Chapter 12
Application of Social Network Analysis to Collaborative Problem Solving Discourse: An Attempt to Capture Dynamics of Collective Knowledge Advancement

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Introduction

Theoretical Assumptions

The theoretical assumption that we base our analysis on is knowledge building. Scardamalia (2002) discusses that the main aim in a knowledge building community is collective knowledge advancement, and that group members should take up their personal cognitive responsibility to contribute to that collective knowledge advancement.

Purpose of the Analysis

We are interested in the analysis of collective knowledge advancement; however, our conjecture is that none of the existing methodologies are fully successful in capturing collective knowledge advancement. First, no existing methodology has been capable of representing dynamic change in collective knowledge advancement as it unfolds over time. Knowledge building is a process in which multiple participants are engaged in building knowledge collaboratively, mainly through their social discourse (Bereiter, 2002). We need an approach for capturing such dynamics in collective knowledge construction. At the same time we are also concerned with individual participants who are involved in collective knowledge advancement and

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D.D. Suthers et al. (eds.), *Productive Multivocality in the Analysis of Group Interactions*, Computer-Supported Collaborative Learning Series 16,
DOI 10.1007/978-1-4614-8960-3_12,

contribution that occurs at that level. In knowledge building practices, participants with different knowledge resources collaborate with one another to build new knowledge objects. At the individual level, the focus of analysis should be on how differently or uniquely each individual contributes rather than on how correctly individuals can develop their own knowledge. In this paper, we propose a social network analysis (SNA) of discourse as an alternative approach to representing both collective knowledge advancement and identification of each individual's contribution to that advancement.

Unit of Interaction

In this chapter, we look at how participants contribute to their collective knowledge advancement through their discourse in a face-to-face context. Therefore, the unit of interaction for us is the exchange of ideas between conversation turns. We do not analyze specifically the exchange between contiguous turns. Rather, we examine how each conversation turn contributes to participants' collective knowledge built through the preceding turns.

The unit of observation we are dealing with in the analysis is transcribed data from oral discourse. The observation is examined at two different levels of analysis. At the collective level (in other words, a group as a whole), we analyze how collective knowledge develops through participants' discourse in solving a chemistry problem. At the individual level, the same representation is more finely segmented into each individual's contribution. Finally, we integrate the two levels of analyses for answering our research questions: (1) how collective knowledge develops through interaction and (2) how each individual contributes to it.

Representations

We apply Social Network Analysis (SNA) to transcribed data from participants' conversation in solving a chemistry problem. In our SNA, the original data representation is a bipartite graph of words selected by analysts and conversational turns. By projecting that bipartite graph into a unimodal projection three different ways in our analysis, we are able to use these disparate representations of interactions to examine the same interactions using three very distinct lenses that bring out different insights. First, we create a network of words. The word network may provide us with insights about how participants' ideas would contribute to the collective knowledge advancement. Second, we create a network of participants (a typical social network). The participants network may inform us how different participants' ideas are related to each other. Finally, we create a network of conversation turns. The turns network shows us how different turns are related to one another on the basis of our selected words with links representing participants' ideas.

Manipulations

As we discussed in the previous section, the networks created based on the original bipartite graph from transcribed data are the first type of analytic representation. We can visually inspect how participants contribute to their collective knowledge advancement through their discourse by examining how the networks are structured turn by turn. In addition, we used several indices for analysis of collective knowledge advancement that can be captured through traditional measures such as network centrality coefficients used in SNA studies. The quantitative analysis using our numerical measures is conducted both at the collective level and at the individual level.

Social Network Analysis Approach to Collective Knowledge Advancement in the Knowledge Creation Metaphor

Recent studies in the learning sciences have discussed a new approach that integrates two prevailing metaphors of learning: acquisition and participation (Paavola, Lipponen, & Hakkarainen, 2004; Sfard, 1998). However, current assessment techniques do not act in concert with the development of such a theoretical approach to learning. Hence, to address this deficiency, social network analysis (SNA) is introduced as a novel assessment approach for learning interactions inspired by the knowledge-creation metaphor. In this chapter, we propose the social network analysis (SNA) of discourse as an alternative approach to analyzing collective knowledge advancement. In the following, we briefly review SNA research in CSCL and how the approach could be applied to learner discourse in knowledge building environments. We then describe our SNA of discourse data by two groups of university students that showed different dynamics in their collective knowledge advancement.

In CSCL research, there have been discussions on the advantages of using SNA to investigate community knowledge advancement and individual learners' engagement in this advancement from the perspective of the knowledge-creation metaphor (e.g., Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003; Reffay, Teplovs, & Blondel, 2011; Reuven, Zippy, Gilad, & Aviva, 2003). de Laat, Lally, Lipponen, and Simons (2007) considered the application of SNA in CSCL research. They outlined an approach to synthesize and extend the understanding of CSCL teaching and learning processes so as to balance SNA, content analysis and critical event recall. In this complementary approach, SNA was used to study interaction patterns within a networked learning community, as well as to study how learners share and construct knowledge. de Laat et al. concluded that SNA would be advantageous to include in any multi-method approach because of the following advantages: (a) researchers and learners are provided with a tool that is capable of illustrating mutual understanding and cohesion with group activities, and (b) a method is made available to researchers for selecting appropriate groups to study.

A limited number of studies have used SNA, especially those espousing the knowledge-creation metaphor in their work. Over a period of 3 years, Zhang, Scardamalia, Reeve, and Messina (2009) implemented a complementary approach that used SNA to visualize and compare classroom collaboration among fourth grade elementary school students through a CSCL environment designed to support them in knowledge building. An analysis of the students' online participatory patterns and knowledge advancement indicated that this learning process facilitated students' knowledge advancement effectively, and that this was the case through critical changes in organizations within the classroom: from fixed small groups in the first year of the study to appropriate collaboration through dynamic formation of small teams based on emergent goals.

In previous work (Oshima, Oshima, & Knowledge Forum® Japan Research Group, 2007), we further extended the potential of SNA as a core assessment technique by describing a different type of social network. Ordinary SNA illustrates the social patterns of learners, namely, the learners' social network. As de Laat et al. (2007) suggested, this approach is thus informative when examining developments or changes in the participatory structure of a community. However, we argued that existing social network models are unable to examine how community knowledge advances through learners' collaboration (Oshima et al., 2007). Instead, we used a procedure similar to ordinary SNA, but proposed a different type of social network, one based on the words learners use in their discourse in a CSCL environment. We compared this social network, in which words were selected as nodes representing learners' knowledge or ideas during discourse on a study topic, with a network of words from the discourse of a group of experts on the same topic. The results showed that there were remarkable differences in the community knowledge of elementary school students and of experts that can be revealed in terms of the words centered within the networks. We concluded that SNA can provide a new type of representation of community knowledge building by learners, enabling researchers to adopt a new complementary assessment technique for investigating knowledge building community models.

Although studies have proposed the application of SNA to learning analysis as a new assessment technique combining word level analysis and the knowledge-creation metaphor, an exact methodology has yet to be established. The purpose of this study is to propose an SNA approach to analyzing students' discourse that is consistent with the knowledge creation metaphor. Using the data provided by Sawyer, Frey, and Brown (this volume a, Chap. 9), we demonstrate how SNA is useful for us to analyze the collective knowledge advancement in either a qualitative or quantitative manner.

SNA of Discourse from the Perspective of Knowledge Creation Metaphor

We analyzed two groups of university students, one from what is called the Gillian class and the other from what is called the Matt class. As Sawyer, Frey, and Brown (Chap. 10, this volume b) discussed, these two groups were quite different in their strategic approaches to solving a chemistry problem, i.e., calculating the wavelength of an electron discharged from an object by utilizing formulas related to the photoelectric effect and the de Broglie equation. In their own conversation analysis, Sawyer and colleagues described the distinct profiles of the two groups as follows: the Gillian group went beyond pure calculation by discussing conceptual ideas about what they had learned and engaged in collaborative knowledge construction through mutual reflection of ideas. The Matt group, on the other hand, was involved in calculation activities without deep, reflective articulation of what they had learned.

With the same data set, we conducted our SNA for how each group of students was engaged in their collective knowledge advancement. In addition, we further analyzed how students in the Gillian class constructed their conceptual understanding after solving the given problem. In the first phase when students solved a problem in the Gillian and Matt classes, our analysis was focused specifically on the collective knowledge advancement. In the second phase when students discussed the trend related to the photoelectric effect and de Broglie wave after solving problems in Gillian class, our analysis was focused on how a peer leader supported students' collective knowledge advancement.

For the analysis of collective knowledge advancement, we referred to Scardamalia (2002) as our theoretical framework. Scardamalia proposed 12 socio-cognitive determinants of a knowledge building community. She discusses that the main aim in such a community is collective knowledge advancement, and that any members should take responsibility to contribute to the collective knowledge advancement.

Indicators for Collective Knowledge Advancement

Our effort in this study is focused on the establishment of indicators for collective knowledge advancement. Referring to Scardamalia's socio-cognitive determinants of a knowledge building community, we selected three aspects for our network analysis: (1) the continuous improvement of ideas, (2) learners' collective responsibility for community knowledge, and (3) their cognitive effort to rise above their previous ideas. What we attempt to do is to computationally measure the three aspects of collective knowledge advancement by the target groups. The basic assumption behind this analysis is that learners' ideas are represented as clusters of nodes, i.e., sets of words as nodes with links among them.

Based on our assumption, the improvement of ideas is captured by measuring degree centrality coefficients of nodes in a network of words. Degree centrality is a straightforward concept that indicates cumulative path lengths by which each node is linked to other nodes in the network. High degree centrality means that the node is at the center of the network as a whole, or near the center of a local cluster in the network. We are interested in the sum of degree centrality coefficients of all nodes as an indicator for the continuous improvement of ideas (i.e., increase in nodes and links). The learners' collective responsibility for collective knowledge is examined by calculating displacements of three centrality coefficients of all nodes by using a stepwise technique (Oshima et al., 2007). By comparing the displacements by three students in each group, we evaluate how each student individually contributes to

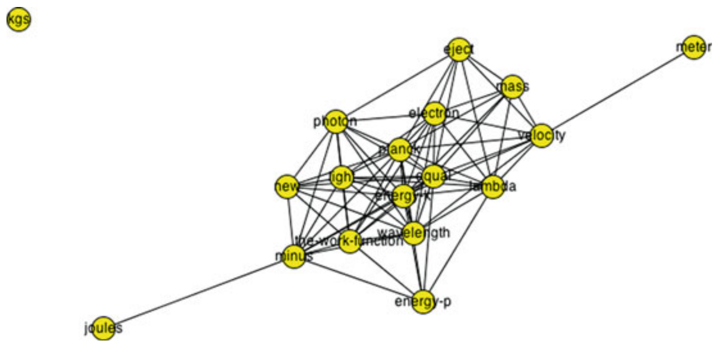

Fig. 12.1 The network structure of conceptual words in Gillian class

collective knowledge advancement. Finally, learners' efforts to rise above their own specific ideas is captured by displacements of closeness and degree centrality coefficients in our stepwise analysis. Closeness centrality is a measure of how close the node is to other nodes in a network, based on the geodesic distance. When a conversation turn works to integrate previous ideas, the turn is considered to contribute to the increase in closeness and degree centrality coefficients more than other conversation turns.

Visual Inspection of Network Structures by Two Groups

We selected words for the analysis that we believe to be representative of student explanations about their problem solving at the conceptual level and calculation level. Words selected to represent the conceptual level are nouns and verbs by which students engaged in planning and motoring their problem solving by referring to related formulas. Words selected at the calculation level are numbers they produced as they worked towards reaching their final answers. The agreement of word selection between two independent researchers was over 90 %. Disagreements were resolved through discussion. There were 18 conceptual words and 14 calculation words selected for the Gillian class. For the Matt class, 14 conceptual and 12 calculation words were selected for the analysis. Using an SNA application we developed in our earlier work (Matsuzawa, Oshima, Oshima, Niihara, & Sakai, 2010), we visually inspected the progressive turn-by-turn development of network structures and found critical differences between the two groups as well as one particular pivotal conversation turn in the discourse.

One critical difference between the two groups was in the cohesiveness of network structure. While the two groups were solving exactly the same problem, their usage of conceptual words in their contributions was quite different from each other. The network structure of conceptual words in the Gillian class was more cohesive. Although one word was isolated, other words were gathered into one big cluster (Fig. 12.1). This suggests that students related these conceptual words in their discussion. On the other hand, the network structure of words in the Matt class was segmented: the network consisted of two completely separate clusters of words

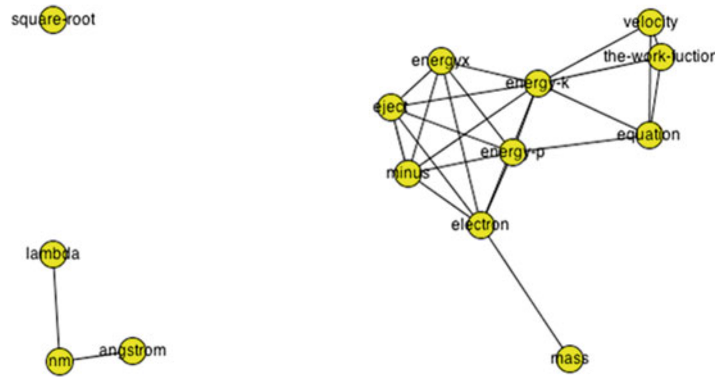

Fig. 12.2 The network structure of conceptual words in Matt class

Table 12.1 An excerpt of discourse by Gillian Group with a pivotal turn found in the network analysis

F1	so we need lambda and its give us the *** so with the wavelength we can find velocity. And with…
F4	And we don't have to works with the-work-function right away.
F1	not right away but we do need the-work-function at the end.
F4	Ok to find the…
F1	Because the important thing that for the lambda we are find the wavelength of the electron not of light.
F4	Right, exactly. So, first for the electron we use Planck/mass velocity because we know the mass of an electron
F1	We need to find the mass of an electron
F4	no, we know the mass of an electron. It's an electron.
F1	very true, very true.
F4	but we don't know…
F1	with this wavelength we would be find velocity
F2	what did they give us. For the following wavelength. So, well lambda equal Planck/mass velocity right?
F1	Yes its tell us to use lambda equal Planck/mass velocity
F1	You can find energy-k.
F4	energy-k of a photon.
F1	use energy-k of the-work-function equal energy-k equal Planck new minus the-work-function equal energy-k of a photon and use energy-k of a photon to find the wavelength of light.

*** inaudible portion

(Fig. 12.2). This result suggests that students in the Matt class were not having a cohesive discussion at the conceptual level of problem solving.

We also found a conversation turn that was pivotal for the cohesiveness of network structure in the Gillian class. By observing changes in the network structure turn by turn, we found a pivotal point at which segmented clusters of conceptual words merged into one cohesive cluster. In this pivotal conversational turn, a student (F1) offered the idea of relating different formulas to one another during their planning before actually calculating the answer using the formulas. Table 12.1

shows their discourse from the beginning until the pivotal conversation turn by F1. Their discourse started with sharing their ideas of formulas for solving a problem. Their problem-solving strategy was a backward-chaining approach setting their final goal of calculating the wavelength of an electron ejected from manganese. They first considered the application of the equation to calculate the wavelength of a matter by finding what was still unknown, the velocity. Then they further explicated their inference to use the equation of the relationship between kinetic energy of matter, mass and velocity. Their focus was mainly discussing de Broglie hypothesis. The last conversation turn by F1 gave a new idea to go back to the correct equation for the photoelectric effect. After this conversation turn, the Gillian group was able to establish their solution and began their calculations in earnest.

Network Analysis with Indicators for Collective Knowledge Advancement

The Continuous Improvement of Ideas

For the analysis of idea improvement, we calculated the sum of degree centrality coefficients of nodes in the network of conceptual words and examined its time-series change turn by turn (Fig. 12.3). The network structure of conceptual words in the Gillian class was more inter-connected than that in the Matt class. We also examined which students had conversation turns that steeply increased the sum of degree centrality coefficients. We referred to these as "jumping turns." There were ten such turns found to increase the degree centrality in this way in the Gillian class and four in the Matt class. In the Gillian class, contribution by each student was quite even. F1, F2 and F4 were involved in the jumping turns by four, three and

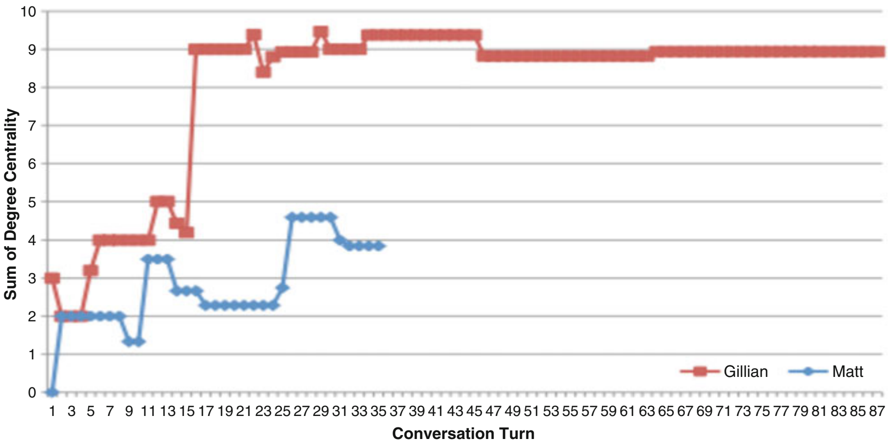

Fig. 12.3 Transition of the sum of degree centrality coefficients by Gillian and Matt groups

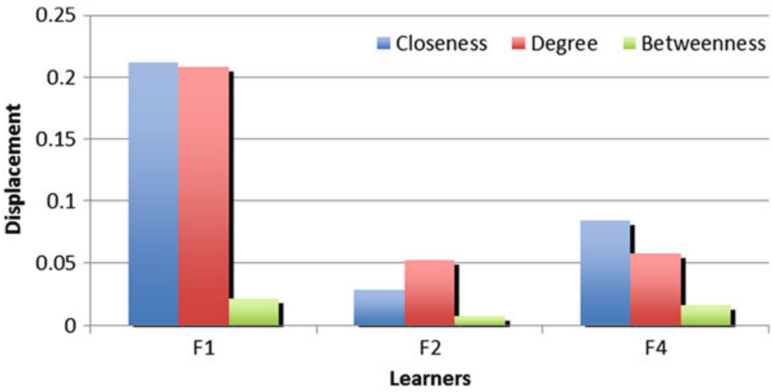

Fig. 12.4 Means of displacements of centralities by learners in Gillian

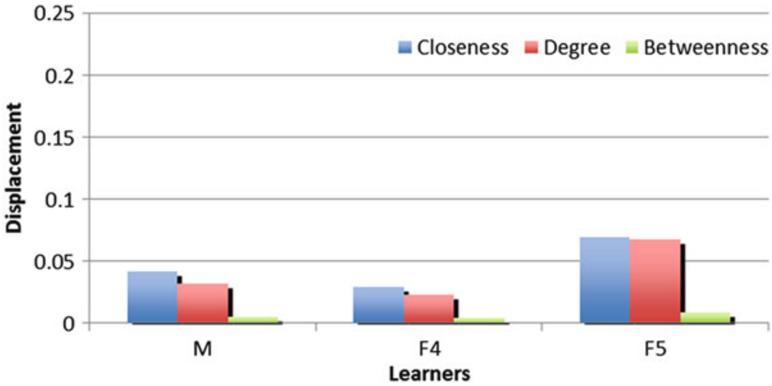

Fig. 12.5 Mean displacements of centralities by learners in Matt

three times, respectively. In the Matt group, F5 was involved in jumping turns three times. M was once. F4 was never. The results suggested that the Gillian class students were more oriented towards continuous idea improvement than were the Matt class students. In addition, the contributions in the Gillian class were more distributed than in the Matt class.

Collective Responsibility for Community Knowledge, and Effort to Rise Above

Learners' collective responsibility was evaluated by the displacements of three centrality coefficients of nodes in their network of conceptual words when their discourse contributions are excluded. Figures 12.4 and 12.5 show mean displacements of nodes by learners. 3 (Learners) × 3 (Centralities) ANOVAs with mean displacement as a dependent variable for the two groups demonstrated that (1) mean displacements of closeness and degree centrality coefficients by F1 were significantly higher than those by two other students in the Gillian class, $F(2, 51) = 7.52$, $p < 0.01$ for closeness centrality, and $F(2,51) = 8.01$, $p < 0.01$ for degree centrality; and that no significant differences were found in the Matt class.

These results suggest that collective responsibility in the Matt class was relatively equal among the three students whereas F1 had more contribution to collective knowledge than did two others in the Gillian class. At a glance, the results here are contradictory to what we discussed in the previous analysis of the continuous idea improvement. In the idea improvement, we found that the Gillian students were more equally engaged in the improvement of collective knowledge than were Matt students. We have to be mindful that the analysis of idea improvement is focused on time-series change in the network structure whereas the analysis here is focused on comparison of each learner's contribution to the final state of the network structure. In other words, the stepwise analysis by excluding each learner's discourse represents how much "unique" contribution (i.e., links or nodes) each learner has in the network structure. In taking the differences in focus of the analyses into consideration, we discuss the differences in closeness and degree centrality coefficients between F1 and others in the Gillian group. One possible interpretation of the differences may be that F1 took a unique role to integrate others' ideas in some way. Closeness and Degree centrality coefficients are considered to be indicators of learners' effort to rise above ideas. Results here suggest that F1 contributed turns that enabled previously disconnected portions of the network to get linked or to move closer to one another.

How a Peer Leader Facilitated Students' Collective Knowledge Advancement

After solving problems, the two sub-groups in the Gillian class were merged as one group of seven students. They discussed the trend from their answers to the two problems under the supervision of the peer leader. This phase was an opportunity for students to make use of their conceptual understanding by explaining their process and what they could find as principles. The peer leader took her role to support students in making progress in constructing their shared meaning. She provided students with five key prompts during their discussion (see Fig. 12.6). We analyzed students' discourse data with two different purposes. First, we were concerned with the contribution by the peer leader to students' collective knowledge advancement. Since we considered that the leader's contribution would affect students' discourse following it, we segmented students' conversation turns into five parts following each key prompt by the peer leader. Second, we conducted stepwise analysis for identifying each student's contribution to each part of the discourse. For creating

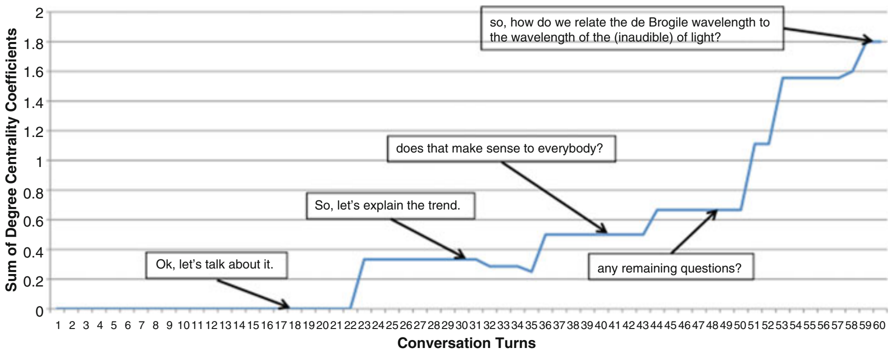

Fig. 12.6 Transition of the sum of degree centrality coefficients during students' discourse following the peer leader's key prompt

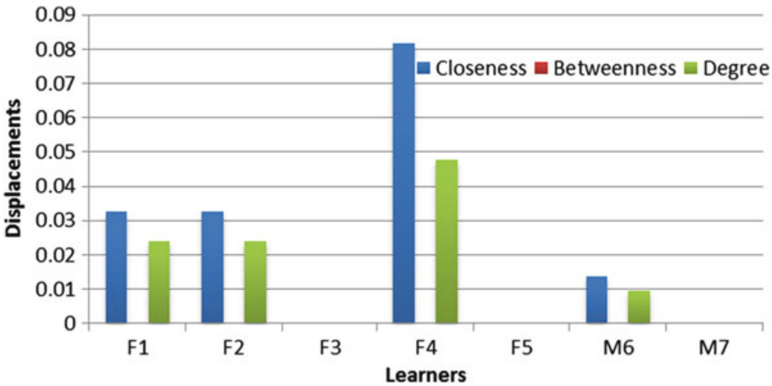

Fig. 12.7 Individual contributions in discourse following the first prompt

network structures, we used a subset of conceptual words that we used in the previous analysis because students did not use all the words we had previously selected.

Figure 12.6 shows the transition of the sum of degree centrality coefficients and conversation turns that the peer leader spoke to students. The first key prompt was "OK, let's talk about it." Here, the peer leader encouraged students to argue about what they found in solving the two problems. In between this first prompt and the second prompt, students "talked about" their answers, e.g., the unit of energy "joules." At this stage, we could not find any links in networks of learners and conversation turns. There was just one link between words, which means that a student used the two words in the same conversation turn. An individual students' contribution to the structure of network of words can be seen in the closeness and degree centrality but not in betweenness centrality (Fig. 12.7).

In the second prompt, the peer leader further directed students' discussion toward what trends they could find, i.e., "So, let's explain the trend." Following this second

Fig. 12.8 The network structure of words in discourse following the second prompt

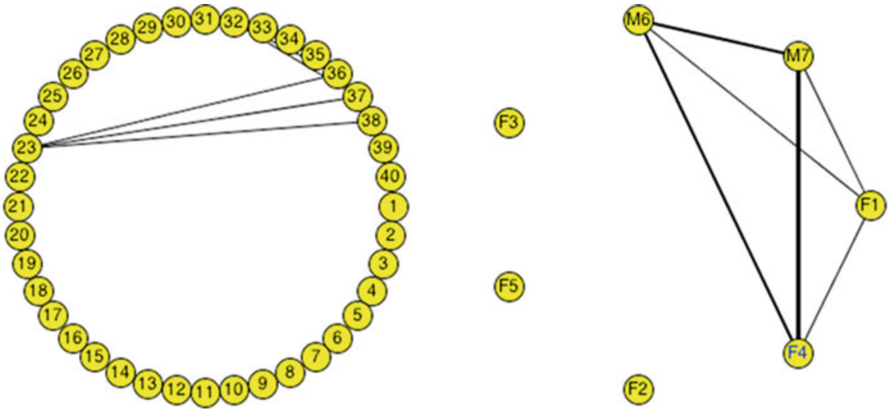

Fig. 12.9 The network structures of conversation turns (*left*) and students (*right*) following the second prompt

prompt, students discussed the relationship between the wavelength and energy (Fig. 12.8). Student F1 and M6 had conversation turns about this issue, e.g., "larger wavelength, less energy." From this second stage, students' conversation turns came to be linked to one another, and a network structure of students appeared (Fig. 12.9). This suggests that their ideas came to be linked to one another as the conversation proceeded. At the end of this stage, each individual student's contribution to the network of words was equally unique except for student F5 who did not use any of the selected words (Fig. 12.10). Students F2 and F3 had unique contributions although they were not linked to anybody in the network of students because there were several unique words used only by them in the conversation.

After encouraging students to explain the trends they found, the peer leader further encouraged their discussion by her third and fourth prompts. As seen in Fig. 12.11, these two prompts were found to stimulate students' further construction of their shared meaning of the trends. In her third prompt ("does that make sense to everybody?"), the peer leader attempted to confirm students' conceptual understanding of the de Broglie wavelength by facilitating reflection on what they had just discussed. With this third prompt, the students' conversation was more focused on what they found as the trend (Fig. 12.11). More conversation turns and students became linked in the networks (Fig. 12.12). After the third stage, however, a

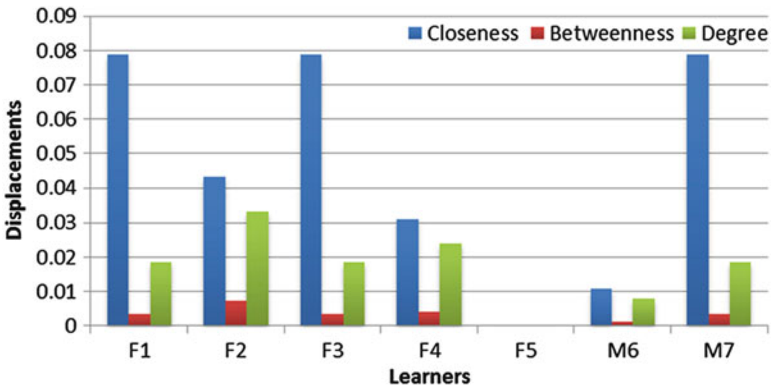

Fig. 12.10 Individual contributions in discourse following the second prompt

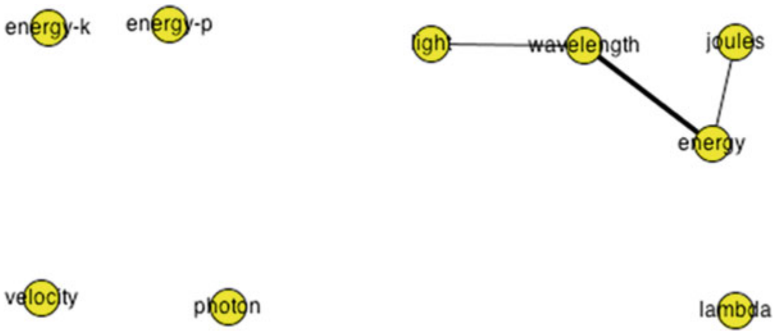

Fig. 12.11 The network structure of words in discourse following the third prompt

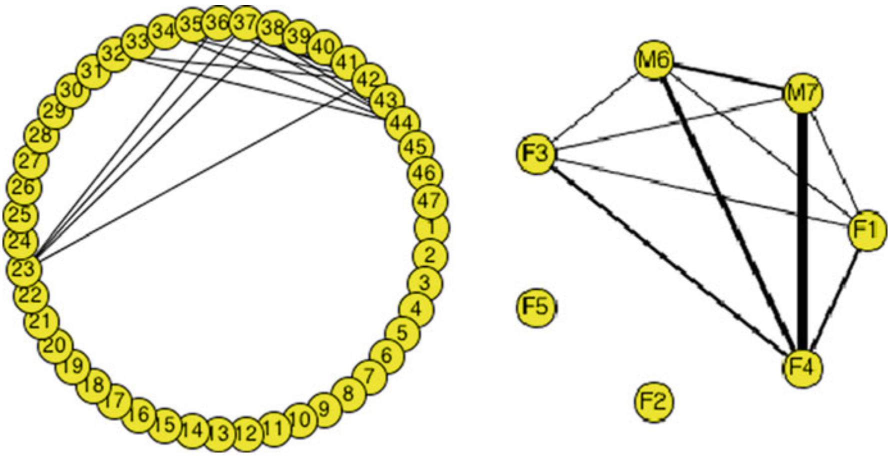

Fig. 12.12 The network structures of conversation turns (*left*) and students (*right*) following the third prompt

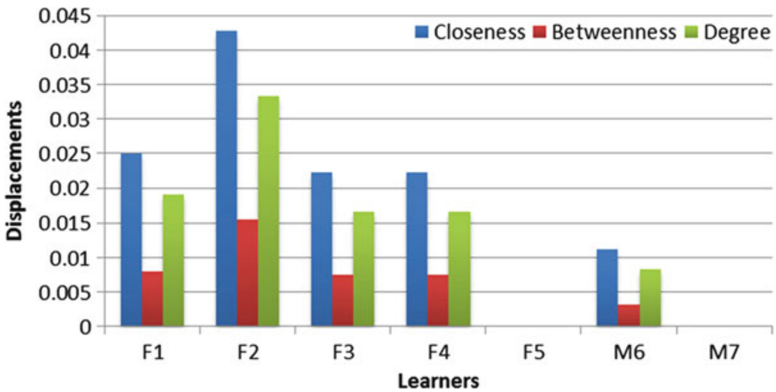

Fig. 12.13 Individual contributions in discourse following the third prompt

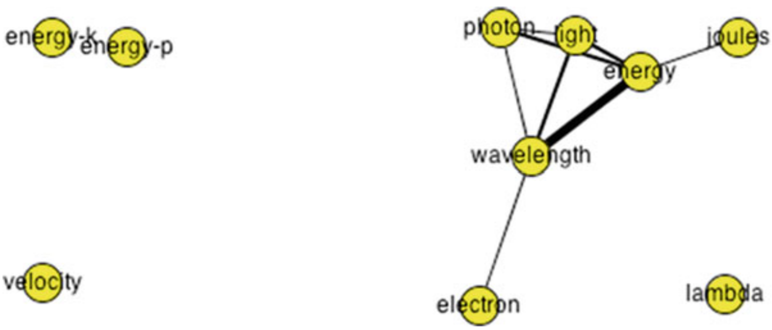

Fig. 12.14 The network structure of words in discourse following the fourth prompt

contribution by one student (M7) disappeared from the evolving representation because other students generated the same links of words in other conversation turns (Fig. 12.13).

The fourth prompt by the peer leader, "any remaining questions?", was found to be so critical that all the students were involved in the construction of shared meaning that followed. We could not identify what prompted the peer leader to utter this turn based on what is visible in the transcription only. But, there must have been some reason for her to prompt her students for further discussion after they had already made sense of the trend. This fourth prompt led students to be deeply involved in a more complete explanation of the trend. Networks of words, students and conversation turns became even more robust in their structure through this process. One of the most remarkable findings here was that all the students finally became linked in their social network at this stage. Based on the more robust network structure of words (Fig. 12.14) with the social network structure of students (right side in Fig. 12.15), we can claim that the fourth stage was a very important discussion process by which every student offered a meaningful contribution to the

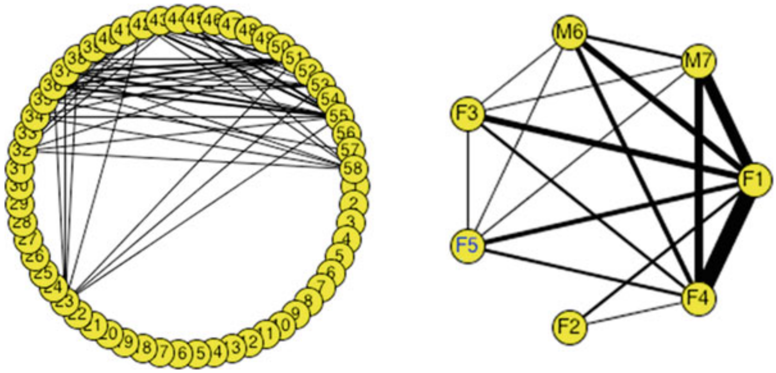

Fig. 12.15 The network structures of conversation turns (*left*) and students (*right*) following the fourth prompt

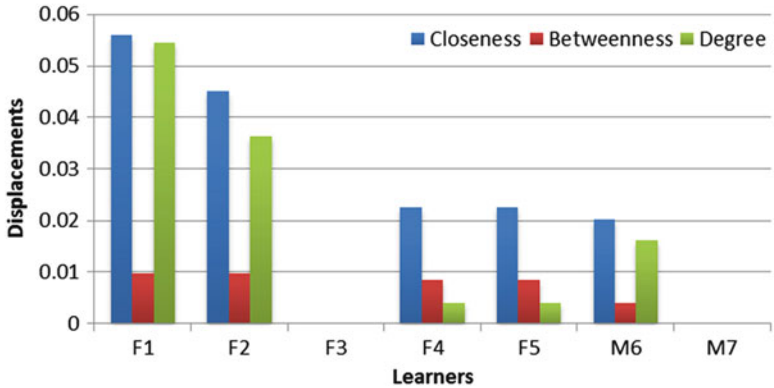

Fig. 12.16 Individual contributions in discourse following the fourth prompt

collective knowledge advancement, although some students did not contribute a unique contribution to it (Fig. 12.16). The fifth prompt "so, how do we relate the de Broglie wavelength to the wavelength of the [inaudible] of light?" was followed by only one conversation turn that did not make a big change in the network structures, we therefore omit description here.

Summary

We have presented two analyses in this chapter: (1) comparison between small group problem solving supervised by two peer leaders (i.e., Gillian and Matt), and (2) student discussion for constructing shared understanding of the de Broglie wavelength after their problem solving activities in the Gillian class. The first analysis was aimed at describing how different the two groups were in solving the same problem from the perspective of the knowledge creation metaphor. The second section was more directed at how we can identify the peer leader's contribution to the students' discussion for the purpose of constructing shared understanding. Based on our visual inspection and network analyses of indicators for collective knowledge advancement in the first section, we developed profiles of the two groups as follows:

Gillian Class. In solving the problem, the Gillian students devoted much effort to conceptual idea improvement. Only after exploring the problem space did they start their calculations. Each learner made a significant contribution to the group idea improvement, but one of them (F1) was found to have a more unique contribution to their collective knowledge advancement. Her contribution was unique in the sense that she attempted to rise above the previously expressed ideas.

Matt Class. The Matt group was calculation-centered. They did not devote much effort to exploration of the problem space. One student (F5) was somewhat involved in conceptual idea improvement. However, the contributions contributed by the three students were not significantly different. The non-significance suggests that the three students used conceptual words in a quite similar way and their conversation turns did not frequently create unique links among nodes in the network.

Peer Leader's Role in Students' Collective Knowledge Advancement

As the first section of analysis suggested, the peer leader in the Gillian class was more concerned with students' intentional involvement in constructing conceptual understanding, and she seemed to have an intention to support her students' engagement in such an activity. We, therefore, further analyzed how the peer leader attempted to be involved in the students' discussion after solving problems. During students' discussion in figuring out the trend, she gave students five key prompts. In early stages, her intention was to direct students' attention to the issue of discussion, i.e., "OK, let's talk about it," and "So, let's explain the trend." After successfully involving students in discussing the trend, she further asked students to reflect on what they found twice, i.e., "does that make sense to everybody?" and "any remaining questions?" We found that these two prompts activated students' deep involvement in conceptual understanding. The fourth prompt, in particular, elicited student discourse that created network structures of words, students and conversation turns and increased robustness in the structure. After the third prompt, students demonstrated their understanding quite visibly. Nevertheless, for some reason the peer leader offered them her fourth prompt. This remains a mystery that should be further examined by conducting more micro-level of analysis or the ethnographic studies in the classroom.

Final Remarks

In this study, we analyzed collaborative problem solving discourse from the perspective of the knowledge creation metaphor. As a methodological tool, we selected the SNA approach by which we can visually and computationally investigate the dynamics of collective knowledge advancement. For computationally analyzing discourse, we referred to the theoretical framework of knowledge building (Scardamalia, 2002) to create indicators for collective knowledge advancement.

Our challenge might be evaluated with the following criteria: (1) whether our findings match those from the original study by Sawyer et al., and (2) whether we can propose new insight beyond their original analysis. Regarding the first criterion, results of analysis mostly match what Sawyer et al. discussed in their original analysis. However, we further found a possibility that one student in the Gillian class, namely, F1, also identified as a leader in the Souflé analysis by Howley and colleagues, might be a key player in their collaborative problem solving. Conversation turns by F1 had significantly higher effect in increasing the extent to which conceptual words became linked and closer to one another within the evolving network structure. Regarding the second criterion, we described our first step to establish the methodological approach by using SNA for interaction analysis with discourse as data. The second section of our analysis might provide readers with a new perspective on the computational analysis of discourse and how instruction (appropriate prompts by the peer leader in our case) can affect students' discourse.

Our future effort will be focused in two directions. One direction will be the development of application software for educational researchers to easily engage in SNA of discourse. Our tools under development are still in a progressive refinement stage. The other direction will be the establishment of indicators for collective knowledge advancement by using SNA. Knowledge building is one possible methodological framework for us to use in creating indicators. However, other possibilities should also be explored.

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