Enhancing Knowledge Building Discourse With Automated Feedback on Idea Complexity

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Abstract: This study aims to improve student knowledge-building discourse with automated analysis and feedback. The automated analysis detects different levels of discourse contributions including questions, ideas, and information sources, achieving an acceptable level of consistency with human coding. The automated analysis was used to create an on-demand feedback tool embedded in Knowledge Forum/Idea Thread Mapper to inform student reflection on their online discourse. Research conducted in four grade 5 science classrooms tested the use of automated feedback for knowledge building. The preliminary results suggest that with the feedback, students were able to revise their notes and contribute more complex explanations as opposed to simple factual information.

Introduction

Classroom innovations to cultivate productive inquiry and collaborative learning center at transforming classroom discourse, which shifts from teacher-directed to student-driven, collaborative discourse. Implementing productive discourse for knowledge building remains a challenge for both teachers and their students. The purpose of this research is to design and test machine-generated feedback as a means to enhance students' reflective contribution to knowledge-building discourse.

Knowledge-building discourse is defined as discursive practice by which participants not only share and examine information but continually advance common understandings beyond what is already understood (Scardamalia & Bereiter, 2014). Such discourse supports collaborative knowledge creation beyond knowledge sharing, clarification and critique (van Aalst, 2009). Students need to engage in what Mercer and colleagues call "exploratory talk" in which participants are encouraged to contribute, listen actively, ask questions, build on what has gone before, and challenge ideas with reasons, in order to advance ideas for a shared purpose (Mercer & Dowes, 2008). A rich set of studies has examined productive moves (patterns) of knowledge-building discourse, including asking productive questions, explaining/theorizing, constructive use of sources and evidence, revising and improving ideas, and rising above diverse perspectives for coherent understanding (van Aalst, 2009; Zhang et al., 2007). These discourse moves are positively associated with students' collective and individual learning outcomes.

Implementing knowledge-building discourse in the classroom is challenging for both teachers and their students. Students need to take on increasing responsibility to make intentional contributions while monitoring their personal and collective progress in the unfolding discourse. The teacher needs to play multiple challenging roles: to attend to students' diverse ideas and questions, monitor emerging progress, needs and challenges, and provide purposeful idea input and just-in-time support (Hammer & van Zee, 2006). In a busy classroom, the teacher does not always have the time and energy to capture the multiple needs and offer timely feedback. Thus, creating analytics tools to trace and feedback on student knowledge-building discourse becomes an emerging area of research (Chen & Zhang, 2016; Resendes et al., 2015).

This study aims to design and test reflective feedback generated through automated content analysis of online discourse contributions. Automated content analysis has been tested by several research teams, who first used manual content analysis to code student discussion entries and then developed content analytics systems to automate this process (Kovanović et al., 2017; McKlin, Harmon, Evans, & Jones, 2002; Rosé et al., 2008). While these tools can automate content analysis with acceptable reliability, researchers are only beginning to explore their classroom use by teachers and students (Borge & Rosé, 2016). This paper presents our design and testing of a real-time, on-demand feedback tool that can be used by students to improve their online knowledge-building discourse, specifically focusing on the epistemic complexity of student idea contributions.

The design of automated feedback

The feedback tool was built on the basis of automated content analysis of knowledge-building discourse. Informed by the prior research on the interactive moves of knowledge-building discourse (van Aalst, 2009; Zhang et al., 2007), we created a classification scheme focused on three most common types of contributions:

formulating questions, introducing and using information sources, and generating/improving ideas, each with different complexity levels. Questions include level 1: a brief question without context or rationale and level 2: a question with a detailed account. Information sources include level 1: introducing a book or online resource without explaining what it is about and why useful and level 2: introducing a source(s) with rationale and thoughts. Each online post (note) contributing ideas was classified based on four levels of epistemic complexity (Zhang et al., 2007). Epistemic complexity demonstrates students' cognitive efforts to produce not only factual descriptions of the material world, but also theoretical explanations and articulation of hidden mechanisms, which are central to the pursuit of science (Salmon, 1984). Each student note written to present new/improved ideas was assessed using a four-point scale: 1–Unelaborated facts (simple description of terms, phenomena or experiences without elaboration); 2–Elaborated facts (elaborated description of terms, phenomena or experiences); 3–Unelaborated explanations (reasons, relationships or mechanisms without detailed elaboration); 4–Elaborated explanations (elaborated versions of reasons, relationships, or mechanisms) (Zhang et al., 2007).

Based on this coding scheme, a researcher experienced with content analysis coded an archived dataset that included 550 online discourse entries (notes) created by four Grade 5 classrooms in their knowledge-building inquiry of ecosystems. A second coder coded 12% of the data independently for inter-rater reliability (Cohen's Kappa = .87). The manually coded data were used as the training data to create analytic models for automated analysis using LightSIDE (Mayfield & Rosé, 2013), a text mining platform that supports machine learning and text feature extraction. It first used the training data to select the best-fit model for the given data, then, applied a six-part analysis to students online posts. Part I determined if the type of post contains questions, resources, ideas, or simply insufficient data to make a decision. Parts II, III, and IV further evaluated the complexity level of the questions, resources, and ideas, respectively. Questions and resources were classified into two levels, as noted in the coding scheme. Student ideas were first distinguished as "fact" vs. "explanation" and apply part V and part VI analyses to classify them into "unelaborated" vs. "elaborated" fact and explanation, respectively. The six-part design of analytics resulted in accuracy of 83.1% against human coding (Kappa = .47).

Based on the automated content analysis, we designed an online discourse feedback tool, which was implemented in Knowledge Forum (Scardamalia & Bereiter, 2014) that interoperates with Idea Thread Mapper (ITM) (Zhang & Chen, 2019). In collaboration with two experienced teachers who had facilitated knowledge building for multiple years, the research team designed the feedback message for each category of discourse contribution. Figure 1 shows the feedback message for a note that shares a brief fact. For each type of posts that can be improved toward a higher level, we further identified 2-3 examples from the training dataset to show what an elaborated question, resource, or idea may look like.

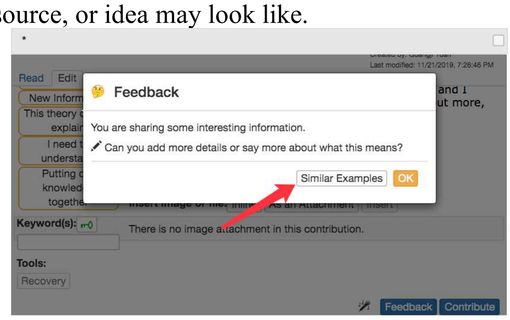


Figure 1. Feedback generated for a note classified as unelaborated facts.

Classroom research

Participants and contexts

We tested the use of the automated feedback tool in four grade 5 classrooms (with a total of 81 students who were 10-to-11 years old), which were taught by two experienced teachers each teaching two classrooms. The students studied ecosystems in their science curriculum using Knowledge Building pedagogy (Scardamalia & Bereiter, 2014), with online discourse taking place on ITM connected with Knowledge Forum. The ecosystem inquiry was started on October 10, 2019, when the students had hands-on observations of their schoolyard and generated interest-driven questions. Then students were introduced to ITM, an online discourse space organized as various idea threads, each addressing an overarching problem and theme. Based on students' initial questions, two main themes emerged: Interactions of living and nonliving things and the flow of matter and energy in ecosystems. The teachers set up two shared wondering areas in ITM, where all four classrooms worked together to develop shared understandings of the challenging issues.

On October 28, the teachers first introduced the feedback function to two classrooms (Class T and M). In each class the teacher first asked students what feedback means, and students reflected that it indicates how well you did something or how you could do better. So the teacher demonstrated creating a brief note and clicked the Feedback button in the note editor. And she explained, “I will let ITM do a little bit work for me, this is almost the same as using a spelling check, but it’s not checking your spelling, it’s checking your content to see if you did a good job with your note.” And the teacher clicked the Feedback, and the feedback message showed: “You shared some interesting information, can you share more details about what this means.” (see Figure 1) So the teacher further demonstrated the tool by typing a more detailed explanation. The other two classes were introduced to this function two weeks later due to their tight classroom schedule.

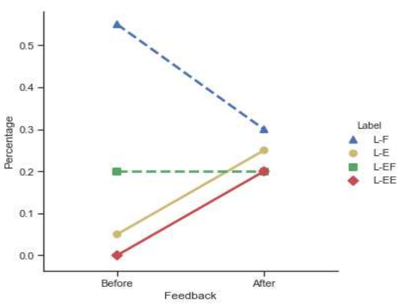
Data collection and analyses

We collected initial data to trace students’ use of the feedback tool during their knowledge-building discourse. The data sources included (a) student online discourse before the introduction of the feedback tool (October 10 to 28) and after (October 29 to November 21), (b) detailed log-file data that recorded who had used the feedback tool, for which note, with what feedback and note revisions, (c) classroom observations, and (d) student interviews. To analyze the quality of students' notes, we conducted content analysis (Chi, 1997) based on the complexity of ideas and the types of questions and resources introduced. To further understand how students’ contribution types changed before and after use the feedback function, we applied the same set of coding schemes and conducted short interviews and analyzed classroom activity videos.

Findings: How did the students use feedback for knowledge building

In a total of 3 weeks since the introduction of the automated feedback, 35 students used the feedback for a total of 69 notes, which received feedback for 138 times. Among the notes that received feedback, 30% of the notes were revised. The average number of words before the feedback was 21.76 and while after the feedback, the average length of the notes increased to 48.90 words. We also applied content analysis to investigate the quality of student notes written in the inquiry of ecosystems before and after the introduction of the feedback tool. As Figure 2 shows, after the introduction of the feedback tool, there was a higher proportion of notes contributing explanations, including both unelaborated explanations and elaborated explanations. At the same time there was a decrease in the proportion of notes sharing brief factual information. We conducted short interviews with students who used the feedback function, and students reflected that the feedback function helped them in three major ways. Table 1 summarizes their typical uses.

Figure 2. Idea complexity changes before and after using the feedback function**.**



L-F: unelaborated fact
L-EF: elaborated fact
L-E: unelaborated explanation
L-EE: elaborated explanation

Table 1: Student uses of the feedback tool

Student use of the feedback	Examples
Use the feedback to develop more elaborated ideas	“Cause it told me how I wrote... if I stopped here, and I wouldn’t have that (extra information), it told me to put more, cause I didn’t put that much...”
Treat the feedback as a measure of the note writing.	“I wanted to know how much I need to write... I think it worked out really nice, it figured things out nicely.”
Guide future research	“I think I can add more detail about each type of energy into my note”

Conclusion

This study explored designing automated discourse feedback drawing upon text mining of student-generated questions, information, and ideas. The automated analysis with LightSIDE achieved an acceptable level of accuracy against human coding. The automated analysis was used to generate reflective feedback to inform student efforts to make productive contributions in knowledge-building discourse. The results show that with the feedback students were able to revise their notes. In the online discourse after using the feedback, students generated more scientific explanations as opposed to simple factual information. More extensive data analysis is underway to examine student use of the feedback at a deeper level and gauge its impact using a cross-condition comparison. Building on this work, we are creating multi-dimensional analytics of knowledge-building discourse that include idea complexity, novelty, and curriculum relevancy, which may provide more informative feedback to students and teachers.

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