An Analytic Tool for Supporting Teachers' Reflection on Classroom Talk

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Abstract: Teachers can reflect on and analyze their classroom talk to inform their instructional practice. When teachers try to do so however, they often face analytic difficulties regarding the data set (data input, data transformation, and utterances by unknown speakers), coding (coding complexity, reliability, and efficiency), visualization (representations of a variety of information, synchronization of displays, and adaptation to the data/codes changes), and tracking and comparison (many students' actions across discussion sessions). This paper introduces an analytic tool called classroom discourse analyzer (CDA) to address these difficulties, as shown in the analyses of classroom discourse from a fourth grade science class. The analyses demonstrate how CDA can be used by teachers to support their reflection on classroom talk and how it can provide personalized, data-supported evidence to inform teachers' classroom practice.

Introduction

Teachers play a crucial role in classroom discussions. Their orchestration of student participations, argumentation and evaluations can affect students' learning processes and outcomes (Resnick, Asterhan, & Clarke, in press). However, currently teachers' performance in helping student learn through discussion is far from satisfactory (Mercer, Dawes, & Staarman, 2009; McNeil & Pimentel, 2010). Given the large benefits of effective classroom talk on students' learning, teachers often find it difficult to engage students into productive discussions involving deep reasoning and argumentation (Clarke et al., 2013; Howe & Abedin, 2013; Pimentel & McNeil, 2013). This raises the challenge of teacher education and professional development (PD) on their classroom discussions with students.

To address this issue, many PD programs have developed instructions to guide teachers' reflection on their classroom interaction. Although reflection has been widely accepted as a useful means of learning in PD programs (Korthagen, & Vasalos, 2005; Pollard et al., 2008), the format of reflection from one's memory has been questioned by some researchers who argued that one's memory cannot always be reliable, neither can it notice and memorize every detail of classroom interaction (McCullagh, 2012; Rosaen, Lundebrg, Cooper, Fritzen & Terpstra, 2008). As such, more recently a growing number of researchers and practitioners have been investigating the use of videos as a facilitator in teacher education and PD (e.g., Baecher, Kung, Jewkes, & Rosalia, 2013; Borko, Koellner, Jacobs, & Seago, 2011; van Es, 2012). Studies have compared various types of video and got mixed research results. For instance, analyzing videos of one's own teaching was shown to be more effective regarding activation experience but less effective regarding emotional/motivational involvement than analyzing others' video (e.g., Kleinknecht & Schneider, 2013). The mixed results encouraged us to explore alternative means of PD that can not only take the advantage of using authentic classroom data as video reflections do, but also provide teachers with data-supported evidence to inform their practice.

The emerging fields of learning analytics provide ample opportunities for the employment of data as evidence for teaching and learning (1st International Conference on Learning Analytics & Knowledge; Baker & Yacef, 2009; Siemens et al., 2011). In particular, discourse analytics in which language is a primary tool for knowledge negotiation and construction (Shum & Ferguson, 2012) allows teachers to identify classroom discussion behaviors and patterns through the analysis of discourse data. As data and analytics are reshaping the way of teaching and learning, tools that can interact with teachers to visualize and track classroom discourse and communicate analytic results should be explored to meet the needs of teachers.

This paper introduces a novel discourse analytic tool called Classroom Discourse Analyzer (CDA) for teachers. We explicate how CDA addresses the difficulties regarding data set, coding, visualization, and tracking and comparison that teachers face in analyzing their classroom discourse data. Data set difficulties include data input, data transformation, and dealing with utterances by unknown speakers. Difficulties involving data coding include the coding of complex classroom discourse, coding reliability, and coding efficiency. The visualization issues include the visual representations of many things, synchronization of different displays, and adaptation to data/codes changes. Lastly, there are also difficulties regarding tracking and comparing teacher's and students' actions across multiple sessions.

We showcase CDA by applying it to the discourse data from a fourth grade science class. The data was first video recorded and transcribed by humans. The female teacher and 16 students (9 males, 7 females)

contributed 1,939 teacher turns and 1,926 student turns in 30 discussion sessions (total duration: 8 hours and 51 minutes). The analyses and visual representations show how CDA can support teachers' reflection on their classroom discussions and how it can provide personalized, data-supported evidence to inform teachers' classroom practice.

Classroom Discourse Analyzer

When trying to reflect on and analyze classroom discourse, teachers often face analytic difficulties regarding the discourse data set, coding, visualization, and tracking and comparison. Table 1 presents the difficulties as well as what strategies that CDA takes to address these difficulties. We classify the difficulties into four categories (i.e., data set, coding, visualization, and tracking and comparison) and discuss below how CDA addresses each of them.

Table 1. Difficulties for teachers in analyzing classroom discourse and CDA strategies.

Analytic Difficulty	Classroom Discourse Analyzer Strategy
Data set	
• Data input	• Simple input template (session, turn, speaker, content)
• Data transformation	• Automated transformation into data of three levels (turn [teacher turn vs. student turn], exchange [teacher-students turn-taking], session [sequences of exchanges])
• Unknown speakers	• Naming array (*individual student* [e.g., *John*; identifiable student], Male [a male student], Female [a female student], SS [a group of students], or S [an unidentifiable student])
Coding	
• Complexity of classroom discourse	• Multi-dimensional coding with mutually exhaustive, exclusive categories
• Coding reliability	• Multi-dimensional coding with mutually exhaustive, exclusive categories
• Coding efficiency	• Automated coding by machine learning software
Visualization	
• Displays of many participants, turns and codes	• Visual displays of many students, many turns, and multiple codes by different colors/shapes and in different frames
• Synchronization of displays	• Automated synchronization of various displays
• Adapting to data/codes changes	• Real-time link of visualization to data and codes
Tracking and comparison	
• Many students' actions over time	• View of anyone's (teacher or students) any actions (e.g., number of words, new ideas, questions) in any discussion sessions

Data Set

CDA addresses the discourse data set issues (data input, data transformation, unknown speakers) with a simple input template, automated transformation, and a student naming array. The input of classroom discourse can include various entries and may take various forms. To minimize the workload of teachers, a simple input template uses four variables to represent a conversational turn, which are session (i.e., session # in a series), turn (i.e., turn # in a session), speaker (i.e., name of the speaker), and content (i.e., entire content of a turn). The input can be any number of sessions, turns, or speakers.

Classroom discourse data often need to be transformed into right types of data sets for subsequent analyses. CDA can automate the data transformation processes, which transforms classroom discourse into three-level data with a nested structure, namely turn, exchange, and session levels. Turns are nested within exchanges and exchanges are nested within sessions. At the turn level, all conversational turns are classified into teacher turns or student turns. At the exchange level, the sequences of teacher student turn-taking are identified (e.g., a sequence of "T->S_1->T->S_2" or "T->S_1->S_2->T"). Lastly, at the session level, the boundaries between any two consecutive discussion sessions are automatically detected.

Classroom discussions often involve a large number of participants (teacher and many students). This may create obstacles for the identification of the participating students in some utterances, especially with audio-taped data. To address this issue, CDA provides a student naming array to classify the speakers into one of the five following categories: *individual student* (e.g., *John*; identifiable student), Male (a male student),

Female (a female student), SS (a group of students), or S (an unidentifiable student). According to the naming array, student speakers are labeled as "S" only if they cannot be classified into the any of the first four categories. This strategy is to retain the relevant information about the speakers for subsequent analyses.

Coding

CDA addresses the coding issues (i.e., complexity of classroom discourse, coding reliability, coding efficiency) with multi-dimensional coding at the unit of conversational turn and the use of machine coding. The complexity nature of classroom discourse often requires a coding framework with many categories. As the number and complexity of categories rise, the training time for teachers and the overall coding time rise, coding conflicts rise, and coding reliability and efficiency fall (Chiu & Khoo, 2005).

By using multi-dimensional coding at the unit of conversational turn, CDA can reduce the number of needed variables, increase coding reliability, and capture the discourse data's complexity. For example, CDA provides a three-dimensional framework to code a student turn. The three dimensions are: evaluation (with "agree", "disagree", and "neutral" as the categories), knowledge content (with "new idea", "repetition", and "no academic content" as the categories), and invitation to participate (with "statement", "question", and "command" as the categories). Because each dimension has three categories, this framework can capture 27 (3×3×3) different types of action. By coding one dimension at a time, a teacher/coder uses clear criteria to choose among only three possible codes, instead of 27. Such categories are mutually exclusive, exhaustive and sufficiently comprehensive to characterize classroom discourse. Meanwhile, the simplification can reduce the coding complexity and likely increase inter-coder reliability.

Coding classroom discourse is often laborious, especially for large data sets. It often needs at least two coders for checking the inter-coder reliability (Krippendorff, 2004). CDA supports the use of automated coding for coding efficiency. Computer coding can be based on either a set of fixed decision rules or human codes for similar data (Erkens & Janssen, 2008; Rosé et al., 2008). For example, lightSIDE can train machine coding models based on a sample of human codes and meanwhile provide a series of coefficients (e.g., reliability test) for measuring the models' performance. Satisfactory models can then be used to code the discourse data automatically and the coding results can be entered into CDA for subsequent analyses.

Visualization

Visualization with the synchronized discourse transcripts is an important function in CDA because it supports teacher reflection of classroom interaction by providing an activating experience similar to that using video as a facilitator for reflection (which is very often referred to as a 'vivid secondhand" experience; Miller & Zhou, 2007; Seidel et al., 2011). CDA can visually display participants, turns, and codes by a variety of shapes and colors, in different frames of the same visible window, and more importantly with a real time update to the changes of data/codes.

In more detail, first as classroom discourse often involve many participants (teacher and many students), many turns, and multiple codes (e.g., codes measuring turns, words, words per turn, teacher-student turn-taking, teacher turn attributes, and student turn attributes), the visual displays of them can be difficult. CDA addresses this issue by using different shapes/colors to represent these components and visualize them in different frames of the same window, so that they do not overlap with each other and can be viewed at the same place. For example, CDA uses the size of a bubble to represent the number of words in a turn, while the color of the bubble represents a particular code (e.g., a new idea) of the turn.

Second, teachers may get lost when navigating between different displays within CDA. To address this issue, CDA's displays in different frames are always synchronized. A teacher's activities in one frame (e.g., zooming in, zooming out, or clicking on a data point) will be automatically synchronized in all other frames. Third, a discourse data set and its codes might change from time to time, which requires visualization to be automatically and dynamically linked to the changes. In CDA, any changes to the participants, turns, or codes will be updated in the visualization instantly. Therefore, no matter what changes teachers have made into the existing discourse data set, the visualization of participants, transcripts, and codes are updated automatically.

Tracking and Comparison

To obtain a deeper understanding of the classroom discourse, teachers often need to interact with the visualization to track individual students' talk over time or compare teacher-student interactions in different sessions. Due to the complex nature of classroom discourse, the visualization often includes many students' many actions (e.g., number of turns, number of words per turn, evaluation of previous turn [agree, disagree, or neutral], knowledge content [new idea, repetition, or no academic content], invitational form [statement, question, or command]) across sessions. Such visual information can sometimes be overwhelming so it might hinder teachers from finding interaction changes across discussion sessions.

To facilitate the tracking and comparison, CDA allows a teacher to select any participants' (teacher and/or students) any actions in any sessions. For example, a teacher may choose to only display a particular

student's turns according to time sequence, in order to see if the student is participating in the discussions more or less frequently over time. Alternatively, a teacher may select to view all students' talk in two different sessions to observe if these students participated in the discussion of the two topics differently. Once a trend or difference is identified, teachers can zoom in to view the visualization in further details.

Showcasing Classroom Discourse Analyzer

In this section, we showcase CDA by applying it to the transcripts from a fourth-grade science class. After describing the data set and coding, we show in what ways that teachers may use CDA to analyze the discourse and thereby inform their classroom talk with students.

Data

The data set includes 1,939 teacher turns and 1,926 student turns transcribed from videotapes of 30 discussion sessions in a 4th grade science class. The participants were a female teacher and 16 students (9 males, 7 females). The total time of discussion was about 8 hours and 51 minutes. Sample discussion topics include: "what causes the water level to rise?"; "Same volume, same weight?"; "How can we measure the volume of a liquid?". The format of the input data in CDA is presented in Table 2. Teachers only need to provide data along the following four columns: session, turn, speaker, and content.

Table 2. Format of the input data in CDA.

Session	Turn	Speaker	Content
1	1	T[a]	What is an earth material? Amalia, what's an earth material?
1	2	Amalia[b]	Materia- Material is like, um, like well, you could say like what's under our feet, you could say like um, maybe like soil and rocks.
1	3	T	OK. What's another way you would describe earth materials? What does that word or that term mean to you? Louie?
.	.	.	...
30	87	T	And what do we call that?
30	88	SS[c]	Water displacement.
30	89	T	I could use my water displacement again to get the exact measurement, because that worked for us with the rock, so I believe that would probably work for us with the gravel.

[a] Teacher. [b] Student name was pseudonym. [c] A group or whole-class of students.

Coding

CDA used multi-dimensional frameworks for coding the teacher and student turns. (Teachers may also create their own coding framework in CDA). CDA automatically computed the number of words in a teacher or student turn and identify teacher student turn-taking patterns over time (e.g., $T \to S_1 \to T \to S_2 \to T$ vs. $T \to S_1 \to S_2 \to T$).

The teacher turns were coded based on the scheme of teacher Accountable Talk[®] during the discussion, which includes eight categories of Accountable Talk moves (i.e., "say more", "revoice", "press for reasoning", "challenge", "restate", "add on", "agree/disagree", and "explain other"; Resnick, Michaels, & O'Connor, 2010). For example, to encourage individual students' thinking, teachers can ask students to say more (e.g., "Can you say more about that?") or to explain their reasoning (e.g., "Why do you think that?"). To facilitate students' thinking with others, teachers can ask students to extend the ideas of others (e.g., "Who can add onto to that idea?") or to evaluate someone else's reasoning (e.g., "Do you agree / disagree?"). Machine coding software (lightSIDE; Mayfield & Rosé, 2013) was used to facilitate the coding of teacher turns.

The student turns were coded using a multi-dimensional framework: a) knowledge content (new idea [with justification or not], repetition, or no academic content), b) evaluation of previous turns (agree, disagree, or being neutral), and c) invitation to participate (statement, question, or command; Chen & Chiu, 2008; Chen, Chiu, & Wang, 2012).

Analyses

We first introduce the overall interface of CDA. We then show how the various displays in CDA help visualize the discourse processes and how they can inform teachers about their talk with students in the classroom.

CDA Interface

Figure 1 shows an overview of the classroom discourse from the 30 sessions. The user interface of CDA includes 5 frames for visualization (see Figure 1). Frame 1 is the place that visualizes the distributions of the

teacher and student turns. The vertical axis is participants and the horizontal axis is timeline. Each line of bubbles represents a student's or the teacher's (the dark red bubbles) talk. Size of bubbles represents the number of words in a turn. The teacher's line of bubbles near the bottom of the frame 1 shows that she talked much more than the students across the 30 sessions.

Frame 2 represents teacher-student turn-taking patterns automatically generated by CDA. The vertical axis is the number of students between two adjacent teacher turns and the horizontal axis is timeline. Frame 3 shows summary statistics for each row of data (e.g., teacher's and student's percentages of total words in the 30 sessions). The transcripts are displayed in frame 4 and the coding frameworks for teacher and student turns are displayed in frame 5. The visual displays in different frames are always synchronized to facilitate viewing. For instance, Figure 1 shows that a particular turn (turn 38 in session 16 by the student Johnny, a pseudo name in this study) can be easily located in frames 1, 2, and 4 simultaneously.

Figure 1. An overall interface of CDA.

Distributions of Teacher and Student Turns in a Session

In addition to the overview of multiple sessions, teachers can use CDA to visualize the speakers' turns and words in a particular session. Figure 2 shows the teacher's and 14 students' turns and words in session 26. (Two students were absent from the session). The discussion topic is "what causes the water level to rise?" There were 71 teacher turns and 70 student turns in the session. The session lasted about 20 minutes and 47 seconds. As shown in Figure 2, the students were sorted by the amount of words this time. While *Mario* only spoke one word in one turn, *Marcel* spoke 233 words in two turns in the session. Based on the information the teacher may balance students' participations in subsequent discussions (e.g., inviting *Mario* to participate more in future sessions).
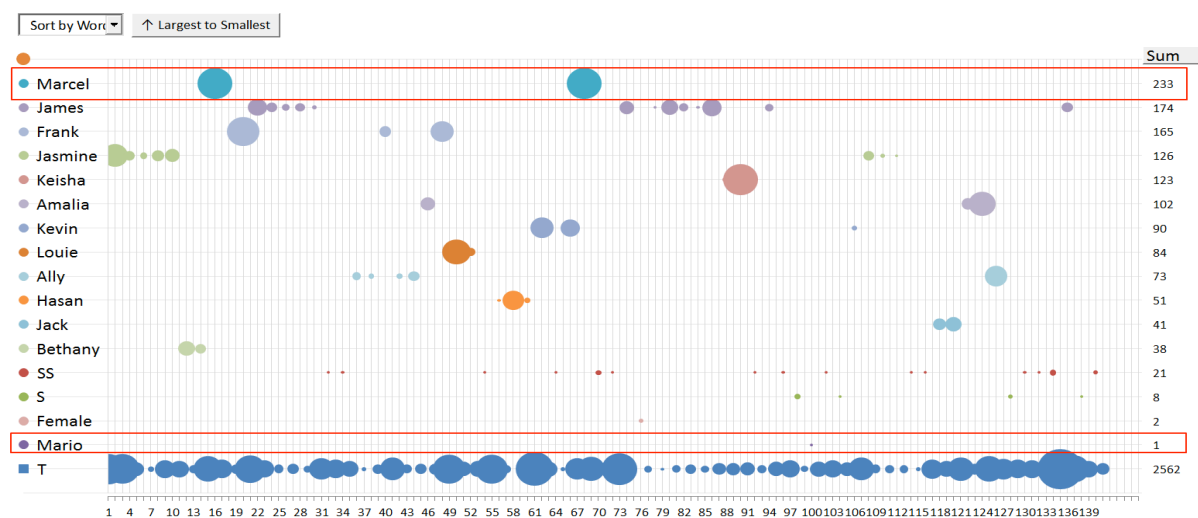

Figure 2. The visualization of students' turns and words in session 26.

Teacher-Student Turn-Taking Patterns in a Session

CDA can automatically generate the visualization of teacher and students' turn-taking patterns during a discussion. There are three major patterns during classroom discussions. The first is teacher's talk with a

particular student for two or more turns (or "T->S$_1$->T->S$_1$"). Another is teacher's talk with one student for one turn and then turn to another student (or "T->S$_1$->T->S$_2$"). The last one is that teacher allows two or more students to talk with each other before taking the turn (or "T->S$_1$->S$_2$->T").

See Figure 3 for the turn-taking patterns in session 26. During this discussion, the teacher and students used many "T->S$_1$->T->S$_1$" patterns (dashed orange lines) and many "T->S$_1$->T->S$_2$" patterns (solid blue areas), but no "T->S$_1$->S$_2$->T" patterns. For example, Figure 3 shows a place where the teacher talked with a particular student for 11 consecutive turns before going to another student ("T->S$_1$->T->S$_1$->T->S$_1$->T->S$_1$->T->S$_1$->T"). This might be the place that the teacher helped the student clarify or expand his or her own thinking. At another place, the teacher went through eight students and talked with each student with only one turn ("T->S$_1$->T->S$_2$->T->S$_3$->T->S$_4$->T->S$_5$->T->S$_6$->T->S$_7$->T->S$_8$->T"). This might be the place where the teacher helped students think with one another. Teachers can click on the visual representation to view the corresponding video/transcripts details and purposefully examine whether a teacher has managed the discourse segments appropriately or whether he/she missed opportunities for fostering student thinking in that context.
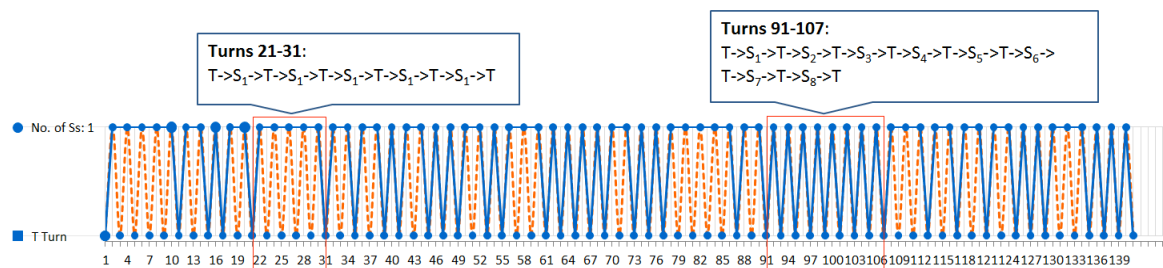

Figure 3. The visualization of teacher-student turn-taking patterns in session 26.

Tracking Teacher and Student Actions in a Session

Teachers can use CDA to track teacher's or any individual students' particular actions during classroom discussions. Figure 4 shows the visualization of a) the teacher's use of "agree/disagree" moves, and b) the students' use of "disagreement" moves in session 26. The purpose was to track how students disagreed with one another during the discussion. From Figure 4 we can see whether they disagreed with one another as a result of the teacher's probes or they disagreed with one another voluntarily.
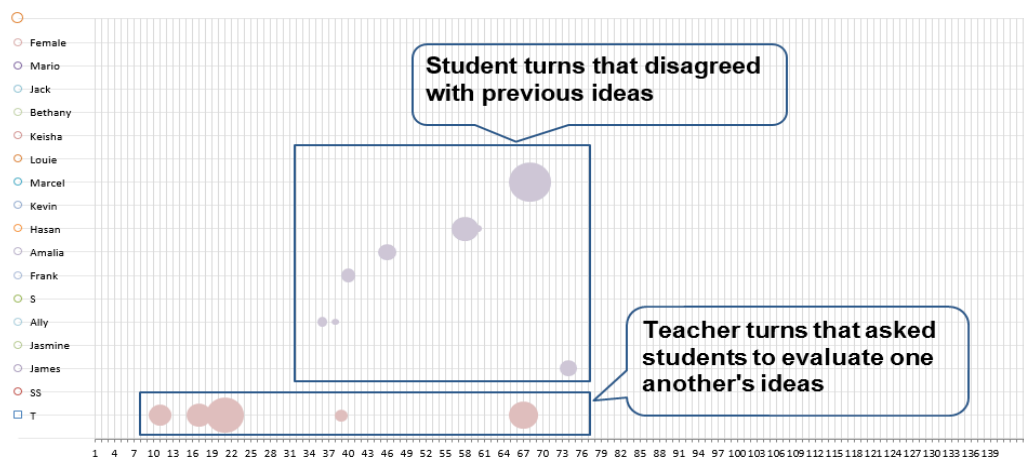

Figure 4. Visualization of teacher's "agree/disagree" turns and students' "disagreement" turns in session 26.

As shown in Figure 4, there were 5 teacher turns that asked students to evaluate one another's ideas and 8 student turns that disagreed with one another's ideas. What is interesting here is that only 2 of the 8 disagreement turns were elicited by the teacher. The other 6 turns were not preceded by teacher "agree/disagree" turns, suggesting that these students were likely to disagree with the ideas by their peers explicitly during the discussion (McNeill & Pimentel, 2010). Teachers may zoom in to reflect on why the students were having conflicting views and how the teacher moderated the disagreements in this episode.

Comparisons Between Classes

Moving beyond a single class, teachers can use CDA to compare their classroom discourse data with those from other teachers. This is a useful function especially in teacher PD because it can help teachers learn from the analyses of one another's classroom talk. Figure 6 shows the teacher-student turn-taking patterns of a discussion

segment from a ninth grade biology class (discussion topic: Punnett square; one male teacher and 16 students; duration: 16' 00"). This visualization is in sharp contrast to that in Figure 3. The ninth grade biology class used much fewer "T->S_1->T->S_1" patterns (dashed orange lines), but a lot more "T->S_1->S_2->T" patterns (higher, blue lines with a peak) than the fourth grade science class. As can be seen in Figure 6, there were as many as five students taking the turns to talk between two teacher turns (e.g., "T->S_1->S_2->S_3->S_4->S_3->S_5->T" as shown in the rectangles). The visualization showed that students in this discussion session had a lot of opportunities to interact with one another directly, which indicates a presence of students' dialogic interactions in the session (Lehesvuori et al., 2013; McNeill & Pimentel, 2010; Schultz & Oyler, 2006).
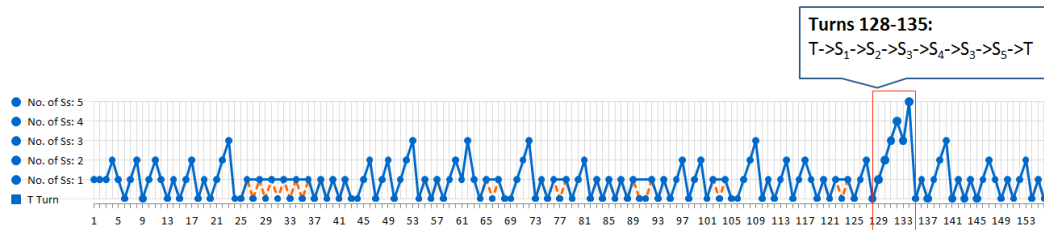

Figure 6. The visualization of teacher-student turn-taking patterns in a session from a 9th grade biology class.

Discussion and Conclusions

In this paper, we explicated how teachers can use CDA to analyze their own classroom discourse. While many difficulties encumber teachers' analysis of their discourse data, CDA addresses each of them. CDA can be used by teachers and teacher educators to support teachers' self-assessment and reflection of their classroom discussion processes and provide personalized, data-supported evidence to inform their classroom practice. Through visualizing, tracking, and comparing classroom discourse processes, CDA can be applied to address questions regarding a) how classroom talk develop over time, b) how teacher and students take turns to interact with one another, and c) how their behaviors differ across sessions and classes.

The CDA results of the above case showed that it can be used to visualize teacher and student talk over time. This allows teachers to track any participants' actions (e.g., students' disagreements with one another, new ideas, justifications) in a discussion session. The information can also be used to inform teacher's guidance and feedback in future discussions. CDA can also automatically visualize teacher and students' turn-taking patterns to reveal at a glance the social structure of a discussion. For example, the occurrences of "T->S_1->S_2->T" pattern (two or more students talk between two adjacent teacher turns) might indicate the places where students voluntarily evaluate someone else's idea, raise a question, or propose a new idea (McNeill & Pimentel, 2010; Schultz & Oyler, 2006). Moving beyond a single session, teachers can use CDA to compare students' behaviors in different sessions. Furthermore, a group of teachers can use CDA to view and compare the discourse from one another's classes, which would also help develop a learning community among teachers.

There are challenges that might limit the application of CDA in practice, which include data collection, transcribing, and coding. All the three processes, especially data transcribing and coding, are laborious and expensive, thereby hindering the rapid feedback and continuous support that CDA can provide. The data of classroom discussions are often collected by audio or video taping (e.g., the data used in the above case). In a classroom discussion that involves a large number of students, it is sometimes difficult to capture the information of who speaks at what time. Alternative ways of recording classroom discussions, such as microphone-array systems (Sun & Canny, 2012), may help address this issue.

The data in the above case were all transcribed manually from videotaped records. The process was often time and labor consuming. New technology in the areas of speaker identification and speech recognition may be used to facilitate the transcribing of classroom discussions (e.g., Vandyke, Wagner, & Goecke, 2013; Walker et al., 2004). Whether computer transcribing is comparable to external human transcribing remains an open research area. Another strategy is that teachers can select to transcribe the small segments that they are interested. (Sampling portions of the data omits substantial data, which can bias the analysis results.)

Coding transcripts of classroom discussions also takes time and effort. It has been showed that computer coding was reasonably acceptable as it coded for some particular categories (Clarke et al., 2013; Mayfield, Laws, Wilson, & Rosé, 2013). In the above case, we have used the machine learning software lightSIDE (Mayfield & Rosé, 2013) to help code for some teacher talk moves that do not require the teacher to be able to paraphrase or interpret the student speaker's "meaning." They are the moves that mainly use general expressions (e.g., press for reasoning: "why do you think that?"; add on: "who can add on?"; agree/disagree: "do you agree/disagree?"). Whether computer coding can be used to code complex categories of classroom talk remains an open research area.

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