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Attainable Range Prediction of Group Product by Aggregation of Individual Products in Group Learning with Kit-build Concept Map

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Abstract: Recently, we can collect and analyze a variety of data in learning with the development of information and communication technology and also expect that the prediction of learning with the data enables a deep reflection for enhancing the learning experience. This paper describes a method for the attainable rage prediction of the group learning products from aggregation of an individual's concept map with the Kit-build (KB) approach. To test this method, we examined the prediction results from the data collected from a classroom lesson. The results show that most of the actual results are in good agreement with the prediction, and the comparison between the actual results and the predictions could be useful for the teacher.

Keywords: Concept map, kit-build, collaborative learning, prediction of group learning product.

1. Introduction

In recent years, the role of teachers in the classroom has changed from instructors who impart knowledge to the students to a facilitator for management of learning with the increase of the diversity of learning forms, for example in the form of lectures, collaborative learning, and problem-based learning (Carey, 1994)(Dillenbourg & Patrick, 2010)(Grabinger & Dunlap, 1995). Expectations for teachers are not only to provide students with information to improve their understanding of the subject but also to monitor and help them in the learning process. To achieve this, teachers need to recognize the subject understanding of the class, compare it with plans, and consequently coordinate the learning activities. con

With the development of information and communication technology (ICT) in recent years, we can collect and analyze a variety of data. Furthermore, it is also possible to predict the learning outcomes, and the products have enabled teachers to deeply reflect on improving the understanding of the whole class. Educational data mining facilitates a variety of techniques to analyze learning data, and learning analytics provides new insight into the consequence of learning from real data (Siemens & Baker, 2012).

Learning analytics can be defined as the "trinity" of following three methodological approaches: i) content-oriented, ii) process-oriented, and iii) network analysis (Hoppe, 2017). The content-oriented approach focuses on artifacts. The traditional way is human-interpretation and coding. Recently, there have been computational methods using text-mining techniques. The process-oriented approach is sequence analysis. Traditionally, in computer-supported collaborative learning (CSCL), many studies have analyzed the system's logfiles. Martinez-Maldonado et al. proposed and developed a multi-tabletop classroom and dashboard to support collaborative learning [0]. Network analysis focuses on the network structures, including actor-actor (social) network as well as actor-artifact networks. Matsuzawa, Oshima, Oshima, Niihara & Sakai (2011) propose a tool for exploring the network structure of collaborative learning discourses. This tool visualizes the dynamics of the network structures of students, but also students and words in discourse units.

The target of this study is the content-oriented analysis of group learning, in which students organize and reflect the understanding of what they have learned in lessons. In the 21st-century skills, creativity and innovation start with "internalize given information; beliefs/actions based on the assumption that someone else has the answer or knows the truth (Scardamalia, Bransford, Kozma & Quellmalz, 2012)." In knowledge-building processes (Stahl, 2012), students make personal beliefs, which are sometimes problematic, and create a shared understanding of collaborative knowledge through social activities.

The goal of this study is the prediction of an attainable range of product in group learning in which students collaboratively organize what they have learned. One of the situations where teachers use group learning is a part of the lesson. Group learning is useful for teachers to let learners organize what the teachers have informed to the learners. However, during group learning, it is difficult for teachers to grasp students' activities and to give feedback to them because students dynamically take actions in parallel. If teachers can predicate group learning products from the understanding of individuals at the beginning of group learning, it is helpful for them to make a plan to facilitate students' activity from the start of group learning. Although it is possible to predict the group learning products from the intermediate products in groups learning, it is very difficult to predict the products from the products at the beginning of group learning. That is the reason that we focus on the understanding of individuals at the beginning of group learning.

This study focuses on the automatic assessment of concept maps (Novak & Canas, 2006) with the kit-build (KB) method (Yamasaki, K., Fukuda, H., Hirashima T. & Funaoi, 2010; Hirashima, Yamasaki, Fukuda & Funai, 2015) to predicate group learning that products from the understanding of individuals for the goal of teachers' facilitation to students during group learning. The KB method requests students to reconstruct concept maps from the components of the concept maps created by a teacher. We call a concept map created by a teacher "goal map" in the KB method. This method allows students to concentrate on considering the relation between concepts and makes it possible for teachers to evaluate students' understanding by the difference from the teachers' concept map (Pairai, Wunnasri, Yoshida, Hayashi, and Hirashima, 2017). Also, in collaborative learning, comparing their kit-build concept maps each other is effective to improve their maps (Nomura, Hayashi, Suzuki, and Hirashima, 2014). Kitamura et al. reported that comfirmation of understanding with kit-build concept map is more effective than comfirmation with fill-in-the-blank questions (Kitamura, Hayashi, and Hirashima, 2019). Nomura et al. also analyzed the propagation of individual opinions represented in their concept maps in group learning (Nomura, Hayashi, Suzuki, and Hirashima, 2014). Hayashi, Nomura & Hirashima (2019a, 2019b) categorized the patterns of aggregation of personal concept maps as group products. In addition to that, the kit-build method can automatically assess learners' concept maps by comparison with the goal map. If each learner represents his/her understanding as a concept map with the KB method before group learning, it can be the source of the prediction of the group learning products.

Here, we propose a prediction method of group learning products from the initial understanding of the members of the group based on a concept map with the KB method (KB map). In this method, each student creates a concept map as their initial understanding of the subject. While learning as a group, students compare their concept maps and construct a kit-build concept map representing a consented understanding of what they have learned. The prediction shows the possibilities of the resulting concept maps from the concept maps of students at the beginning of the lesson. This paper also demonstrates an example of the prediction result of data from experience.

2. The Automatic Assessment of Concept Maps on Kit-build Method

This study uses the KB map for checking each learner's understanding at the beginning of group learning as well as a learning activity for learners to organize and share the information they have obtained in lessons. The characteristics of the KB map is the automatic assessment of concept maps created by learners as the comparison with the goal map created by their teachers.

In the KB map, students organize their understanding through the reconstruction of the reference concept map created by a teacher (called "goal map"), and the teacher can assess the understanding of learners with the automatic comparison between the goal map and students' concept maps. Wunnasri, Pailai, Hayashi & Hirashima (2018) confirmed the validity of the automated assessment. Students and teachers can discuss a shared understanding based on the difference between their concept maps.

The goal map is a concept map created by the teacher as information that the teacher wants to provide for learners in a lecture. In the KB map, the concept map created by the teacher is called "goal map" and the decomposed one delivered to the node and link-level (kit), which is distributed to the student. Students generate their concept maps by assembling the kit.

The KB map offers a unique framework where the goal map and student maps share the same component enabling the diagnosis of the system and extraction of the difference between them. It also helps create a superimposed map from multiple students' concept maps and facilitates the assessment of the common understanding of the students. The match rate student maps and the goal map help generate a score of comprehension for the group. Information about the matches and differences of knowledge and understanding of the students can be extracted from the superimposed maps. Further, during the process of creating concept maps, the discussion and comparison of individual concept maps among the students help in unifying the components and improve the students' understanding of the concepts.

The KB map system has been proposed as a system for realizing interaction between the teacher and the students (Sugihara, Nino, Moriyama, Moriyama, Ishida, Osada, Mizuta, Hirashima, & Funaoi, 2012). This system consists of a kit build concept map creation tool "KB Map Editor" and the evaluation and support tool "KB map analyzer." KB map editor can be used to create the student map, which is functional in the tablet terminal. As these maps represent the understanding and opinions of the individuals, they are instrumental in the discussions. The KB map analyzer promptly generates a superimposed map immediately. In addition, the diagnosis of the system makes it possible for the teacher to recognize the common understanding of the entire class.

The KB map can automatically compare the concept maps since the components of the goal map and students map are unified. The comparison may be performed for each proposition, and between students for each link, by comparing the goal map, to realize the group product prediction function. Proposition, which is determined from the above-described problems of group activities, becomes a goal map. Individual concept maps represent the understanding of each member of the group at the beginning of the learning process. The classification between the propositions, such as "the same proposition as the goal map," "divergent proposition from the goal map," and "no proposition (the link is not connected with any concepts)" is obtained by comparing the individual maps and the goal map. Then, it is possible to aggregate a combination thereof or matching rate for each group.

In the present study, the KB map analyzer processes the predictions of the products. Thus, by using the KB map analyzer, it is possible to grasp the predicted score and predict the group learning products in the form of an agreement rate for the entire class in real-time. In addition, it is possible to refer to the superimposition of individual maps of the group members for each group and to understand the particular state of the group.

3. Prediction of the group learning products with Kit-build Concept Maps

Here we employ the Kit-build concept map as the digital tool for representation and assessment of students' understanding. First, each student makes a concept map using the components provided by the teacher. The concept maps represent his/her understanding. After that, through a group discussion using the concept maps, students exchange their opinions to reach a shared agreement of the group.

We classify the proposition made by individuals in the group and pattern them. There are three types of propositions based on the link between concepts: ***same*** (the link connects the same concepts as the reference map), ***divergent*** (the link connects the divergent concepts from the reference map), and ***no*** (the link does not connect any concepts).

Based on the classification, Table 1 shows the possible state of personal propositions in group learning. Patterns A, B, and C indicate that all members have the same type of proposition. For example, in pattern A, all the members have the *same* proposition as the reference concept map. By contrast, in patterns D - G, there is a conflict of propositions in the group. For example, in the pattern D, some members have the *same* proposition as the reference map, but other members have *divergent* ones from the reference map.

Table 1. Proposition patterns in a group

pattern	***Same***	***Divergent***	***No***	**Prediction**
A	exist	non-existent	non-existent	***Same***
B	non-existent	exist	non-existent	***Divergent***
C	non-existent	non-existent	exist	***Same/Divergent/No***
D	exist	exist	non-existent	***Same/Divergent***
E	exist	non-existent	exist	***Same***
F	non-existent	exist	exist	***Divergent***
G	exist	exist	exist	***Same/Divergent***

When a group has a shared understanding of a proposition through group discussion, in which the state of the proposition moves to pattern A ~ C, there are three types of changes, i) "they select existing propositions," ii) "they generate a new proposition," and iii) "they do not make a proposition." For example, from the pattern D, if they select the existing proposition, the shared understanding of the group is "the *same* proposition" or "*divergent* proposition." However, if they generate a new proposition, they must create a *divergent* proposition as a shared understanding of their group.

We can anticipate the shared understanding of each proposition from the patterns of propositions in the group. The basic rules of prediction in this study are straightforward. If anyone in a group makes a proposition with a link, they select the proposition as their decision. This is based on the analysis of the group learing products and individual concept maps. Nomura et al. (2014) reported that learners choose the existing propositions in individual concept maps as the group learning products. However, if no one has any proposition with a link, they create the *same* or divergent proposition or do not generate any proposition. For example, in pattern A, their product is uniquely decided into the *same* proposition. However, in pattern D, they can create the *same* or divergent proposition. Besides, in patterns C, E, F, and G, they can also decide not to create any propositions.

The proposed prediction of propositions enable to calculate the prediction of the maximum and the minimum resultant map score from the proposition patterns in the group. The maximum occurs when the students in a group choose only the *same* propositions. The minimum occurs when they choose some *divergent* propositions even if a single member in the group has opted for some of the *same* propositions. In the patterns D or G, the maximum result is derived when they choose the *same* proposition, and the minimum score is derived when they choose the *divergent* proposition. Table 2 show an example of the prediction of propositions and map score. The range of map score expected their propositions are from 80 to 20. In addition to that, their resultant map score might be 100, if they would find the *same* proposition as the GM about Prop. C in their group discussion. Therefore, the attainable range of map score of the group is from 20 to 100.

Table 2. An example of the prediction of propositions and the attainable range of map score

	Prop. A	Prop. B	Prop. C	Prop. D	Prop. E	Map score (0-100)
Learner 1	*same*	*div.*	*no*	*same*	*div.*	40
Learner 2	*div.*	*same*	*no*	*same*	*same*	60
Learner 3	*same*	*no*	*no*	*same*	*same*	60
Prediction	*same/div.*	*same/div.*	*same/div./no*	*same*	*same/div.*	100-80-20

same: the same proposition as the GM, *div.*: divergent proposition from the GM, *no*: no proposition

4. Experimental application to the lesson data

4.1 lesson design

This study used the data from a lesson where a total of 70 people from two classes in the second grade of the junior high school participated. These lessons were taught as one lesson for each class. The topic was the Tohoku region of Japan in geography. The purpose of this lesson was to frame together with the knowledge of nature, industry, traditions, and the culture of the Tohoku region as one structure and to make a common background for the discussion on their proposals for the reconstruction of the region in later lessons.

Figure 1 shows the basic flow of the lesson. In the first phase, like the introduction, the teacher reviewed the previous lessons about the Tohoku region with the students. In the second phase, the students created a concept map from the kit individually, and then in groups of three or four students, they combined their maps to create a group concept map. If needed, they could change their individual concept map. Finally, in the last phase, the students compared the group leanring products and discussed how to make a better structure with the teacher.

In this lesson, each student used a tablet computer to create a personal map. In addition, each group had another tablet for creating a group map.

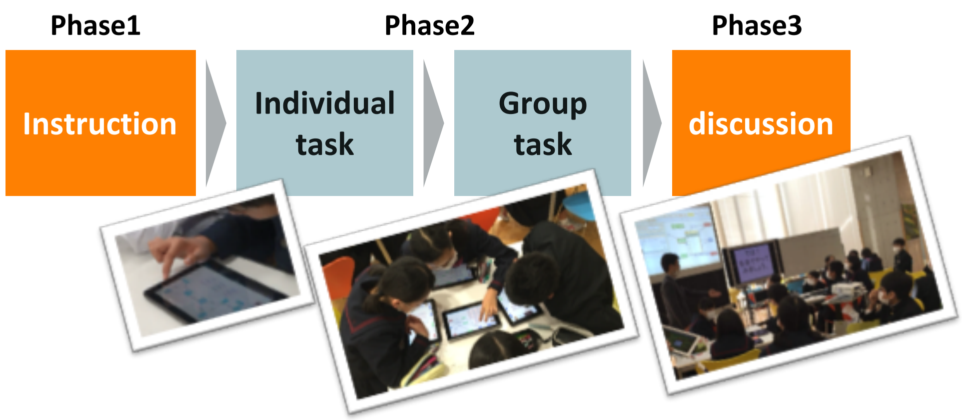

Fig. 1. the basic flow of the lesson.

Figure 2 shows the goal map and Fig. 3 shows a kit made from the goal map. Although a kit is generally made by separating all the nodes and linksin the goal map, in the kit links and nodes connected to the central topic of the kit were not separated to show the the core structure of this map. The core structure represents the viwpoints to organize the the characteristics of

Tohoku region, "nature," "industry," and "culture." The tasks of the students for creating a map were to organize the instances of the viewpoints and to find intersections of the viewpoints. The students used this kit to create both a personal map and a group map.

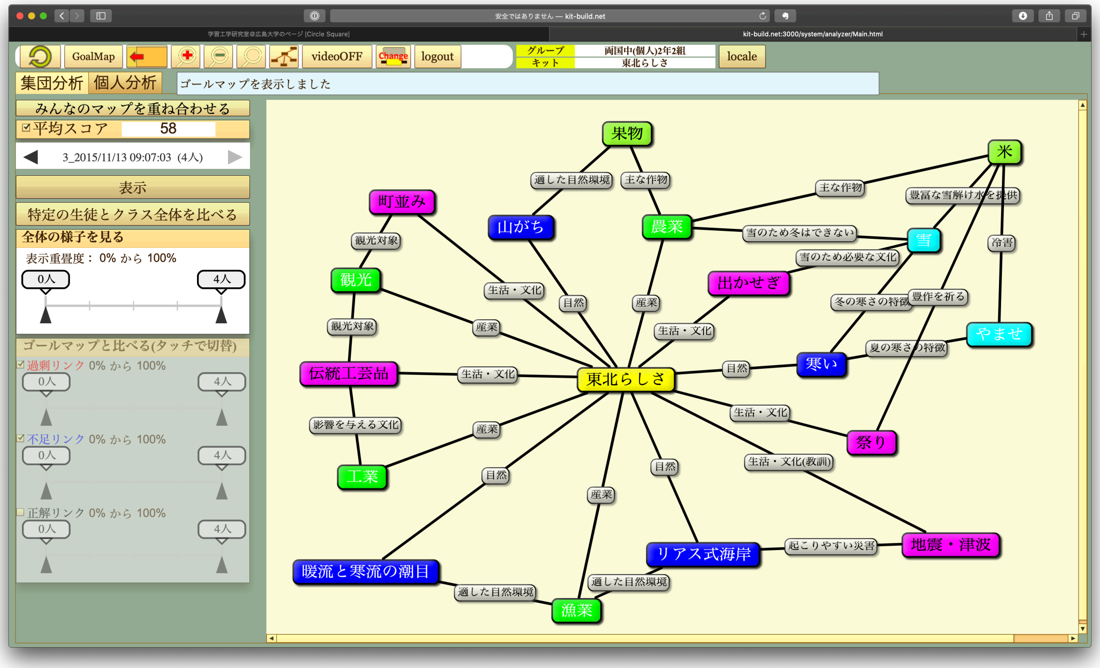

Fig. 2. The goal map (in Japanese)

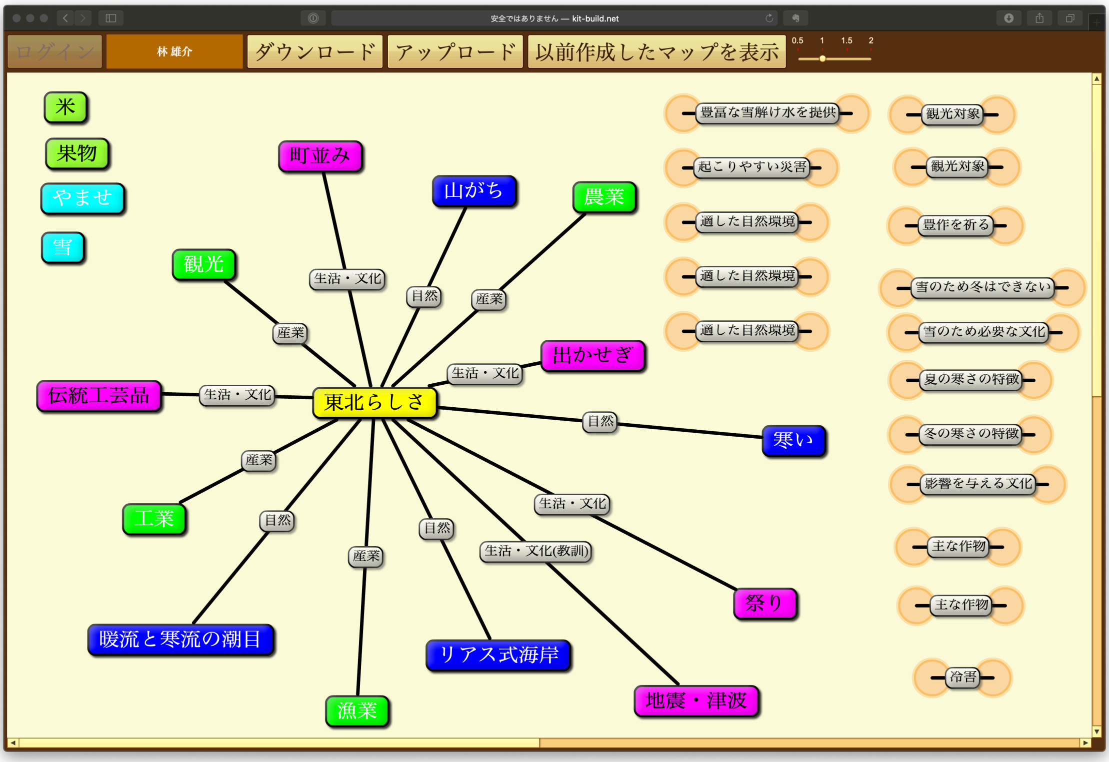

Fig. 3. The kit made from the goal map (in Japanese)

4.2 Verificationg group learning product prediction

In this study, we verified the accuracy of the prediction of group activity outcomes. The accuracy is measured by the range of the expected score and its validity. The range is the difference between the possible maximum and the minimum scores calculated from individual maps. The validity is whether the scores of the group maps fall into the predicted ranges. We used the data of the actual lesson described in the previous section.

This study represents the consistent ratio of the actual score and predicted scores in the format shown in Fig. 4 and Fig. 5. The vertical axis represents the predicted score in the interval scale. The horizontal axis represents the match rate. The maximum and minimum values on the vertical axis and the horizontal axes are the maximum and minimum of the values taken by all the groups. The solid bar indicates the minimum score from the maximum score. The dotted bar chart without color indicates the maximum possible score from the maximum score. The middle number of the bar graph indicates an ID that represents the group.

Figures 4 and 5 show the actual scores of the group learning products. The triangle indicates the actual group map score. The solid boxes represent the range of predictecd score from the *same* and the *divergent* propositions in each group and the dotted boxes represent the range of predicted score if the groups generate the *same* propositions from *no* propositions in individual maps. The actual group map score in the solid box means the group has collected their *same* and the *divergent* propositions in the individual maps. If the actual group map score is out of the solid box, it means they generate the *same* propositions from *no* propositions in individual maps or from only *divergent* propositions in individual maps.

In Class A score prediction, the average prediction width was 23%, and the range of predicted scores were approximately in 20 points. Further, as shown in Fig. 5, seven out of nine groups are in the expected range, with an accuracy of approximately 80%. In Class B score prediction, the average prediction width was 17%, and nine out of ten groups were in the expected range; the prediction scores were approximately 20 points with 90% accuracy.

To verify the validity of the prediction, we compared the predicted and the measured values for each proposition in a pattern. Table 3 shows the number of propositions in each pattern and the percentage of propositions conforming to the prediction rules for each pattern in the total of two classes. Most of the patterns were found to be in accordance with the prediction rule. However, in pattern B and F, the ratio of the proposition conforming to the rules is low.

Table 3. Prediction accuracy of each pattern

Patterns	*Same*	*Div.*	*No*	Result of prediction	# of total propositions	# of successful prediction	Prediction Accuracy
A	x			***Same***	26	26	1.00
B		x		***Div.***	13	5	0.36
C			x	***Same/Div./No***	49	49	1.00
D	x	x		***Same/Div.***	22	20	0.91
E	x		x	***Same***	81	73	0.90
F		x	x	***Div.***	70	29	0.41
G	x	x	x	***Same/Div.***	43	40	0.93

Pattern B is the case where the group exclusively possesses *divergent* propositions. In this case, there may be several *divergent* propositions in the group. For example, all the members have different *divergent* propositions. Although the rule assumes that they adopt one of the *divergent* propositions, they actually have made a new *divergent* proposition in many cases. In 46.2% of Pattern B, the laerners adopt a new *divergent* proposition. While this does not change the predicted score, this is different from the assumption of the rule. Furthermore, in 83.3% of the case where the laerners adopt a new *divergent* proposition, the groups had some *divergent* propositions.

Pattern F is a case where *divergent* proposition and *no* proposition exist at the *same* time. In this case, the prediction rule assumes that the group adopts the existing *divergent* proposition in the group. In fact, unlike the rule, 39.2% of the groups were to build a new *divergent* proposition. In addition, the "*divergent* proposition" in the case of 87% of which was exclusive. Even in such a case, it is considered that there is a tendency to create a new "*divergent* proposition" through discussion. However, to clarify the cause, further analysis is required.

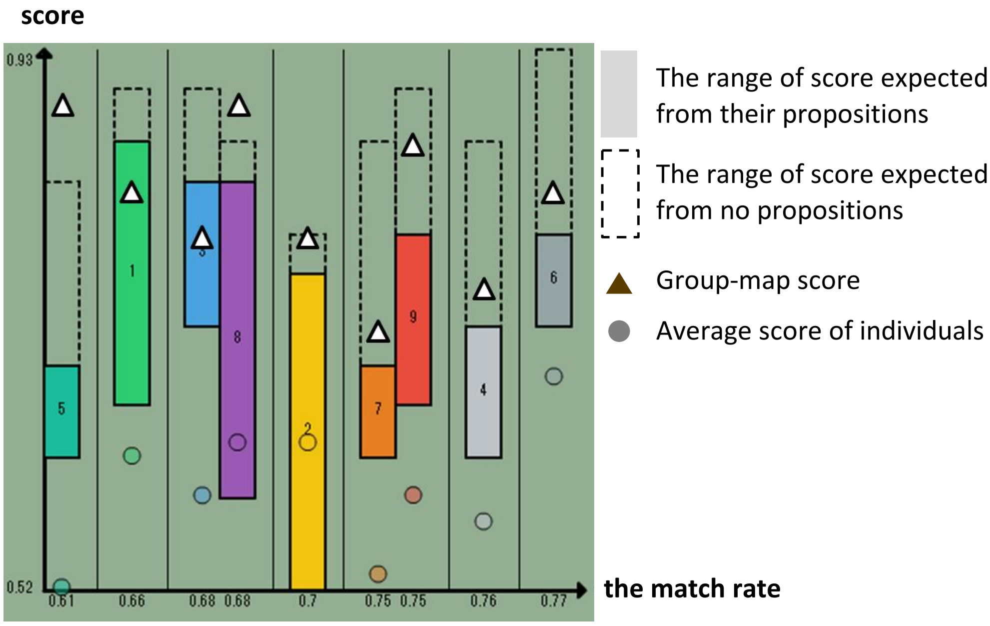

Fig. 4. Prediction of class A (sorted by the match rate)

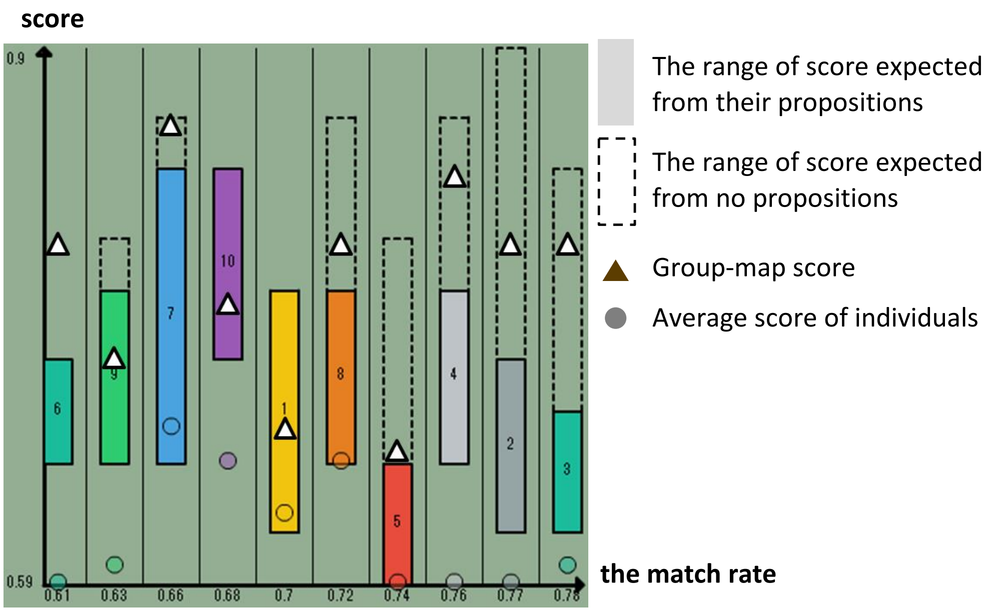

Fig. 5. Prediction of class B (sorted by the match rate)

4.3 Questionnaire and Interviews

We conducted a questionnaire and interviews with the teacher about the prediction using the kit build concept map. The contents of the questionnaire are shown in Table 4. The answers are on a scale of "Yes, I think so strongly," "Yes, I think so," "Yes and no," "No, I do not think so," and "No, I do not think so strongly" with respect to each question in the questionnaire.

In Questions 1 and 2, since the answer is "Yes, I think so," the teacher could predict the outcome of group activities to some extent from his experience in the ordinary lesson, and the prediction by the Kit-build concept map provided similar prediction. The teacher answered, "No, I do not think so" in Question 3 and "I think so," in Question 4 on the condition that teachers are familiar with the interpretation of the graph. This suggests that the prediction can be helpful for the facilitation of the groups, although it is challenging to facilitate group learning in ordinary lessons.

The teacher also gave feedback about the prediction. The teacher considered that he could judge which groups needed help with the prediction. The teacher said that in the prediction, he wanted to check the detail of the group having a long dotted rectangle, that is, the groups have no idea about many propositions. The group with a high concordance rate of propositions is also the target of the check. It was also argued that the comparison between the actual result and the prediction is also helpful for analysis after the lesson. For example, Group 5 in Class A could have a good discussion because they have improved their map more than the potential, that is, they made some new *same* propositions in the group through the discussion. Meanwhile, Group 10 in Class B did not have a good discussion because their group map score is low in the predicted range; that is, they have adopted *divergent* propositions from the ideas in their group. He said that teachers could analyze what happens in the group learning during and after lessons if teachers could understand the graph.

Table 4. the result of the questionnaire (n = 1)

	Question	answer
1	Can you predict the group learning result in ordinary lessons?	2
2	Did the prediction by the Kit-build concept map provide a similar prediction of you?	2
3	Can you consider the treatments of learning in groups?	4
4	Could you consider the treatments of learning in groups with the prediction by the Kit-build concept map?	2

Answers:
1: "Yes, I think so strongly," 2: "Yes, I think so," 3: "Yes and no,"
4: "No, I do not think so," and 5: "No, I do not think so strongly."

5. Conclusion and Future Challenges

This paper proposes the attainable range prediction of group learning products by a simple aggregation of individual concept maps of group members. This is based on the automated assessment of concept maps on KBmap. KBmap provide common component of concept maps for learnres and it is easy to compare concept maps made of the common componets. The proposed method in this paper simply aggregates personal concept maps of group members with this mechanism and predicts group learning products.

In this case study, the score of the group activities had a 20% width, with more than 80% of the group scoring in the range of the predicted score as a result. About 80% of the proposition, even in the detailed analysis, has put the group learning products with the prediction rules. This shows the validity of the proposed prediction method in this study. In the questionnaire, the teacher pointed out the availability of the prediction graph. The group learning product prediction graph is expected to perform as the representation of the grasping ability of each group and the facilitation of group activities.

Future challenges are the verification of the use of the attainable range prediction f group learing products in the classroom by teachers and the learning effect of facilitation of group learning based on the prediction.

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