In Search of Conversational Grain Size: Modeling Semantic Structure Using Moving Stanza Windows

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Abstract: Analyses of learning based on student discourse need to account not only for the content of the utterances but also for the ways in which students make connections across turns of talk. This requires segmentation of the discourse data to define when connections are likely to be meaningful. In this paper, we present a novel approach to segmenting data for the purposes of modeling connections in discourse. Specifically, we use epistemic network analysis to model connections in student discourse using a temporal segmentation method adapted from recent work in the learning sciences. We compare the results to a purely topic-based segmentation method to examine the affordances of temporal segmentation for modeling connections in discourse.

Keywords: sliding window, epistemic network analysis, segmentation, discourse analysis

Introduction

Analyzing high-volume discourse data is a challenge in computer-supported collaborative learning (CSCL) environments because student conversations in these environments are characterized not only by what is said but by combinations of language use within social practices (Gee, 1990). This suggests that analyses of learning based on student discourse need to account not only for the content of the utterances but also for the ways in which students make connections across turns of talk. Any analysis of such connections, however, requires *segmentation* of discourse data to identify the conditions under which connections are likely to be meaningful (Hearst, 1994). In this paper, we present a novel approach to segmenting data for the purposes of modeling connections in discourse. Specifically, we use *epistemic network analysis* (Shaffer et al., 2009) to model connections in student discourse using a novel *temporal segmentation* method adapted from recent work in the learning sciences (Dyke, Kumar, Ai, & Rosé, 2012; Suthers & Desiato, 2012). We compare the results to a purely *topic-based segmentation* method to examine the affordances of temporal segmentation for modeling connections in discourse.

Theory

There are a number of theoretical perspectives in the learning sciences that describe understanding of a topic, process, domain, or practice in terms of the organization of students' understanding—that is, the way concepts, skills, and habits of mind are related to one another systematically. Chi and colleagues (1981), for example, found that experts in physics organize their understanding differently than novices. Bransford and colleagues (1999) showed that the organization of experts' content knowledge reflects their deep understanding of subject matter. diSessa (1988) suggests that that while solving physics problems does require understanding basic concepts from the discipline, deep and systematic understanding comes from linking those concepts to one another within a theoretical framework. Shaffer (2012) similarly characterizes learning as the development of an *epistemic frame*: a pattern of associations among knowledge, skills, habits of mind, and other cognitive elements that characterizes communities of practice, or groups of people who share similar ways of framing, investigating, and solving complex problems.

Not surprisingly, research on discourse processing suggests that connections between concepts are made primarily on a topic-by-topic basis rather than across discourse as a whole. Gernsbacher's (1991; see also Graesser, Gernsbacher, and Goldman, 1997) theory of language processing, for example, suggests that students use the hierarchical organization of content to build understanding. Discourse is structured by topic, with concepts having clear relationships to one another within topics and few relationships across topics.

Based on this idea, *epistemic network analysis* (ENA) analyzes the structure of connections in student discourse by looking at the co-occurrence of concepts within the topics or activities that take place during learning. Building on the idea of learning as the development of an epistemic frame, ENA creates a network model of thinking as based on the co-occurrence of skills, knowledge, values, and other elements of work in some community of practice (Shaffer et al., 2009). In practical terms, ENA measures the structure of the connections among types of talk by grouping utterances by activity into *stanzas*, or collections of related utterances. In other words, like many lines of work in CSCL and the learning sciences more generally, ENA looks at *activities* as a fundamental unit of analysis.

There are, however, two problems with such an approach. First, as Stahl, Koschmann, and Suthers (2006) argue, learning needs to be analyzed at both the group and the individual level. Stahl (2009), for example, conducted parallel qualitative analyses of the mathematics learning of a group and of the individuals in the group. But as Cress and Hesse (2013) point out, because learners work in groups, simple t-tests and ANOVAs do not do a good job of modeling the influence that groupmates have on one another. Providing a quantitative model of group discourse that accounts for the contributions of any single individual within the group discussion is thus a challenging problem.

A second problem is that aggregating connections by activity may take these connections out of context (Arvaja, Salovaara, Häkkinen, & Järvelä, 2007). While ideas are surely connected within topics or activities, those connections are most likely to occur in close temporal proximity. During discussions, students simultaneously build group and individual understanding by "saying" and replying to "what is said" (Wells, 1999). Speech typically addresses another instance of speech and anticipates a response (Bakhtin, 1986). Because "thinking and speech are, in this sense, always derivative of prior thinking and speech" (Smagorinsky, 2013, p. 23), students build on the ideas of their team members to mediate their discussion of concepts. Therefore, to measure connections in conversations, we need a method to model connection-making on shorter time scales than entire activities.

Recent work by Dyke and colleagues (2012) and Suthers and Desiato (2012) proposes using *sliding window analyses* to model temporal connections in discourse. Rather than creating summary values for all utterances in an activity, a sliding window computes a value for a smaller section of an activity—typically a small amount of time (e.g., 10 seconds) or a small number of utterances (e.g., three turns of talk; Dyke et al., 2012). The window is *sliding* in the sense that a summary value is computed for each utterance, based on the preceding lines of talk (e.g., the preceding 10 seconds or three lines of talk). This type of analysis has been used to identify shifts in topic (Rosé et al., 2008), and more generally to provide new insights on previously analyzed data (Dyke et al., 2012). Suthers and Desiato (2012) have used a sliding window approach to build a model of uptake—that is, to model connections in discourse. However, while their model showed when each actor used another actor's contribution, this model only showed whether a connection was made, not *what* connection was made.

In what follows, we use ideas from Gee (1991) to create an ENA model of connections in discourse using a moving window approach. When analyzing discourse, Gee argues that single *lines* or utterances in talk are grouped together into sets of related lines he calls stanzas. His analogy is to stanzas in a poem, and this is the sense in which ENA groups turns of talk to model the co-occurrence of ideas. But Gee also suggests that stanzas themselves are grouped together into related sets that he calls *strophes*.

In this study, we use the idea of strophes and stanzas to delineate two different approaches to modeling connections using ENA, although it may be useful in other modeling approaches as well. In both cases, ENA models connections among concepts: (1) by identifying coherent topics, activities, and/or conversations in the data as strophes; and (2) by defining collections of utterances within strophes that are related to one another as stanzas. The two methods differ in the relationship between strophes and stanzas. Specifically:

1. The **Strophe Method** models connections within an entire activity or strophe: that is, all the utterances within an activity are related to one another. Or, equivalently, each strophe is composed of a single stanza.
2. The **Moving Stanza Window Method** models connections within an activity or strophe by *dividing* the strophe into multiple stanzas: that is, utterances are related to one another only within some designated stanza window. In other words, the moving stanza window method models connections only when utterances are in close temporal proximity within a strophe.

In what follows, we compare these two models by looking at data from a CSCL learning environment in which students collaboratively design solutions to engineering problems. To evaluate the strengths and limitations of these two approaches to segmentation, we created ENA models for 10 teams using both the strophe method and the moving stanza method. We focus here on the discourse of one team, and we ask:

What are the similarities and differences in how the strophe method and the moving stanza window method of segmenting data in ENA characterize the nature of connections in discourse?

Methods

The engineering virtual internship *RescuShell*

In this study, we analyzed how students who are roleplaying as engineering interns in a virtual internship interact within their teammates. In *RescuShell*, student teams conduct research and simulated experiments to develop the robotic legs for a mechanical exoskeleton for use by rescue personnel. The virtual internship is separated into 17 activities that simulate various steps in the design process, including reviewing and summarizing research reports, creating device prototypes, discussing design choices with teammates, and working to meet the needs of various internal consultants and external clients. In this study, we focused on the first eleven activities of the internship, in which students were assigned to one of five teams, each of which explores the use of a particular actuator in the design (Hydraulic, PAM, Electric, Pneumatic, or Series Elastic). Forty-four first-year engineering students participated in the virtual internship, which took approximately 15 hours to complete. From this sample, we selected one team and analyzed how these five students (4 male, 1 female) discussed the design problem in the first half of the internship.

Discourse analyses

Coding student chats

We coded each line of chat data using our Engineering Epistemic Frame Coding scheme, which identifies domain-specific epistemic frame elements (Shaffer & Arastoopour, 2014). We applied this coding scheme by using an automated key word coding process that has been validated by comparing agreement between human and computer codes with resulting Cohen's kappa scores between 0.80 and 0.98 (Chesler et al., 2015). The scheme includes 10 codes:

Data-based Justifications: Justifying decisions using data such as graphs, results, or numerical values.

Design-based Justifications: Justifying decisions using design references such as prioritization.

Client-based Justifications: Justifying decisions by referring to the client's safety, health, or comfort.

Consultant-based Justifications: Justifying decisions by stating the internal consultants' preferences.

Skill of Data: The action of using numerical values, results tables, graphs, or research papers.

Skill of Design: The action of design development, prioritizing, tradeoffs, and design decisions.

Skill of Collaboration: The action of facilitating a team meeting.

Identity of Engineer: Identifying as an engineer; possession or ownership of work.

Knowledge of Attributes: Referring to attributes: payload, recharge interval, agility, safety, or cost.

Knowledge of Inputs: Referring to inputs: actuators, ROM, materials, power sources, or sensors.

We then performed a Chronologically-Oriented Representations of Discourse and Tool-Related Activity (CORDTRA) analysis (Hmelo-Silver, Liu, & Jordan, 2009) during one activity to show the temporal pattern of the 10 codes in student discourse.

Epistemic Network Analysis

ENA models the structure of connections among engineering epistemic frame elements by quantifying the co-occurrences of codes within a stanza (Shaffer et al., 2009; Shaffer 2014). After defining the segmentation structure, ENA creates an adjacency matrix representing the co-occurrences of codes in each stanza. To construct an adjacency matrix, ENA assigns a one for each unique pair of codes that co-occur one or more times in those utterances, and a zero for each unique pair that does not appear anywhere in the stanza. ENA sums the adjacency matrices into a cumulative adjacency matrix, where each cell represents the number of stanzas (i.e., the number of adjacency matrices) in which that unique pair of codes was present. Each unit of analysis is thus represented by a cumulative adjacency matrix that summarizes the pattern of connections among codes.

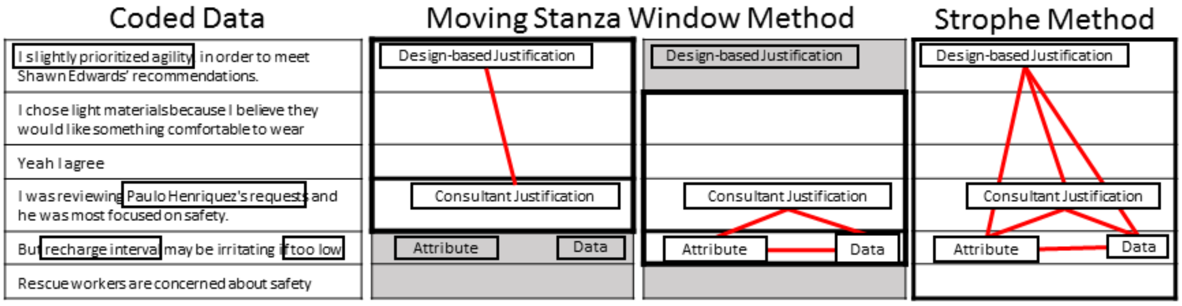
ENA then converts the cumulative adjacency matrices into cumulative adjacency vectors that are projected into a high-dimensional space based on the co-occurrence of codes across segments. These cumulative adjacency vectors are normalized to control for the varying lengths of vectors by dividing each vector by its length; the resulting vector thus represents the relative frequency of co-occurrences. ENA then performs a singular value decomposition on the normalized vectors. This produces a rotation of the original high-dimensional space, such that the rotated space provides a reduced number of dimensions that capture the maximum variance in the data.

The resulting models can be visualized as networks in which the nodes in the model are the codes and the lines connecting the nodes represent the co-occurrence of two codes. Thus we can quantify and visualize the structure of connections among engineering epistemic frame codes, making it possible to characterize student discourse during the virtual internship.

Comparison of segmentation procedures

In this study, we compared two methods of segmenting data for use in ENA: the strophe method and the moving stanza window method. For the *strophe method*, ENA creates one adjacency matrix for each activity and then sums the matrices across the 11 activities for a given team.

The *moving stanza window method* creates a *referent adjacency matrix* for each utterance, known as the *referring utterance*. The referent adjacency matrix for each utterance is constructed of two types of co-occurrences of codes: (1) co-occurrences within the referring utterance, and (2) co-occurrences of codes between the referring utterance and a specific number of previous utterances, known as the *window*. The moving window then moves to the next referring utterance and creates the next referent adjacency matrix. This process continues until the end of the strophe and then ENA sums the matrices across all utterances for that unit. No windows are made across activities (strophes), only within them. Figure 1 shows how the strophe method and the moving stanza window method create different models of connectivity.



(a) (b) (c) (d)

Figure 1. Example of coded data from one activity (a). The moving stanza window method analyzes connections within the referring utterance and between the referring utterance and the window (b). After analyzing a window, the moving stanza method slides to the next utterance and repeats the process of finding connections within and between the referring utterance and the window. The strophe method analyzes all connections in an activity (d).

Co-occurrences of codes within or across non-referring utterances are not included in the referent adjacency matrix, which eliminates double-counting of connections when the cumulative adjacency matrix is computed.

Comparison of network models

To analyze the different segmentation methods using ENA, we created three models: (1) a strophe model for all teams in the sample, (2) a moving stanza window model with a window size of three for all teams in the sample, and (3) a moving stanza window model with a window size of three for all students in the sample, based on a qualitative analysis of the data that suggested most explicit connections between ideas in the discourse occurred within a span of 4 or fewer lines (the referring utterance plus the preceding three turns of talk). All three of these sets were projected into the dimensional reduction for the team moving stanza model (Model 1) so the resulting networks could be compared. To analyze the differences between the two segmentation methods, we examined the discourse of one team whose models appeared to show different conclusions between methods. First, we compared Model 1 with Model 2 to understand how each segmentation type modeled team discourse, then we used Model 3 to contrast connections between individuals.

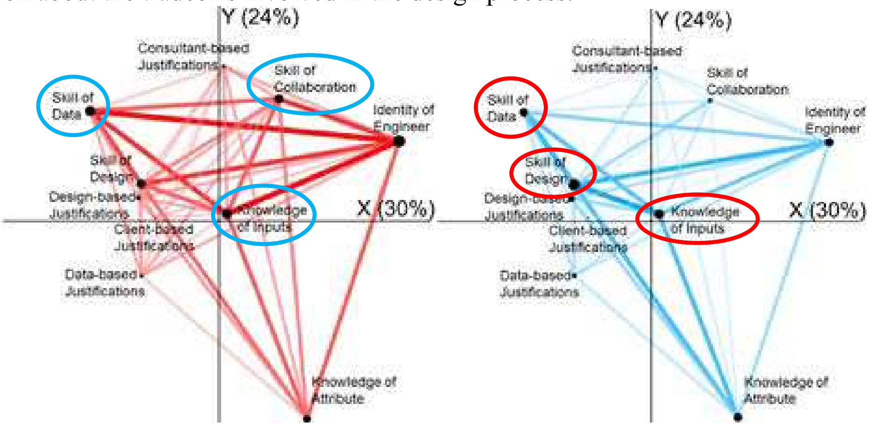
Results

For the purposes of this analysis, we looked at the conversations of one student project team. The Hydraulic team had five team members: Arden, Connor, Margaret, Jimmy, and Jordan. In what follows, we examine their collaborative design work over the first 11 activities of the virtual internship, which include background research into principles of biomechanics, as well as the design, testing, and evaluation of an initial prototype for a robotic exoskeleton.

Strophe and moving stanza window models for the hydraulic team

We used the strophe method and the moving stanza window method to model the discourse of the team. Both models (see Figure 1) show that the connections to and between the Skill of Data and the Knowledge of Inputs were prominent in the group's design discussions. This is represented by larger node sizes and thicker lines in the ENA network graph linking the nodes that correspond to those discourse elements. This is, of course, hardly surprising, as the group's primary goal was to choose appropriate design features (inputs) to maximize the function of their device.

However, the strophe method (Figure 2a) suggests that the Hydraulic team connected these features of design with explicit discussion of their collaboration process; in contrast, the moving stanza window method (Figure 2b) suggests that the team spent less time explicitly connecting talk about collaboration to their design work and more time talking linking the Skill of Design to other elements of the problem space, representing explicit discussion about the tradeoffs involved in the design process.



(a) (b)

Figure 2. Network graphs of the Hydraulic team's discourse produced using (a) the strophe method and (b) the moving stanza window method. Thicker lines denote more frequent connections between codes. Percentages indicate the amount of variance explained by each dimension, in this analysis, 54% of the total variance is accounted for in this data set.

This contrast is shown more clearly by computing the *difference* between the two network models (Figure 3). Figure 3 shows a higher number of connections in the strophe method (red lines in the figure) to the node for Skill of Collaboration, suggesting that links between the Skill of Collaboration and other elements of the epistemic frame of engineering are a prominent feature of student discourse in this model. In contrast, the moving stanza window method (blue) suggests that students made more connections to the Skill of Design.

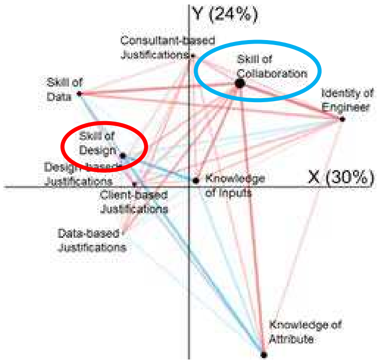


Figure 3. Subtracted network of the Hydraulic team's discourse, in which blue connections occur more frequently with the moving stanza method and red connections occur more frequently with the strophe method.

Comparing connections within activities

To explore these differences between the two models, we examined the frequency of codes within each activity in the virtual internship. For example, when students met with their teammates to design devices, the discourse included references to the Skill of Collaboration, which was one of the key differences between the two models. To understand why there was such a substantial difference in connections to the Skill of Collaboration, we examined the CORDTRA for this activity (Figure 4).

The CORDTRA shows that students explicitly talked about collaboration only at the start and at the end of the activity. Applying the strophe method to this activity produced connections between Skill of Collaboration and codes that appeared *at any point within the activity*, even though students only talked explicitly about collaboration at the beginning and the end of the discussion.

In contrast, applying the moving stanza window produced connections between codes only if they co-occurred within close proximity, that is, within three utterances of the referring utterance. Thus, the moving stanza window model shows a less prominent role for the Skill of Collaboration.

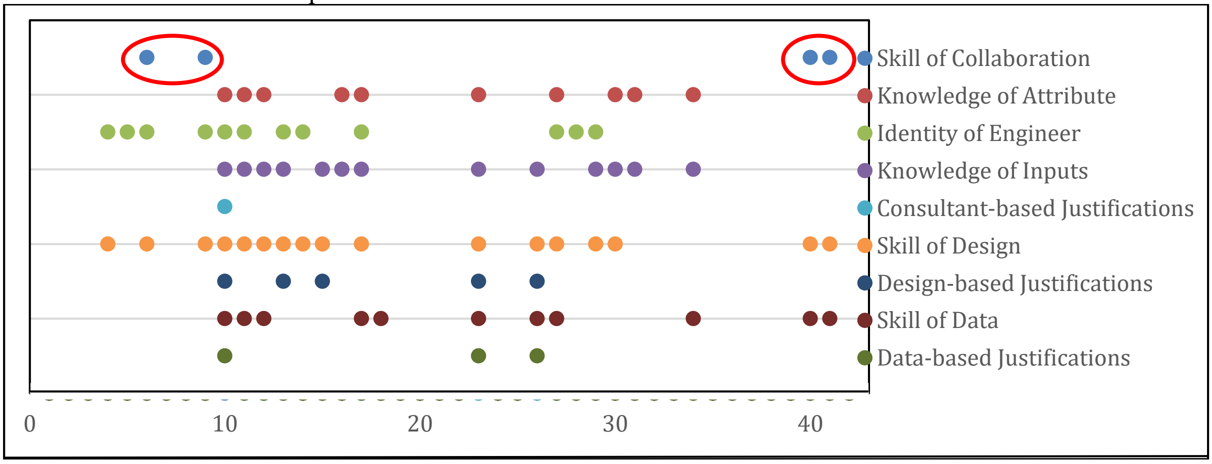


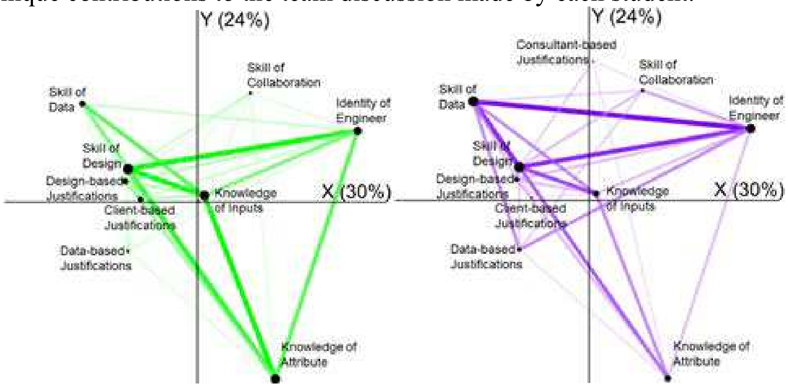
Figure 4. CORDTRA diagram of Hydraulic team discourse codes during one activity.

Contrasting connections between individuals

A second consideration in comparing the strophe method and the moving stanza window method is that the strophe method suffers from the same limitation as many extant techniques for modeling CSCL: it can model a group conversation, but it does not do a good job of modeling the participation of one individual *in the context of* a group discussion. The moving stanza window method, in contrast, can account for this important component of collaborative learning.

The reason for this difference is that the strophe method uses a *single adjacency matrix to model each activity*, and that matrix incorporates the contributions of all members of the group. There is thus no good way to disentangle the contribution of any one individual. The moving stanza window method, on the other hand, *models each utterance as an adjacency matrix*, showing the connections it contributes to the group discourse. As a result, we can use the moving stanza window method to examine the connections that each individual makes to the collaborative discussion of the group.

For example, we modeled the contributions of two students, Connor and Jimmy, to the Hydraulic team's discussion. We constructed a network model of each of two students' contributions, where each model includes only those stanza windows in which the referring utterance belonged to that individual (Figure 5). These models thus represent the unique contributions to the team discussion made by each student.



(a) (b)

Figure 5. Moving stanza window model for Connor (a) and Jimmy (b). Thicker lines denote more frequent connections between codes.

The networks using a moving stanza window method show that across all eleven activities, Connor and Jimmy's individual contributions to the group discourse differ. Connor's network (Figure 5a) shows a higher number of connections between Knowledge elements in the design domain suggesting that he commonly contributed information about Attributes and Inputs in design discussion. On the other hand, Jimmy's network

(Figure 5b) shows a higher number of connections between Skill of Data and Skill of Design suggesting that his utterances integrated design tradeoffs into the group conversation.

Table 1 illustrates this in a short excerpt from one of the group's discussions about interpreting experimental data. In this excerpt, Jimmy's second comment (Line 2) makes a connection between the Skill of Data and the Skill of Design. He argues that graphs showing the results of benchmark testing (Skill of Data) help the team make an "informed decision" (Skill of Design) about their design choices. Two turns later (Line 4), Connor adds to the discussion by introducing information about specific attributes and inputs of the design: he talks about the performance parameters (payload, agility, and battery life) of some of the design choices that the team is considering (cadmium batteries and piezoelectric sensors).

Critically, this model using the moving stanza window method shows that it is Connor who builds on Jimmy's discussion about data and design by contributing information about inputs and attributes. The moving stanza window methods separately models both Jimmy's original contributions to the team discussion and the fact that Connor's contribution builds on Jimmy's utterance two lines before.

Table 1: Brief excerpt of the Hydraulic team's discussion of findings during the graphing activity.

	Student	Chat Utterance	Code
1	Jimmy	They all had both advantages and disadvantages. There was no "obvious" best choice.	
2	Jimmy	The **graphs** indicated the properties of all the **different options** and made a comparable visual illustration to make an **informed decision** on which combination to use.	**Skill of Data**, **Skill of Design**
3	Jordan	The graphs detailed what aspects of power sources and control sensors are important--namely, the numerical data.	Skill of Data, Knowledge of Inputs
4	Connor	I suggested using **cadmium batteries** with **piezoelectric sensors**, together they make a strong combination of **payload** and **agility** while keeping **costs** in a moderate range and having **strong battery life**.	**Knowledge of Inputs**, **Knowledge of Attributes**

Discussion

Our results thus suggest that the strophe method and the moving stanza window method identified different types of connection-making in student discourse. In particular, the strophe method summarized the connections made by student teams based on activity, but it could not differentiate individual contributions to team discussions. The moving stanza method, in contrast, accounted for the connections that were made based on activity and temporal proximity; importantly, this method was also able to model the contributions of individual students to team conversations.

Of course, which of these models is most appropriate depends on the theory of discourse that is being modeled. For example, if we assume that talk at the beginning of an activity frames everything that follows—or similarly, if talk at the end of an activity builds on everything that preceded it—then the strophe method is more appropriate, because it models connections among all of the talk within a single activity. If, on the other hand, we want a model that is sensitive to the temporal proximity of talk, then the moving stanza window method is a better choice, as it models connections locally within an activity, such that very early turns of talk are not related to ideas that arise much later in the discussion. In addition, the moving stanza window has the benefit of also modeling the role of individual contributions to group discussions.

This study, of course, is limited in that it focused on the activities of one group of students working in one CSCL context. However, this work highlights empirically a key theoretical distinction between models of connectivity in discourse, and perhaps more importantly, it demonstrates that the moving stanza window method makes it possible to use ENA to model both group discourse and the contributions of individuals to the group within a CSCL context.

References

Arvaja, M., Salovaara, H., Häkkinen, P., & Järvelä, S. (2007). Combining individual and group-level perspectives for studying collaborative knowledge construction in context. *Learning and Instruction, 17*(4), 448-459.

Bakhtin, M. (1986). *Speech genres and other late essays*. Trans. Vern W. McGee. University of Texas Press.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (1999). *How people learn: Brain, mind, experience, and school*. National Academy Press.

Chi, M. T., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science*, *5*(2), 121-152.

Chesler, N. C., Ruis, A. R., Collier, W., Swiecki, Z., Arastoopour, G., & Shaffer, D. W. (2015). A novel paradigm for engineering education: Virtual internships with individualized mentoring and assessment of engineering thinking. *Journal of biomechanical engineering*, *137*(2), 024701.

Cress, U., & Hesse, F. W. (2013). Quantitative methods for studying small groups. In C. E. Hmelo-Silver, C. A. Chinn, C. K. K. Chan, and A. O'Donnell (Eds.), *The international handbook of collaborative learning*, (pp. 93-111). Routledge.

DiSessa, A. A. (1988). Knowledge in pieces. In G. Forman & P. Pufall (Eds.), *Constructivism in the computer age* (pp. 47-70). Lawrence Erlbaum Publishers.

Dyke, G., Kumar, R., Ai, H., & Rosé, C. P. (2012). Challenging assumptions: Using sliding window visualizations to reveal time-based irregularities in CSCL processes. In *Proceedings of the 10th International Conference of the Learning Sciences* (Vol. 1, pp. 363-370).

Gee, J. P. (1990). *Social linguistics and literacies: Ideology in discourses*. Falmer Press.

Gernsbacher, M. A. (1991). Cognitive processes and mechanisms in language comprehension: The structure building framework. In G. H. Bower (Ed.), *The psychology of learning and motivation* (pp. 217-263). Academic Press.

Graesser, A. C., Gernsbacher, M. A., & Goldman, S.R. (1997). Cognition. In T. A. van Dijk (Ed.), *Discourse: A multidisciplinary introduction* (pp. 292-319). Sage.

Hearst, M. A. (1994). Multi-paragraph segmentation of expository text. In *Proceedings of the 32nd annual meeting on Association for Computational Linguistics* (pp. 9-16). Association for Computational Linguistics.

Hmelo-Silver, C. E., Liu, L., & Jordan, R. (2009). Visual Representation of a Multidimensional Coding Scheme for Understanding Technology-Mediated Learning about Complex Natural Systems. *Research and Practice in Technology Enhanced Learning, 4*(3), 253-280.

Rosé, C., Wang, Y. C., Cui, Y., Arguello, J., Stegmann, K., Weinberger, A., & Fischer, F. (2008). Analyzing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning*, *3*(3), 237-271.

Shaffer, D. W. (2012). Models of situated action: Computer games and the problem of transfer. In C. Steinkuehler, K. Squire, S. Barab (Eds.), *Games learning, and society: Learning and meaning in the digital age*, (pp. 403-433). Cambridge University Press.

Shaffer, D. W. (2014). *User guide for Epistemic Network Analysis web version 3.3*. Madison, WI: Games and Professional Simulations Technical Report 2014-1.

Shaffer, D. W., & Arastoopour, G. (2014). *Guide to RSdata.csv sample ENA data set*. Madison, WI: Games and Professional Simulations Technical Report 2014-3

Shaffer, D. W., Hatfield, D., Svarovsky, G., Nash, P., Nulty, A., Bagley, E. A., … Mislevy, R. J. (2009). Epistemic Network Analysis: A prototype for 21st century assessment of learning. *The International Journal of Learning and Media*, *1*(1), 1-21.

Smagorinsky, P. (2012). *Vygotsky and literacy research: A methodological framework* (Vol. 2). Sense Publishers.

Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. *Cambridge handbook of the learning sciences*, (pp. 409-426). Cambridge University Press.

Stahl, G. (2009). *Studying virtual math teams*. Springer Science and Business Media.

Suthers, D. D., & Desiato, C. (2012, January). Exposing chat features through analysis of uptake between contributions. In *45th Hawaii International Conference on System Science* (pp. 3368-3377). IEEE.

Webb, N. M. (2009). The teacher's role in promoting collaborative dialogue in the classroom. *British Journal of Educational Psychology, 79*(1), 1-28.

Wells, G. (1999). *Dialogic inquiry: Towards a sociocultural practice and theory of education*. Cambridge, England: Cambridge University Press.

Wenger, E. (1999). *Communities of practice: Learning, meaning, and identity*. Cambridge University Press.

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