A Visualization System of Discussion Structure in Case Method Learning

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Abstract: In the case method learning to develop learners' problem-solving skills, an instructor plays a role on the facilitation of the discussion. As one of facilitators' techniques to support learners' discussion, visualization of discussion structure based on graph representation is often used. Automatic visualization of the discussion structure without the facilitator will contribute to expanding the learning opportunities for learners. So we propose a visualization system of the discussion structure by a graph representation with nodes and links through speech recognition of learners' voice. The proposed method improves the conventional method to visualize discussion structure by considering the relation in the sequence of learners' opinions.

1 INTRODUCTION

It is necessary to obtain problem-solving skills to analyze problems and to propose solutions to the problems (Schwarz, 2002). Case method learning is one of the ways of developing problem-solving skills (Hammond, 1980). In the case method learning, an instructor makes a documented case that describes what happens in the past. The sentences in the documented case imply some problems in the case. The learners exchanges their opinions regarding what are problems and how to solve the problems in the documented case. This enables the learners to share the knowledge about how to deal with the problem.

In the discussion, it sometimes happens that the learners get off the arguing point or become too inactive to express their opinions. In this case, the learners can not share the knowledge sufficiently. Therefore, the instructor facilitates the discussion neutrally by asking some questions or showing summary of discussion in order to make the learners aware of what point to be argued (Brooke, 2006).

As one of facilitator's techniques to support learners' discussion, visualizing the structure of the discussion by a graph representation is often used (Yamashita, 2000). Learners can intuitively understand and share the arguing point of the discussion and its structure by the visualization. The graph representation of the discussion consists of 'node' and 'link'. The nodes represent learners' opinions and the links between nodes represent relations between the opinions. Every time the learners speak their opinions, the facilitator adds the opinions as the nodes to the graph of the discussion structure. Watching the graph made by the facilitator, the learners can recognize the arguing point and find when they miss the arguing point. This enables to lead the learners to the effective discussion (Gragg, 1951). However, facilitators are lacking for learners. Learners can not always receive the facilitator's support of visualizing the discussion structure.

So we propose a visualization system of the discussion structure as a graph representation in the case method learning. In using the proposed system, the learners speak their opinions to a microphone. The proposed system captures the learners' opinions by speech recognition. Analyzing the opinions, the proposed method makes the graph of the discussion structure and displays to the learners.

The rest of the paper is organized as follows. Section 2 describes the literature review of visualizing discussion structure. Section 3 outlines our proposed system of visualizing discussion structure. Section 4 shows the experimental results in applying the proposed method to the real data from learners. Section 5 deals with the conclusion derived from the experimental results.

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2 LITERATURE REVIEW

2.1 Visualization of Discussion Structure by Graph Representation

In order to improve the discussion, there are some researches on argument diagramming method for facilitators (Conklin and Begeman, 1988; Rienks et al., 2005; Werner and Rittel, 1970). The discussion structure is visualized by using nodes as opinions and links as relations between opinions. Figure 1 shows a graph representation of an example of discussion structure by argument diagramming. In the graph, an opinion at the top is related to 2 nodes in parallel. The relations to the other opinions in the discussion are positive or negative response, proposal, additional explanation, and so on (Hobbs, 1990). The facilitator creates links between two opinions which have such relations. In the graph of Figure 1, opinions of 'I think a dolphin is the most intelligent animal.' and 'A monkey is the most intelligent I think.' are answers to the opinion of 'Which animal is the most intelligent?'. And an opinion of 'A monkey can identify itself in the mirror.' complements the opinion of 'A monkey is the most intelligent I think.' Watching this graph makes it easy to understand the progress of the discussion. For the purpose of supporting discussion without facilitators, we propose an automatic graph visualization system of the discussion structure as the previously described graph.

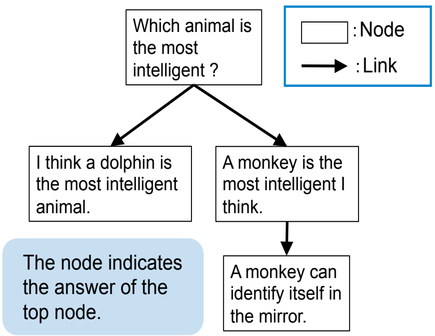

Figure 1: Graph representation of discussion structure.

2.2 Conventional Method of Automatic Discussion Graph Generation

Zhao et al. proposed a visualization method of the relation between keywords extracted from the minutes of the meeting (Zhao et al., 2006). However, learners have to comprehend not only the relation between the keywords but also the relations between the opinions. So, this conventional method is insufficient for the learners to understand the discussion structure. On the other hand, based on the change of the word frequency in a minute of the discussion, Matsumura et al. addressed visualizing the relations of opinions after the discussion (Matsumura et al., 2003). For n opinions recorded in the minute, let $S_t(t = 1,2,\cdots,n)$ denote the tth opinion by a learner. A set of the series from the 1st opinion to the nth opinion is represented as a window of opinions $W(1,n) = \{S_1,S_2,S_3,\cdots,S_n\}$. Subsequently, a feature vector of the each opinion $V_t = \{I_{1t},I_{2t},I_{3t},\cdots,I_{nt}\}$ is calculated to clarify what the opinion means (Gerard and McGill, 1983). $I_{it}(i = 1,2,3,\cdots,n)$ represents the weight of the each ith word $w_i(i = 1,2,3,\cdots,n)$ in the opinion S_t by the following formula:

$$I_{it} = tf(w_i,S_t) \times \left(\log \frac{tf(w_i,W(1,n))}{tf(w_i.W(1,n)) - tf(w_i,S_t)} + 1\right) \quad (1)$$

where $tf(w_i,S_t)$ is the frequency of the word w_i in the opinion S_t and $tf(w_i,W(1,n))$ is the frequency of the word w_i in the window $W(1,n)$. The conventional method extracts the words from each opinion by morphological analysis and calculates $tf(w_i,S_t)$ and $tf(w_i,W(1,n))$ automatically. Top 20 weights of words as the significant words are used for the feature vector words V_t.

In the discussion, learners often rephrase the past opinions for summarizing or clarifying past opinions (Okumura and Takeo, 1994). Because there are similar words between an opinion and its rephrased one, this conventional method identifies the similar words with thesaurus, unifies the similar words to one word, and creates links between similar opinions (Hearst, 1997). The similarity is calculated as the following cosine similarity between V_1 and V_2:

$$sim(V_1,V_2) = \frac{V_1 \cdot V_2}{|V_1| \cdot |V_2|} \quad (2)$$

If a learner speaks an opinion B long after an opinion A from a learner, the opinions A and B rarely have a relation each other. So, links should be created to the recent opinions by calculating similarity between the opinions. When an opinion is inputted, feature vectors of all opinions $V_t(t = 1,2,\cdots,n)$ are decided by the formula (1). Then similarities between V_t and $V_{t+1},V_{t+2},\cdots,V_{t+a}(t+a \le n)$ are calculated by the formula (2) where a is a parameter that indicates how many recent opinions influence the current opinion. If the similarity is more than or equal to a certain threshold, the link is created between these opinions.

2.3 Research Issue

Matsumura's method visualizes the discussion structure from a minute after the discussion. The minute is well written by a secretary with adding some information. However, the learners often speak their opinions with referring the past opinions in discussion. Most of the opinions include less words than the minutes include (Fillmore, 2011). So the links are not created between opinions by the conventional method even if the opinions have a relation. In order to create the link, it is necessary to find the related opinions by not only the similar words but also the other words such as demonstratives. In addition, the sequence of opinions would be useful to understand the discussion as people can understand the context from the sequence of the opinions. We also need to consider the sequence of opinions to create the link.

3 VISUALIZATION SYSTEM OF DISCUSSION STRUCTURE

3.1 Outline of the Visualization System

Figure 2 is the outline of our proposed system. The input of this system is a sequential opinion from learners through a microphone mounted on the system.

The proposed system converts learners' voice to a sentence by speech recognition. We adopted a speech recognition software 'Julius' that is based on large-scale speech corpus (Lee and Kawahara, 2009). However, it is known that precision of speech recognition is not enough to support discussion (Zhao et al., 2006). So, in order to improve the accuracy, we preliminary input the documented case to the Julius, and emphasize on the words in the document for speech recognition by maximum likelihood estimation. This means that the learners tend to use the words that appear in the documented case. In this way, accuracy of recognizing the speech related to the documented case can be improved.

After extracting nodes as the sentences converted from learners' voice, the system identifies the relation between nodes and visualizes the structure of the discussion. First, the proposed method identifies the relation by the dictionary of demonstratives and connectives that indicate the relation between opinions. Then we apply Matsumura's method using the similarity between recent opinions. Finally, based on the sequence of opinions that have been already linked each other, the proposed system complements links to the nodes that still have no links.

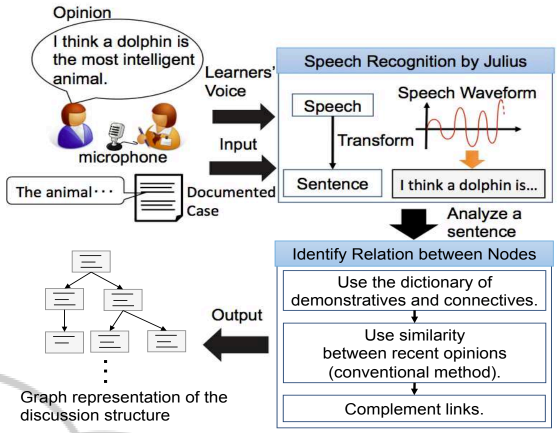

Figure 2: Configuration of discussion support system.

In the following sections, we describe the step of only identifying the relations between nodes because we have already confirmed that the speech recognition is well done by the existing tool.

3.2 Graph Visualization by Demonstratives and Connective

Opinions in the discussion sometimes include demonstratives, such as "this", "that", "as you said" etc., that refer a past opinion. The learners need to understand the past opinion referred by the demonstrative in order to understand the opinion including demonstratives. So the opinions including the demonstratives tend to have a relation to other opinions referred by the demonstratives. Therefore when the opinions include the demonstratives, the system identifies the opinion including a word or a sentence referred by the demonstrative, and creates a link between them.

In this system, when the opinion has the demonstratives, the opinion links with the previous opinion with assuming that a demonstrative may point to the previous opinion. In addition, connectives are the words which represent the relation between the sentences. So the opinions including the connective can have a relation to the recent opinions.

The proposed system identifies the opinions that include demonstratives or connectives by keyword matching to the words in the dictionary that the facilitators preliminary define the demonstratives and connectives on. This enables to find the relation between opinions more accurately.

3.3 Graph Visualization by Similarity between Recent Opinions

The Matsumura's method of the visualization of dis-

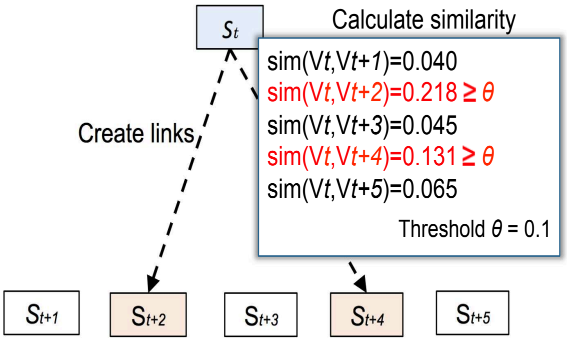

Figure 3: Create links based on the similarity between recent opinions.

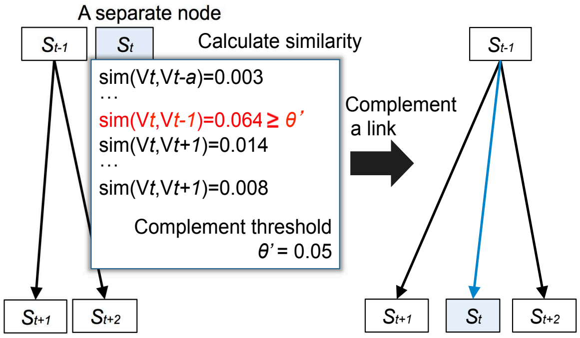

Figure 4: Complement links into separate nodes.

cussion structure, introduced in section 2.2, is also effective to identify the relation between opinions. So, we apply the conventional method to the opinions. When an opinion is inputted, the system calculates similarity between opinions and creates links as shown in Figure 3. In the Figure 3, in case of $a = 5$ as the number of recent opinions where a opinion has an influence, the similarities between S_t and $S_{t+1}, S_{t+2}, \cdots, S_{t+5}$ are calculated. Then links are created from S_t to S_{t+2} and S_{t+4} because $sim(V_t, V_{t+2})$ and $sim(V_t, V_{t+4})$ are over the threshold θ.

3.4 Link Complement Considering the Relation in Sequence of Opinions

In discussion, learners often speak their opinions with referring the past opinions. Even if we visualize the structure of discussion only by the method of using demonstratives, connectives, and similarity between recent opinions, some of links are not created between opinions because the learners do not always use the same words for the same meaning. So, the opinions that have different words from other opinions tend to be separate nodes. However, as the discussion goes on, the different similar words are gradually used by the learners, which increases the similarity and enables to create links with the separate nodes without any links to other nodes.

So we link the separate nodes to other nodes before and after the separate node. An opinion of the separate node may be connected to earlier or later opinions than the opinion on the separate node by considering the relation in the sequence of learners' opinion. Figure 4 shows the process of link complement. First, the similarity of the separate node to the other opinions before and after the separate node are calculated by the formula (2). The number of opinions whose similarities are calculated is the same as the number of recent opinions a in section 3.2. Because the separate node has not been linked by the method described in section 3.2, the similarity of each separate node must be below the threshold θ. So we introduce another threshold θ' that is smaller than θ in order to create links with the separate nodes. When the similarity is more than or equal to threshold θ', a link is complemented between the nodes. In Figure 4, S_t is a separate node, and earlier or later opinions $S_{t-1}, S_{t+1}, S_{t+2}$ have links. Then a new link is created between S_{t-1} and S_t because the similarity of them is more than or equal to complement threshold θ'.

4 EXPERIMENT

4.1 Outline of the Experiment

In this experiment, we use a documented case that is really used in an educational institute for project managers. The documented case describes problems about delay in information system development project because of lack of communication in the project, difficult process of agreement, and so on. We ask 2 groups of 3 students, Group A and Group B, to discuss the case for 20 minutes. The numbers of learners' opinions in Group A and in Group B are 50 and 65, respectively. During their discussion, a facilitator updated the graph of discussion structure automatically using two methods shown in the followings:

- Conventional method : Visualize discussion structure based on conventional method described in section 2.2 (Matsumura et al., 2003).
- Proposed method : Visualize discussion structure using demonstratives and connectives, similarity between recent opinions and link complement considering the relation in the sequence of opinions.

In order to evaluate these graphs , we compare the graphs by both methods to the graph made by a facilitator. Total number of the links in the graph made by a facilitator was 45 for Group A and 57 for Group B.

Figure 5 shows the part of the graph made by the facilitator for Group A. The nodes are numbered in serial order. We evaluate these methods by precision rate and recall rate calculated by the formulas (3) and (4). We determined $a = 5$ as the number of recent opinions where a opinion has an influence, and set thresholds as $\theta = 0.1$, $\theta' = 0.05$.

$$\textit{Precision rate} = \frac{\text{The number of links created correctly}}{\text{Total amount of links}} \qquad (3)$$

$$\textit{Recall rate} = \frac{\text{The number of links created correctly}}{\text{The number of correct links judged by a facilitator}} \qquad (4)$$

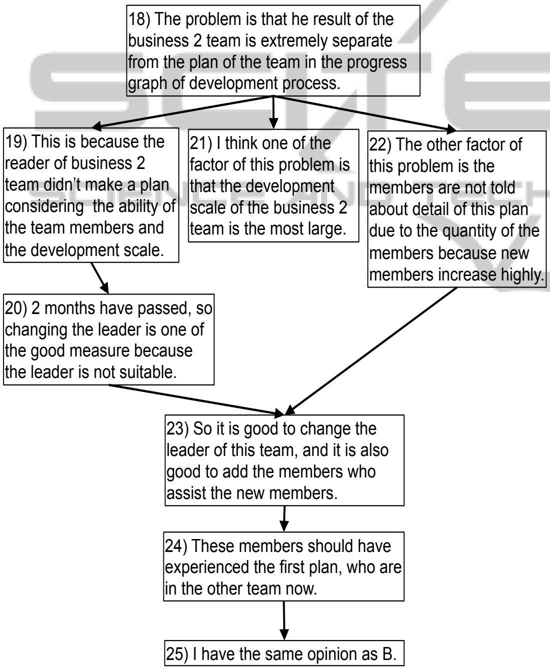

Figure 5: Graph representation of discussion structure made by a facilitator for Group A.

4.2 Experimental Result

Figure 6 and 7 show the transition of precision rate and recall rate by both methods during discussion by Group A. Figure 8 and 9 show the transition of precision rate and recall rate by both methods during discussion by Group B. The number of complemented links is also shown in both graphs. And the final precision rate and recall rate after the discussion are shown in Table 1. According to Figure 6, 7, 8 and 9, the proposed method improves both precision rate and recall rate during the discussion compared to the conventional method. On average, the proposed method improves both precision rate and recall rate by 5.6% and

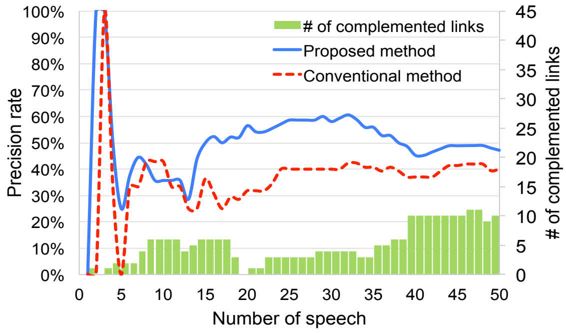

Figure 6: Transition of precision rate for Group A.

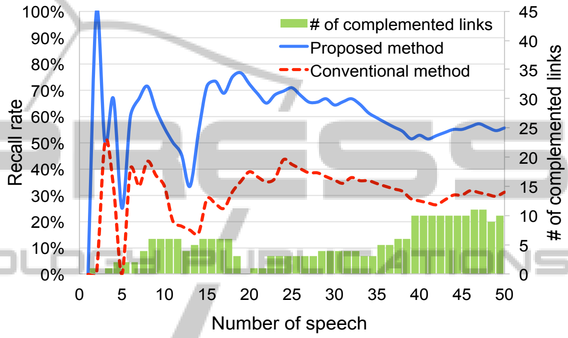

Figure 7: Transition of recall rate for Group A.

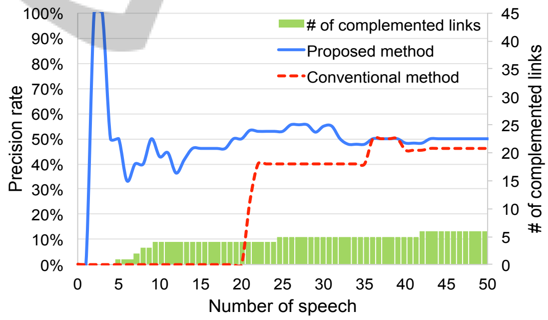

Figure 8: Transition of precision rate for Group B.

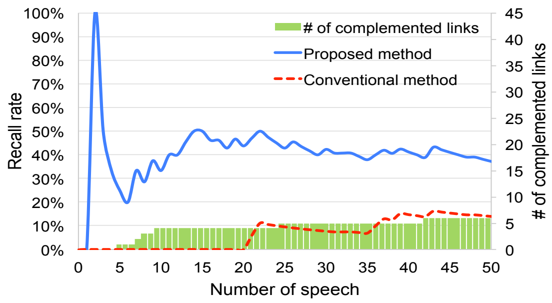

Figure 9: Transition of recall rate for Group B.

23.8% respectively after the discussion. So precision rate and recall rate can be improved by identifying the relation with demonstratives and connectives, similar-

Table 1: Precision rate and recall rate after the discussion.

(B	method	Precision rate	Recall rate
Group A	Conventional method	14/35 (40.0%)	14/45 (31.1%)
	Proposed method	26/53 (49.1%)	25/45 (57.8%)
Group B	Conventional method	9/18 (50.0%)	9/57 (15.8%)
	Proposed method	21/41 (51.2%)	21/57 (36.8%)
Average	Conventional method	44.6%	23.5%
	Proposed method	50.2%	47.3%

ity between recent opinions, and link complement.

The graph of visualized discussion structure by the conventional method and the proposed method for Group A are shown in Figure 10 and 11, respectively. The graph by the proposed method has less separate nodes than the graph by the conventional method. As these graphs show, the separate nodes can be reduced by complementing links considering the relation in the sequence of learners' opinions, even if the opinions do not include the same words.

We discuss the effectiveness of additional steps in the proposed method: creating links by demonstratives and connectives and complementing links by the sequence of opinions. Focusing on the separate nodes in Figure 10, we find that opinions of (19) and (21) include the demonstrative words of "That", "This", and "the same as". So, these opinions and an opinion of (18) that is linked to (19) can have links to the other opinions. As shown in Figure 6, Figure7, Figure 8 and Figure 9, the proposed method can improve the recall rate and the precision rate during the discussion compared to the conventional method. This is because links are complemented by the sequence of opinions every time a learner speeches a new opinion. At the 8th and 9th opinions in Group A, the precision rate by the conventional method is a little bit better than one by the proposed method. But, at the same opinions, the proposed can improve the recall rate drastically. Because it is important to visualize the discussion structure during the discussion, it can be expected that the proposed system contributes to supporting the discussion.

Finally, we evaluate the understandability of those graphs. The graph made by the conventional method has many nodes that are not connected to any other nodes. For learners, to see this graph is almost the same as to see the history of opinions, which makes little sense. On the other hand, the graph made by the proposed method has more node that are connected to other nodes. It gets easier for learners to understand the relation.

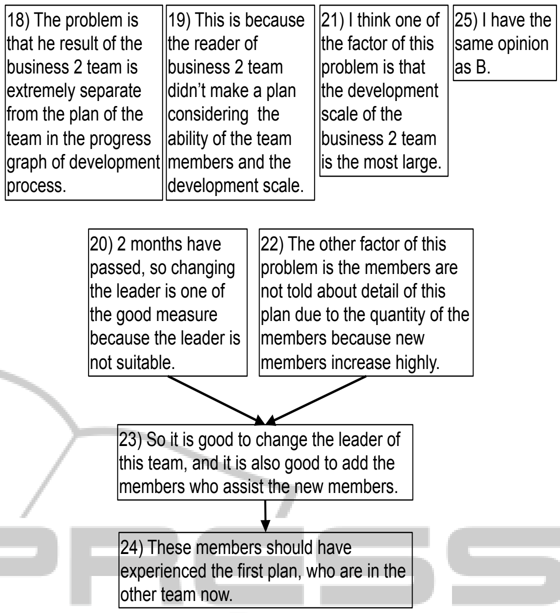

Figure 10: Graph representation of discussion structure by conventional method for Group A.

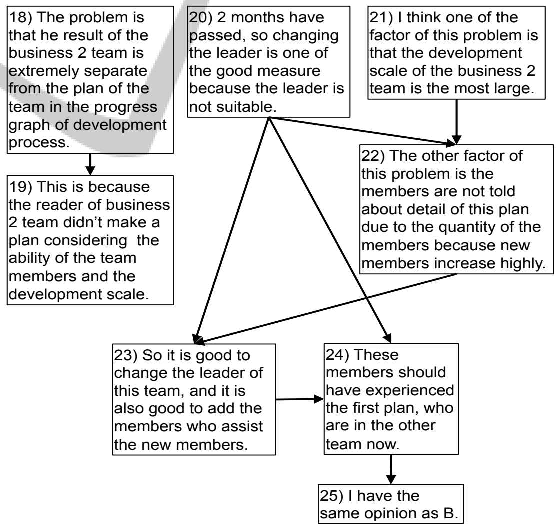

Figure 11: Graph representation of discussion structure by proposed method for Group A.

4.3 Future Issues

As Figure 6, Figure7, Figure 8 and Figure 9 show, the recall rate and the precision rate are still not so good even if we apply the proposed method. In the case method learning, the learners often uses domain-specific words such as “parent company”, “sub system”, and so on. The proposed system has not found the relations based on the domain-specific words. As our future work, we will try to obtain the knowledge including the domain-specific words from the other resources, i.e. the documented case, the other lecture book, wikipedia and so on. In addition, the size of the graph gets larger than we expects. Some learners indicate difficulty in finding the past opinions and their relations. So, contraction of the discussion structure is also necessary. Furthermore, coloring nodes of important opinions will help the learners’ understandings.

5 CONCLUSION

We proposed the method identifying opinions which have relations by demonstratives and connectives, and complementing links with the separate nodes by considering the relation in the sequence of learners’ opinions. In the experiment, on average, we confirmed that the proposed method could improve both precision rate and recall rate by 5.6% and 23.8% respectively compared with the conventional method. Opinions including demonstratives and connectives are linked with the previous opinion in this method. However, it is necessary to create links by extracting the content correctly, so we will improve the method in the future. In addition, we will develop the method in order to complement links more precisely.

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