Predicting Roles and Knowledge Construction Processes in Asynchronous Discussion Using Machine Learning

Minkyung Lee[1], Priya Sharma[2]

[1,2] Department of Learning and Performance Systems, Pennsylvania State University

Abstract

Collaborative learning in asynchronous environments offers opportunities for deeper reflection and engagement but poses challenges due to delays in communication and feedback. This study leverages Machine Learning (ML) models to predict participants' roles and knowledge construction processes within asynchronous discussions. Using textual data from structured and unstructured group discussions, roles such as Summarizer, Skeptic, and Theoretician were predicted with high accuracy. Knowledge construction processes, including Externalization, Elicitation, and Conflict Consensus, were also predicted with varying degrees of success. The results demonstrate the effectiveness of ML in distinguishing participant roles and interaction patterns, providing valuable insights for designing more effective collaborative learning environments. Implications include the potential for intelligent support systems that enhance real-time collaborative learning by identifying and reinforcing productive roles and interactions. Limitations and suggestions for future research are also discussed.

Introduction

Collaborative learning enhances critical thinking, problem-solving skills, and deep content engagement (Dillenbourg, 2002; Scardamalia & Bereiter, 1994). In asynchronous discussions, participants from varied backgrounds collaborate across different times and spaces, enriching the learning process. However, the asynchronous nature of these interactions poses challenges, such as delays in communication and feedback, which can disrupt the necessary fluidity for effective collaborative learning (Anderson et al., 2001). This study explores using Machine Learning (ML) to better understand the roles and processes that participants take on in collaborative learning activities. By employing ML techniques, we aim to provide insights that could support instructors in identifying learners' roles and knowledge construction processes in asynchronous discussions. This approach may offer a new way to enhance support systems in educational settings.

Collaborative Learning in Asynchronous Settings

Collaborative learning, traditionally focused on synchronous environments with immediate communication, has shifted toward asynchronous settings due to technological advancements and the need for flexibility (Stahl, 2002). These asynchronous environments also offer opportunities for deeper engagement through reflective thinking (Dillenbourg, 2002). Tools like discussion boards and shared digital workspaces are crucial, fostering a sense of community and facilitating the collaborative process (Jeong et al., 2014). Proper design and structure in these settings enhance interaction quality and learning outcomes (De Wever et al., 2010).

Roles and Knowledge Construction Processes

Knowledge construction in collaborative learning can be categorized into several processes: externalization, elicitation, integration consensus, and conflict consensus (Fischer et al., 2002). Externalization involves expressing personal knowledge and ideas to the group. Elicitation refers to drawing out ideas and information from group members. Quick consensus occurs when the group rapidly agrees on a solution, while integration consensus involves combining different perspectives into a coherent understanding. Conflict consensus, though less common, involves resolving disagreements through discussion and negotiation.

Collaboration scripts scaffold the knowledge construction process by delineating clear roles and responsibilities, prompting learners to engage actively with discussion tasks, and providing a coherent sequence for activities (Kollar et al., 2007; Vogel et al., 2017). These scripts help create an environment that emulates the immediacy and directness of synchronous collaboration, guiding learners to engage deeply with the learning content and each other (Strijbos et al., 2005). Effective role assignment and collaboration scripts ensure that all participants are actively engaged and their contributions are directed toward the group's learning objectives, fostering a deeper cognitive process and supporting the construction of knowledge (Weinberger, 2010).

In structured collaborative learning environments, assigning specific roles to group members can enhance group dynamics and learning outcomes. Roles help ensure productive and focused group interactions (Strijbos et al., 2005). Each role contributes uniquely to the group's collective knowledge construction process, facilitating different aspects of learning and interaction. While many types of roles have been proposed in the literature, some examples include the role of Summarizer that synthesizes group discussions, consolidating understanding and identifying key points and the role of Skeptic that challenges ideas and encourages critical evaluation. The Source Searcher provides relevant information and resources, while the Moderator facilitates group discussions and maintains focus. The Theoretician connects theoretical concepts to practical applications, enriching the group's understanding (De Wever et al., 2007).

Therefore, the examination of collaborative learning within asynchronous environments offers valuable insights into how social interaction, mediated by technology, contributes to the knowledge construction process.

Machine Learning in Educational Settings

ML applications in education are rapidly transforming how we understand and enhance learning processes (Zawacki-Richter et al., 2019). In educational settings, ML is utilized to predict various student outcomes, such as academic performance, dropout rates, and engagement levels. Common methodologies in ML applications for education include supervised learning, where models are trained on labeled datasets to recognize patterns and make predictions. Techniques such as classification, regression, and clustering are widely used (Romero & Ventura, 2013). For example, classification algorithms can predict student roles in collaborative tasks, while clustering can group students based on similar behavior patterns. Natural Language Processing techniques are also frequently employed to analyze textual data from student interactions, enabling the detection of themes and sentiments that correlate with successful learning outcomes (Roll & Wylie, 2016).

Purpose of the Study

The primary purpose of this study is to investigate the effectiveness of ML models in predicting participant roles and knowledge construction processes in asynchronous collaborative learning environments. By leveraging these models, we aim to develop intelligent support systems that enable instructors to quickly identify learners' roles and knowledge construction processes.

Research Questions

- How accurately can ML models predict the roles in collaborative learning environments?
- How accurately can ML models predict each knowledge construction process?
- How accurately can ML models predict participant roles in knowledge construction?

By addressing these research questions, the study seeks to contribute to the field by providing insights into the role of advanced ML techniques in understanding collaborative learning dynamics.

Data Collection

The data was collected from a series of asynchronous discussions. Each discussion was structured around specific tasks designed to promote knowledge construction through assigned roles. The dataset includes textual interactions from these discussions, annotated for both role identification and knowledge construction processes.

Participants

An online introductory course in Information Systems was chosen due to its emphasis on discussion as a core component of academic achievement, requiring complex levels of thinking to analyze different information systems and their capabilities. Approximately 400 students participated over two semesters. From this cohort, 103 undergraduate students—45 from 10 unstructured groups and 58 from 14 structured groups—gave their consent to participate in the study. Participants were randomly allocated to either structured or unstructured groups, ranging from four to six members. During the eighth week, instructors presented all groups with a problem to address over a three-week discussion period. In structured groups, students selected from four predefined roles—moderator, summarizer, theoretician, and source searcher—based on extant literature. Their task was to collaboratively solve the problem within their roles. In contrast, unstructured groups engaged in the same problem-solving task without role assignments. All groups were required to submit their final collective and individual reports by the twelfth week.

Data processing

The preprocessing of data involved transforming the textual data into numerical features suitable for ML models. The study used TF-IDF (Term Frequency-Inverse Document Frequency) to convert the text into feature vectors. This method quantifies the importance of each term within the individual documents and across the corpus. Additionally, Part of Speech (PoS) tagging was used to capture syntactic information, providing insights into the roles of different words in sentences.

The dataset consisted of 236 total data points. In each fold of 5-fold cross-validation, 189 data points (80%) were used for training, while 27 data points (20%) were reserved for testing.

The base model employed was logistic regression, selected for its simplicity and effciency in handling both binary and multiclass classification tasks. This model was trained using the preprocessed feature vectors, with the target variable encompassing roles and knowledge construction processes annotated in the dataset.

The performance of the logistic regression model was evaluated using standard classification metrics: Precision, Recall, and F1-Score. These metrics provide a comprehensive view of the model's accuracy, considering the accuracy of predictions and the balance between precision and recall.

- **Precision** measures the proportion of true positive predictions among all positive predictions, indicating the model's ability to avoid false positives.

- **Recall** measures the proportion of true positive predictions among all actual positives, indicating the model's ability to capture all relevant instances.
- **F1-Score** is the harmonic mean of precision and recall, providing a single metric that balances both aspects.

Results

Predicting Roles in Collaborative Learning Environments

The ML models demonstrated varying degrees of accuracy in predicting the roles assigned within collaborative learning environments.

As shown in Table 1, the roles of Summarizer, Skeptic, Source Searcher, and Theoretician were predicted with high accuracy, as evidenced by precision, recall, and F1-scores above 0.86. Specifically, the role of Theoretician had the highest predictive accuracy with a precision and recall of 0.92, resulting in an F1-score of 0.91. However, the roles of Moderator and participants with No Role were predicted with lower accuracy. The Moderator role had an F1-score of 0.77, while the No Role category had an F1-score of 0.79. These findings suggest that these two categories may have overlapping features with other roles or are less distinct in their language use, which complicates accurate classification by the model.

Predicting Knowledge Construction Processes

The ML models also varied in their ability to predict different knowledge construction processes (Table 2). The model predicted Conflict Consensus with the highest accuracy, achieving an F1-score of 0.93. Elicitation and Externalization were also predicted with relatively high accuracy, with F1-scores of 0.84 and 0.81, respectively. On the other hand, Quick Consensus and Integration Consensus were predicted with moderate accuracy, with F1-scores of 0.79 and 0.71, respectively. These results indicate that certain knowledge construction processes, such as Conflict Consensus, are more distinguishable and easier for the model to predict accurately compared to others.

Predicting Participant Roles in Knowledge Construction

The interaction between participant roles and knowledge construction processes revealed further insights (Table 3). For example, the model struggled to predict Elicitation for the No Role group, with an F1-score of 0.17. In contrast, Externalization was relatively well-predicted for the Summarizer role, with an F1-score of 0.74. Roles such as Source Searcher and Theoretician had higher predictive accuracy for Externalization, with F1-scores of 0.87 and 0.84, respectively. The role of Skeptic was moderately predicted for Quick Consensus and Integration Consensus, with F1-scores of 0.57 and 0.57, respectively, but the model could not predict Elicitation or Conflict Consensus for this role. These findings suggest that the ML models are better at predicting certain knowledge construction processes for specific roles. The higher accuracy for roles like Source Searcher and Theoretician in predicting Externalization implies that these roles have more distinct interaction patterns that the model can recognize.

Discussion and Implications

The findings highlight the potential of ML models to enhance collaborative learning by predicting roles and knowledge construction processes. The high predictive accuracy for roles indicates distinct interaction patterns that can be leveraged for more effective learning. This insight can aid in designing structured group activities with clear role assignments, leading to more focused discussions. The moderate accuracy in predicting roles like Moderator and No Role suggests a need for refining role definitions and integrating additional contextual features. These roles may benefit from clearer guidelines and support mechanisms to distinguish their contributions, improving predictability and effectiveness.

ML models' ability to predict knowledge construction processes, particularly Conflict Consensus, indicates that certain interactions are more identifiable and can be better supported through targeted interventions. High accuracy for Conflict Consensus suggests models can detect and encourage constructive conflict, crucial for deep learning. However, moderate accuracy for Quick Consensus and Integration Consensus points to these processes' complexity, requiring more sophisticated modeling techniques or additional data features.

Implications for practice include the potential for intelligent support systems to monitor and facilitate collaborative learning in real-time. By identifying and reinforcing effective roles and interactions, these systems can help instructors and learners navigate tasks more effectively, ensuring meaningful engagement.

Limitations of this study include the focus on a single course and potential variability in role adoption and engagement across different cohorts. Additionally, relying on textual data may overlook non-verbal cues and other critical interaction dynamics. Future research should address these limitations to provide a more comprehensive understanding of collaborative learning.

Conclusion

This study demonstrates the efficacy of ML models in predicting roles and knowledge construction processes in collaborative learning environments. The insights can inform the design of more structured and supportive activities, enhancing learner engagement and outcomes. By leveraging these models, educators can facilitate and optimize collaborative learning, leading to more dynamic and effective educational experiences.

Reference

Anderson, L. W., & Krathwohl, D. R. (2001). *A Taxonomy for Learning, Teaching and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives: Complete Edition*. New York: Longman.

De Wever, B., Schellens, T., Valcke, M., & Van Keer, H. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers & education*, *46*(1), 6-28.

De Wever, B., Van Keer, H., Schellens, T., & Valcke, M. (2010). Structuring asynchronous discussion groups: Comparing scripting by assigning roles with regulation by cross-age peer tutors. *Learning and Instruction*, *20* (5), 349-360.

Dillenbourg, P. (2002). Over-scripting CSCL: The risks of blending collaborative learning with instructional design. In P. A. Kirschner (Ed.), Three worlds of CSCL. Can we support CSCL (pp. 61-91). Heerlen: Open Universiteit Nederland.

Fischer, F., Bruhn, J., Gräsel, C., & Mandl, H. (2002). Fostering collaborative knowledge construction with visualization tools. *Learning and Instruction*, *12*(2), 213-232.

Jeong, H., Hmelo-Silver, C. E., & Yu, Y. (2014). An examination of CSCL methodological practices and the influence of theoretical frameworks 2005–2009. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 305–334. https://doi.org/10.1007/s11412-014-9198-3

Kollar, I., Fischer, F., & Slotta, J. D. (2007). Internal and external scripts in computer-supported collaborative inquiry learning. *Learning and Instruction*, *17*(6), 708-721.

Romero, C., & Ventura, S. (2013). Data mining in education. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 3(1), 12-27.
Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, 26(2), 582-599.

Scardamalia, M., & Bereiter, C. (1994). Computer support for knowledge-building communities. *The journal of the learning sciences*, *3*(3), 265-283.

Stahl, G. (2002, January). Contributions to a theoretical framework for CSCL. In *CSCL* (Vol. 2, pp. 62-71).

Strijbos, J. W., De Laat, M. F., Martens, R. L., & Jochems, W. M. G. (2005). Functional versus spontaneous roles during CSCL. In T. Koschmann, D. Suthers, & T. W. Chan (Eds.), *Computer supported collaborative learning 2005: The next 10 years!* (pp 647-656). Mahwah, NJ: Lawrence Erlbaum Associates.

Vogel, F., Wecker, C., Kollar, I., & Fischer, F. (2017). Socio-cognitive scaffolding with computer-supported collaboration scripts: A meta-analysis. *Educational Psychology Review*, *29*, 477-511.

Weinberger, A., Stegmann, K., & Fischer, F. (2010). Learning to argue online: Scripted groups surpass individuals (unscripted groups do not). *Computers in Human behavior*, *26*(4), 506-515.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), 39.

Table 1: Role Prediction Accuracy

Role	Precision	Recall	F1-Score
No Role	0.79	0.79	0.79
Moderator (m)	0.76	0.78	0.77

Role	Precision	Recall	F1-Score
Summarizer (s)	0.88	0.88	0.86
Skeptic (sk)	0.90	0.91	0.90
Source Searcher (ss)	0.90	0.92	0.90
Theoretician (t)	0.92	0.92	0.91

Table 2: Knowledge Construction Prediction Accuracy

Theme	Precision	Recall	F1-Score
Externalization	0.81	0.81	0.81
Elicitation	0.83	0.85	0.84
Quick Consensus	0.79	0.80	0.79
Integration Consensus	0.73	0.72	0.71
Conflict Consensus	0.93	0.94	0.93

Table 3: Role and Knowledge Construction Interaction (Average F1-Score)

Role	Externalization	Elicitation	Quick Consensus	Integration Consensus	Conflict Consensus
No Role	0.70	0.18	0.35	0.41	0.00
Moderator (m)	0.65	0.00	0.30	0.44	0.00
Summarizer (s)	0.74	0.00	0.73	0.55	N/A
Skeptic (sk)	0.62	0.00	0.57	0.57	N/A
Source Searcher (ss)	0.88	N/A	0.75	0.36	N/A
Theoretician (t)	0.84	N/A	0.67	0.53	0.33