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Estimating Divergence-or-Convergence in Discussions Based on Abstractness of Words in Utterance

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Abstract: Estimating divergence-or-convergence of discussions is expected to increase the productivity of the discussions. Divergence means expanding ideas and convergence means summarizing ideas. However, previous estimating methods can only be applied to limited discussions. In this study, divergence and convergence are estimated using the abstractness of utterances. Divergence is assumed to be a concrete state and convergence an abstract state, respectively. The estimated results in the three discussions are compared to human judgment. As a result, agreement rates are 69.2%, 87.9% and 54.3%. Additionally, the abstractness of utterances in two discussions are low in divergence and high in convergence. The activeness in three discussions may cause the difference of the abstractness in utterances. These results suggest that abstractness of utterances has a potential to estimate divergence-or-convergence in general discussions.

Keywords: Discussion divergence, discussion convergence, discussion support system, abstractness of words, dialog analysis

1. Introduction

Dialog analysis in educational technology is used to support group learning. Especially, researchers have focused on estimating divergence-or-convergence of discussions, the expanding or summarizing of ideas respectively. This definition is based on divergent thinking and convergent thinking (Guilford, 1967; Cropley, 2006).

Estimating these two states, learners can learn strategies to diverge or converge discussion because learners understand good examples of utterances that contribute to divergence-or-convergence of discussion. For example, Mochizuki et al (2007) shows that estimating two states can help self-assessment of learners. Attritionary, good reflection is conceptualizing concrete experiences (Moon, 2013). From the above, learners can learn strategies to make divergent arguments converge by reviewing which of the two states the participants' comments enhance. This can increase the productivity of the discussion. In this study, we proposed a method for estimating the divergence and convergence of a discussion using the abstractness of words in the utterance. We also verified the effectiveness of the proposed method.

2. Related works

Abstractness of words is related to idea generation. Schön (1979) found that metaphors facilitate idea generation. This suggests that divergent thinking is encouraged when abstract problems are embodied by metaphors. Gonalves, Cardoso and Badke-Schaub (2012) quantitatively investigated the quality of idea generation for high abstractness text. In this study, it was observed that the group given a text about "Wizard of Oz" generated more ideas than those with a text on "Straddling Bus" (an example of transportation in the future). This suggests that the abstraction of object movement promotes idea divergence. Therefore, expanding ideas can be considered as embodying ideas.

On the other hand, in the idea convergence method such as the KJ method (Scupin, 1997), ideas related to a theme are written on cards, grouped, and headings are added to converge ideas. The headings provide a concise summary of the contents of the grouped cards. Therefore, the abstractness of the word in the heading is considered higher than the idea on the card. That means summarizing ideas can be considered as abstraction of ideas.

From these studies, assuming that the same relationship holds in the discussion, estimating the divergence and convergence of arguments by calculating the portions where the abstractness of words in an utterance switch from high to low and otherwise is possible. Therefore, in this study, we use abstractness of words to estimate divergence-or-convergence of discussions. However, for an argument that produces a concrete answer, the abstractness of the words in the utterance may not be high upon discussion convergence. Therefore, this study focuses on discussions in abstract themes that do not have a single answer.

Additionally, previous divergence-or-convergence estimation methods can apply only to a specific discussion. Ichino (2011) estimated the divergence and convergence of an argument using nonverbal information from time-series utterance patterns. Here, the divergence-or-convergence of an argument was estimated by supervised learning using five features: frequency of utterances, percentage of overlapped utterances, length of utterances, the time between utterances, and the number of speaker transitions. She applied the results to a system that supports meetings in terms of both divergence and convergence. The results showed that the agreement among the three raters ranged from 77% to 85%. However, this study was conducted for a discussion on the 20-questions game, in which participants guessed the words that the contestant had in mind by answering 20 yes/no questions. Therefore, introducing the system into a discussion without specifying the format is difficult. In this study, we apply the method to general discussions.

3. Estimating divergence-or-convergence of a discussion based on abstractness

In this study, we considered abstractness as a value corresponding to a word. This abstractness may be changed by people's general and specific knowledge. Therefore, an abstractness dictionary based on crowdsourcing is used. The abstractness can be calculated using the dictionary.

Additionally, we assume divergence as embodying and convergence as abstraction. In other words, absolute abstractness may not be low in divergence and high in convergence. For this reason, we estimate divergence-or-convergence using relative abstractness of words. In this study, the validity of the estimation method is examined. Additionally, the results of estimating the divergence-or-convergence of discussion using the proposed method were compared with those of human recognition. We verified the relationship between the divergence and convergence of an argument and the abstractness of words in an utterance from the comparison results.

4. Methods

Figure 1 shows the method of estimation. First, a voice recording of the discussion was obtained and converted into text data using natural language processing and cleaning. In the cleaning process, the stilted were removed and misrecognized parts of speech were replaced with correct words based on the recording. Next, the obtained text data were divided into utterance units by meaning of the utterance and extracted nouns using morphological analysis for each utterance. Then, nouns with little relevance to the discussion, such as function words were removed. Next, the abstractness of each utterance and the abstractness of difference which represents the relative variation of abstractness were calculated.

In this study, utterances with relatively low and high-abstractness contributed to divergence and convergence, respectively. Therefore, the estimate of the divergence and convergence of the discussion with the negative abstractness of difference diverged and that with the positive abstractness of difference are converged. Notably, a three-valued or higher classification such as divergence-or-convergence, or neither was not used because labeling by a human concentrated in intermediate categories and appropriate evaluation of estimation accuracy was impossible. In the following, we described how we calculated the three abstractions used in the estimation of the divergence and convergence in the discussion.

4.1 Abstractness of a word

The abstractness of a word is a quantification of abstractness at the word level. The database of the abstractness of words for common Japanese words (Social Computing Laboratory, NAIST, 2019) was used for this study. There are two types of Japanese abstractness dictionaries: AWD-J Core (15220 words), in which abstractness is assigned by humans, and AWD-J EX (437299 words), in which abstractness is assigned by machine learning using the AWD-J Core as training data. In this study, AWD-J EX was used as the abstractness of a word dictionary because of its noun coverage. The abstractness of a word is a real number ranging from 1 to 5. The lower abstractness of a word indicates that the word is more concrete, whereas the higher abstractness of a word indicates that the word is more abstract. For example, the abstractness of "Tokyo" is 1.3, the abstractness of "city" is 2.0, and "metropolis" is 2.09.

4.2 Abstractness of each utterance

The abstractness of each utterance is defined as the average of the abstractness of a word in the utterance, where only words included in the AWD-J database are considered in the calculation of abstractness of each utterance. For example, "I have dogs and cats." has "dogs" and "cats" whose abstractness of a word is 1.45 and 1.54 respectively, the abstractness of the above utterance is (1.45 + 1.54)/2 = 1.495.

4.3 Abstractness of difference

The abstractness of difference is the relative abstractness of each utterance. It is defined as the difference between the abstractness of the utterance and the average of the abstractness of the four preceding utterances. If the four preceding utterances include utterances that do not have an abstractness of each utterance, they are excluded from the calculation. For example, it assumes that the abstractness of utterance A is 2.0 and the abstractness of the five preceding utterances are 2.0, 1.0, null (no abstractness), 2.0, and 2.0. Then, the abstractness of difference for utterance A is calculated without the utterance with null abstractness. Therefore, $(2.0 - (2.0+1.0+2.0+2.0))/4 = 0.25$ is the abstractness of difference for utterance A. The first four utterances have no abstractness of difference because they do not have any preceding four utterances.

In this study, we estimate divergence-or-convergence of discussions based on abstractness of difference. If the abstractness of difference is negative, the utterance is estimated as the divergence. If the abstractness of difference is positive or 0, the utterance is estimated as the divergence.

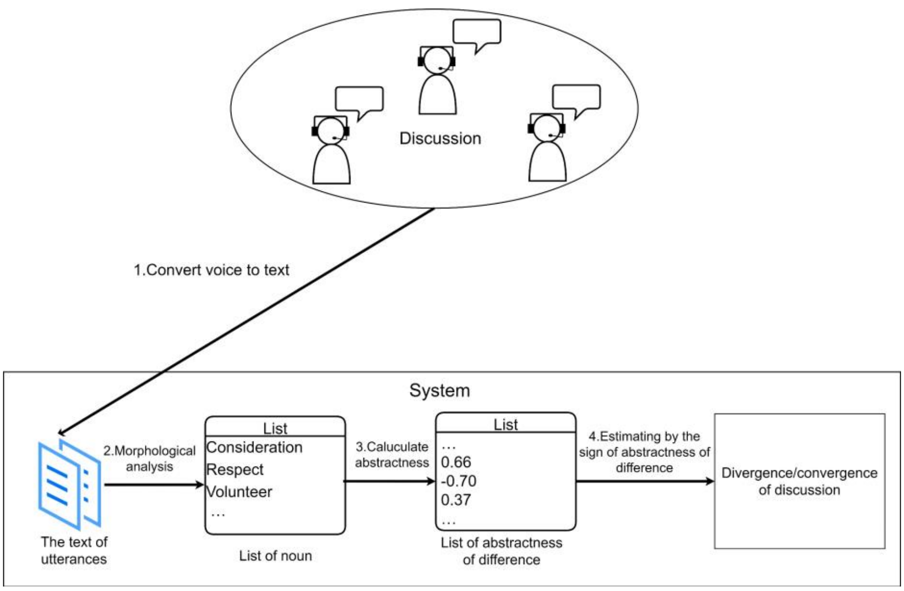

Figure 1. Procedure for estimating divergence or convergence discussion

5. Experiments

An experiment was conducted to survey the relationship between abstractness and divergence-or-convergence in a discussion and to evaluate estimation accuracy. Participants are undergraduate and graduate students of a science and engineering university in Japan. First, we collected three sets of 30-minutes discussion data under the topic “What is a thoughtful consideration?” from two groups of three participants and “Why is youth turnout low?” from one group of three participants. In this theme, turnout means voter turnout in elections. We define two discussions of “What is thoughtful consideration?” and a discussion of “Why is youth turnout low?” as Consideration 1, Consideration 2, and Turnout 1.

After the discussion, we asked the undergraduate and graduate students who did not participate in the discussion to label each utterance and collected the data of divergence and convergence as recognized by humans. These participants are instructed on how to determine the divergence and convergence of the discussion. For example, utterances were tagged as divergence when ideas were expanded and those with the immediately preceding summary were reexplained, whereas they were tagged as convergence in those utterances in which ideas were summarized and referred to the rules and regularities of “What is thoughtful Consideration?” (or “Why youth turnout is low?”). In this labeling, the participants seated in front of the monitor, read the text of the four previous utterances displayed on the input screen, and labeled each utterance as divergence-or-convergence. The reason for limiting the range of human speech reading to the four immediately preceding utterances was the need to restrict the information used for the recognition (estimation) of divergence and convergence. For instance, if there is no restriction on the range of utterances, participants will focus on different parts of the discussion depending on their comprehension of the content of the argument and their value criteria. Additionally, skimming may result in inaccurate results. For these reasons, participants labeled divergence and convergence as contextualized by the four immediately preceding utterances, which are the same as the system’s estimation criterion.

In the labeling, the subjects were given printed materials containing the same contents as those explained in the divergence-or-convergence of discussion, so they checked the definitions when necessary. Additionally, subjects were told to label the utterance they judged contributed more when they were unsure whether to label an utterance as divergence-or-convergence. The participants took breaks and asked questions on the definitions of divergence and convergence at any time during the experiment. After the labeling, they were asked about any difficulties they had in labeling. The number of participants who had to label the discussions were 31 for the theme of “What is thoughtful consideration?” and 30 for the theme of “Why youth turnout is low?”.

6. Results

6.1 Relationship between abstractness of each utterance and divergence-or-convergence of discussion.

We examined the difference in abstractness of each utterance between utterances labeled divergent or convergent by 80% of participants. The percentage was not set to 50% (over half) or 100% (unanimous) because the result of labeling was subjective. Here the groups of utterances labeled divergence and convergence by more than 80% of all subjects are referred to as the divergence and convergence set, respectively. The Brunner-Munzel test (Brunner and Munzel, 2000) was used as the statistical test method because the distribution of abstraction has two peaks (Brysbaert, Warriner and Kuperman, 2014), unequal sample sizes for the divergence and convergence set, and homoscedasticity of the population cannot be assumed. Table 2 shows the results of the Brunner-Munzel test for the divergence and convergence set for Consideration 1 and 2 and Turnout 1. There is a significant difference at the 1% level in the mean ranking of abstractness of each utterance between the divergence and convergence set in the “What is thoughtful consideration?” discussion, as shown in Table 2. This indicates that in the “What is thoughtful consideration?” discussion, abstractness of each utterance is low in the divergence of discussion and high in the convergence of discussion. The 95% confidence intervals for the estimates of P(X1 < X2) + 0.5P(X1 = X2) were 0.657-0.909, 0.757-0.950 for Consideration 1 and 2, respectively, and 0.393-0.803 for Turnout 1.

Table 2. *The result of Brunner-Munzel test between the divergence set and the convergence set*

Group	p-value	Estimation values of P(X1 < X2) + 0.5P(X1 = X2)
Consideration 1	3.924×10!"	0.783
Consideration 2	2.754×10!#	0.853
Turnout 1	0.3351	0.598

6.2 Agreement between the labeling and estimation

Table 3 shows the agreement rates for both divergence and convergence in Consideration 1, Consideration 2, and Turnout 1.

Table 3. *Agreement between the labeling and estimation (divergence and convergence)*

Group	# of matches	Number of utterances with the same label by 80% of participants	# of utterances	Agreement (%)
Consideration 1	36	52	178	69.2
Consideration 2	58	66	158	87.9
Turnout 1	19	35	102	54.3

7. Discussion

7.1 Relationship between abstractness of each utterance and divergence-or-convergence of discussion.

Table 2 shows that the abstractness of each utterance is high and low for the divergence and convergence of discussion, respectively. The data confirmed our hypothesis in the discussion that has an abstract theme. This implies that people may talk about concrete topics like examples or experiences in divergence and talk about abstract topics like generalization or abstracted rules in convergence.

However, no significant difference exists between the divergence and convergence set in Turnout 1. The abstractness of the theme possibly affects the abstractness of the discussion. That is, embodying ideas may be hampered by the concrete theme because it is difficult to embody concrete concepts. Additionally, if divergence is insufficient, convergence may be also insufficient because discussions state alternately switches from divergence to convergence and from convergence to divergence.

7.2 Agreement between the labeling and estimation

Table 3 shows that the agreement between the abstractness method and human recognition is 69.2% at Consideration 1, 87.9% at Consideration 2, and 54.3% at Turnout 1. Therefore, estimating divergence-or-convergence of discussion by abstractness is reliable because the accuracy of the estimation is 50% if we choose the two states randomly. However, the accuracy of Turnout 1 is lower than that of Consideration 1 and 2. This can be attributed to the number of utterances since the number of utterances in Turnout 1 is about 100 utterances, whereas those in Consideration 1 and 2 are from 160 to 180. Nonetheless, the discussion time of Turnout 1 equals that of Consideration 1 and 2. Since the number of utterances per time is small, Turnout 1 does not diverge and converge sufficiently. The stagnant may lower the agreement of Turnout 1 because labeling is difficult for the participants.

The agreement in Consideration 2 is 20% higher than that in Consideration 1. This difference may be attributed to participants' speaking types. In the following, utterances in the divergence set that has high-abstractness of each utterance are referred to as the high-abstractness divergence set, whereas utterances in the convergence set that has low-abstractness of each utterance are referred to as the low-abstractness convergence set. For example, "In short, I think it is considerate to give what others need, but not expecting reward," is the low-abstractness convergence set in Consideration 1. This utterance has a concrete assumption that "It is considerate to give what others need." This decreases the abstractness of the utterance than "Consideration is not expecting reward." Another example, "If it continues to go unrecognized, it becomes commonplace," is the high-abstractness divergence set in Convergence 1. This utterance has few nouns such as recognition and commonplace. As a result, the abstractness of each utterance may be relatively high. Summarily, the type of utterance in Consideration 1 affects the estimation accuracy.

8. Conclusion

In this paper, we showed the relation between the divergence-or-convergence of discussion and the abstractness of words. Here, two significant results were obtained: the abstractness of words is low in divergence and high in convergence and the abstractness of words is fundamental to estimating the discussion state. Our study gives a quantitative perspective of abstractness in the discussion using qualitative analysis of abstractness and divergent/convergent thinking.

However, this study has some limitations. In this study, we used only the abstractness of difference. Therefore, it may be difficult to compare the contribution of utterances to divergence or convergence. Therefore, the abstractness of each utterance can be included in estimating as an indicator of absolute abstractness.

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