussions. We used Chi's (2009) Interactive-Constructive-Active-Passive framework to assess cognitive engagement and social network analysis to assess behavioral engagement. We used the Long-Short-Term-Memory (LSTM) model to automatically classify discourse data. The model was trained based on 4000 human-rater coded posts and despite imbalanced data, the model shows relatively high accuracy. Three use case scenarios of the visualizations show that network and discourse analyses together support the instructor in ascertaining students' cognitive and behavioral engagement. Next steps for addressing model accuracy and improving visualizations are presented.

Introduction

This project emerged from our experiences as designers and facilitators of online higher education courses. We wanted to understand how to support the design of effective online experiences that foster interaction between students, instructor, and content. Interaction is a critical component of learning (Vygotsky, 1978) and in computer-supported collaborative learning (CSCL), social interaction is critical to participants' construction and negotiation of shared understanding and increased student engagement (Stahl et al., 1995). Engaging students in collaborative interaction is a complex task requiring instructor guidance (Kreijns et al., 2013). However, it is challenging for instructors in online courses to quickly assess large amounts of discourse and pivot their pedagogical design. We present an initial prototype of a learning analytics dashboard that aims to provide instructors with rapid insight into student engagement and interaction in online discussions.

Interaction and engagement in online environments

Engagement and interaction are key to the design and process of online learning. We use the term "engagement," which has behavioral, emotional, and cognitive components (Fredricks et al., 2004). Student engagement positively affects achievement of learning outcomes, and engaged students are more likely to learn in multiple ways and interact with peers and teachers (M. Wang & Kang, 2006). Behavioral engagement can be measured by student actions such as posting on discussion forums and accessing content. Cognitive engagement is broadly construed as students' investment of effort to master complex ideas and skills (Fredricks et al., 2004). Chi (2009) proposed the Interactive-Constructive-Active-Passive (ICAP) cognitive engagement assessment framework that classifies learning activities into a taxonomy where passive is at the lowest level of the framework and interactive at the highest. The ICAP framework has been applied in various learning settings (Menekse et al., 2013; X. Wang et al., 2015), is effective in differentiating learning activities and predicting performance, thus making the framework useful for instructors to evaluate cognitive engagement.

Pivoting pedagogical or learning design to sustain engagement

By capturing student engagement, we hope to support instructors in providing student feedback and modifying their pedagogical design. Timely and good feedback is essential for sustaining learning engagement (Alemayehu & Chen, 2021), and instructor guidance is important for learner outcomes (Ma et al., 2015). Assessing student interactions and discourse in CSCL is complex, and teachers require support in monitoring multiple groups and their dialogic strategies (Hu & Chen, 2021). The integration of artificial intelligence, data mining, and visual learning analytic tools holds great promise for helping instructors and students to examine and reflect on behavioral and cognitive engagement in the course (Hu & Chen, 2021). In this work, we identified the pedagogical intent behind learning activities and designed analytic visualizations to inform learning design (Jivet et al., 2018). Aligning learning design to learning analytics requires active consideration of the pedagogical context when interpreting analytics (Bakharia et al., 2016), and the instructor is central in making decisions based on analytics.

Design of visualizations and context

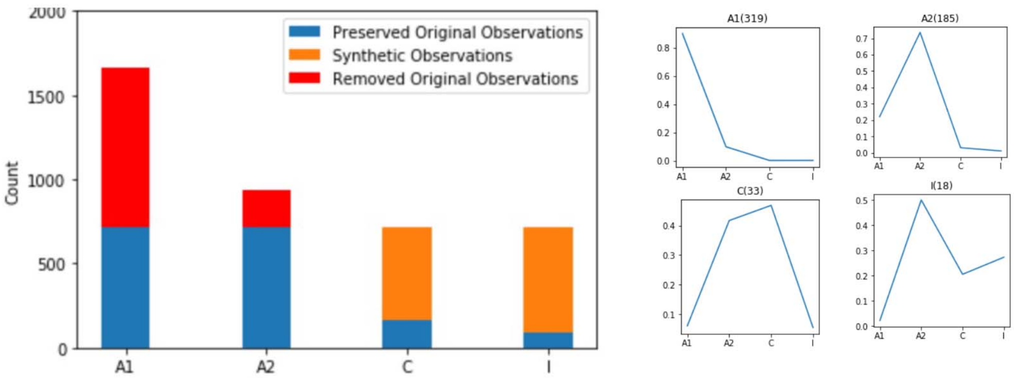
We focused on one instructor as a stakeholder to design and refine prototypes of our visualizations. The context was an undergraduate information sciences and technology course within a large northeastern university in the US. Multiple course sections enrolling 50 students each are offered each semester. Our focus was to support the instructor in making data-informed decisions about the quality of student engagement and collaborative discussion in the online sections. We developed two modules to visualize student behavioral and cognitive engagement. For behavioral engagement, we developed sociograms based on network analyses of student discussions, and for cognitive engagement, we designed a chart displaying cognitive engagement levels for each student in the discussion. A key feature underlying the visualizations is a machine learning model which uses deep learning algorithms, specifically Long-Short-Term-Memory (LSTM), to analyze discourse quality based on an adapted version of the ICAP framework. We removed the passive category (not easily visible online) and created two categories of active for content-related talk (A2) or general course talk, including assignments, schedules, etc., (A1). In constructive talk, learners explained, elaborated, or provided new information related to class content. Interactive talk showed substantial dialoguing and building on contributions or artifacts of other learners.

Development and refinement of a Deep Learning Model

We developed and refined the deep learning model over multiple iterations of data collection, human rater coding, and model training. Two human raters coded approximately 4000 posts collected over two years from the information technology course and together assigned one final code for each student post. Off-topic posts were removed, with a remaining total of 2852 posts coded as follows: A1 (1666, ~60%), A2 (932, ~32%), C (166, ~5%), and I (87, ~3%). Oversampling techniques are usually used to compensate for insufficient information from unbalanced data. SMOTE (Synthetic Minority Over-sampling TEchnique) (Chawla et al., 2002) was used to create synthetic observations for unrepresentative categories (Figure 1). Our model reached an 85% accuracy rate with better performance on A1 and A2 categories. Its performance on C and I categories was weaker because of the lower sample size (Figure 1). We plan to continue data collection for training the model with better discriminatory features of discourse between A2, C, and I discourses.

Figure 1

Rebalancing training set with SMOTE and classifier performance at each class



Sample use case scenarios

In this section, we present three cases that show how social network and cognitive engagement visualizations can support an instructor's understanding of student engagement in online discussions. These cases are based on data collected over two years.

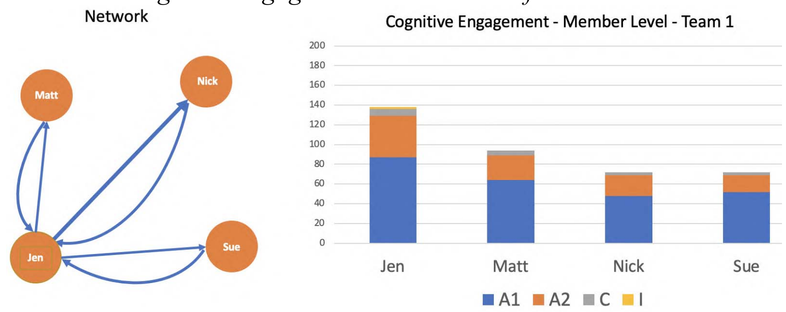
Use case for team 1

Visualizations generated from online discussions of team 1 (Figure 2) suggest that Jen is most active with many posts at the A1 and A2 levels, but proportionally more C and I messages. Matt, the second most active member, posted about two-thirds of the messages that Jen posted. Most messages sent by Matt were also at the A1 level, with some content related (A2) posts and only two interactive posts. Nick and Sue posted about half as much as Jen with mostly A1 posts, and only three messages classified as constructive. The high proportion of AI messages suggests the team engaged in course-related talk that didn't reference content. When referencing content, the team primarily paraphrased or identified existing course resources (A2). The low occurrence of C and I categories suggests that the team did not propose new ideas or challenge their group members' ideas. The sociogram offers potential insight into this low level of team engagement and shows that only Jen was connected to all other group members, whereas Matt, Nick, and Sue were not connected to each other. Jen appeared to dominate the discussion.

Using these visualizations, the instructor can suggest strategies to engage students in more constructive and interactive behaviors and prevent one member from dominating the discussion. For example, students can be asked to analyze the problem task individually, share their ideas about the task with the team without dominating the discussion, and elaborate on or challenge their group members' ideas (Interactive engagement).

Figure 2

Behavioral and cognitive engagement visualizations for team 1

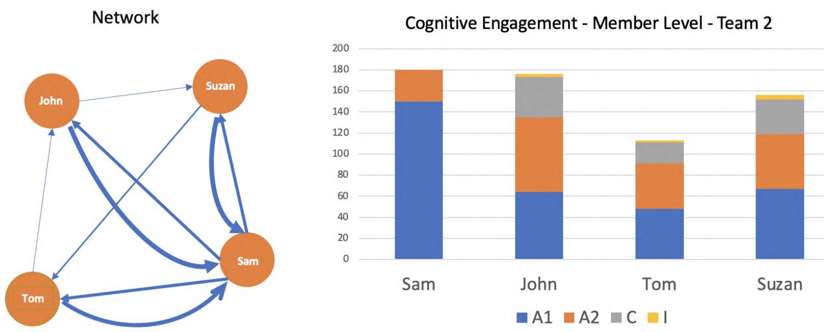


Use case for team 2

In team 2, three members, John, Tom, and Suzan, posted primarily A2 and A1 messages (Figure 3). They had a higher proportion of C messages, compared to Team 1, which means that they went beyond the content presented in course materials and proposed new ideas. However, low numbers of I messages posted by these students suggest that engagement with their peers' ideas was very limited, which is confirmed by the network diagram that shows loose connections among Tom, John, and Suzan. All had a strong connection with Sam who appeared to dominate the discussion. More than two-third of Sam's messages are classified as A1, and none of his messages was classified as C or I. He seemed to coordinate group discussions without adding much content-related talk. Based on the visualizations, the instructor can develop strategies that encourage John, Tom, and Suzan to build on each other's ideas to advance them, which may lead to a new interaction pattern within the team that can also help Sam to be more constructive.

Figure 3

Behavioral and cognitive engagement visualizations for team 2

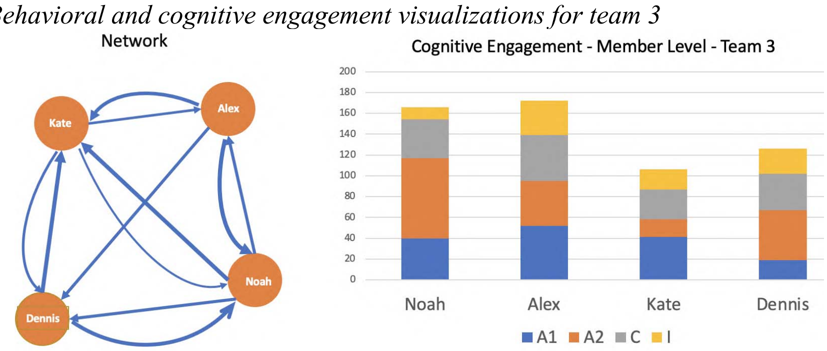


Use case for team 3

Figure 4 shows visualizations generated for Team 3, which illustrates an ideal case of interaction and engagement.

Figure 4

Behavioral and cognitive engagement visualizations for team 3



The four students interacted with each other and built on each other's ideas. Students did not post only A1 messages; all of them either proposed new ideas or elaborated on existing ones (C) and built on their peer's contributions (I). The network visualization further supports this perspective showing that all team members were connected and interacted with each other, with no apparently dominant members as visible in Teams 1 and 2. In such a case, the instructor can provide supportive feedback and reinforce the positive cognitive and behavioral engagement illustrated by team members.

Next steps

We will continue improving the accuracy of the deep learning model and creating more robust and useful visualizations to support the instructor. We continue to collect and code data to oversample *constructive* (C) & *interactive* (I) codes and compensate for the current data imbalance. Bias encoded in data is one of the primary reasons influencing fairness in machine learning (Chouldechova & Roth, 2018), and we plan to address human biases encoded in the training data and also account for different linguistic approaches used by students. We will continue to closely link analytics and visualization design to theories of learning and design (Jivet et al., 2018), such as adding redundancy to develop meaningful visualizations that use multiple data points about concepts of interest. We have already used redundancy in our sociograms to help the instructor decode student interaction. Our intent is to balance aesthetics, comprehensibility, readability, and usability to design interactive visualizations that consider different levels of granularity and value of the information in use for the instructor.

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