A Dynamic Group Composition Method to Refine Collaborative Learning Group Formation

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ABSTRACT
Group formation strategies have the goal of providing the participating students with the good initial conditions for collaborative learning. Continuing with the existing methods to set up the initial conditions to make peer interaction more likely happen, we propose a method for dynamically recomposing learning groups based on intra-group iteration analysis to optimize the learning group formation iteratively.

Keywords
Group Formation, Educational Data Mining, Collaborative Learning, Dynamic Group Composition, Interaction Analysis

1. INTRODUCTION
Group formation plays a critical role for the success of collaborative learning groups [2]. Through pedagogical experiments, both homogeneous and heterogeneous group formation strategies can effectively promote collaboration [1]. In order to compose heterogeneous or homogeneous learning groups, plenty of composition approaches have been suggested [2; 3; 6]. These approaches pay most attention to the performance of the proposed algorithms, such as solution optimization and time cost, while the peer interaction within the formed groups is typically not considered for refining the groups. In addition, some data mining technologies have recently been proposed to analyze the peer interaction, with results indicating that there are recurring interactions within groups with strong peer interaction [7]. Therefore, if we could find some way of group composition which would lead to groups showing these interaction patterns, then an effective peer interaction within these groups might be triggered with higher probability.

2. PROPOSED APPROACH
The proposed method is to dynamically recompose groups based on interaction analysis. We expect to distinguish groups with strong interaction from weaker ones and learn group composition rules from this. In this paper, group composition rules denote that which types of group members work together could trigger either strong or weak peer interaction. Initially, the collaborative groups are composed by existing composition approaches (e.g. Graf and Bekele's method)[2]. Learners in each group are then instructed to complete team tasks collaboratively. After the completion of the tasks, the peer interaction in the learning groups is analyzed. Data mining technologies are used to extract interaction patterns (e.g. sequential patterns) from group interaction logfile. These patterns together with tutor's assessment could be used to distinguish the effective interaction groups from the weak ones. Based on this classification and group member compositions, the group composition rules can be learned using decision tree induction methods. These composition rules are used to re-group the learners into a new group formation. At the new group formation, learners are given new collaborative learning tasks. After the completion of these new tasks, new interaction patterns are extracted again, and new group composition rules are learned as well. Then, this new set of composition rules is utilized to re-group learners again. This grouping process is kept on iteratively. Over time, the group formation will change dynamically, with the goal of composing the groups with highest chances for effective peer interactions.

3. PLANS FOR SYSTEM DESIGN
A software system for the proposed method of dynamically recomposing learning groups is designed, which is outlined as shown in Figure 1. The following sections describe the primary components of the system.

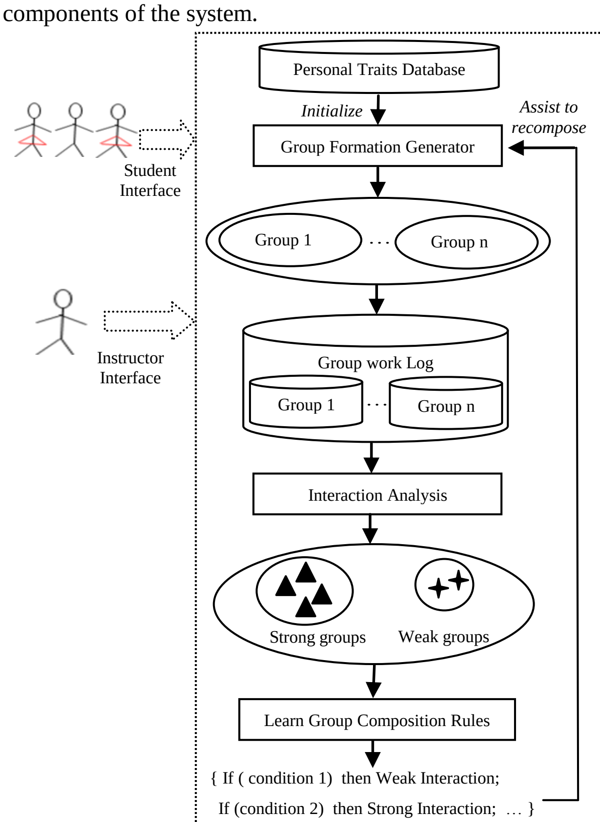

Figure 1. Outline of dynamically recomposing system

3.1 Student Interface

Student interface of the system has twofold functions. First of all, it is designed to collect learners' personal characteristics. In the light of the previous research on this topic [2-4; 6], leadership, previous knowledge, interest for the subject, group work attitude, self-confidence, shyness, gender are surveyed by questionnaires. The surveyed result for each student is then stored in a personal traits database. In addition, learners can choose one or more group members to interact with each other through the student interface.

3.2 Instructor Interface

Using instructor interface to the system, tutors can post collaborative tasks for each group, monitor groups working collaboratively, and assess the groups (e.g., for outcome quality).

3.3 Group Formation Generator

Group formation generator includes two functions. One is to generate the initial group formation and the other is to produce a new group formation at each recomposing iteration. Initially, we employ the Graf and Bekele's approach to compose heterogeneous learning groups [2]. At each iteration of recomposing, we first use an exhaustive method to generate all possible group formations. For each group formation, we then count up the groups which are predicted to produce strong peer interaction according to group composition rules. At the end, the group formation with the most "high potential" groups is selected as the final group formation for the next iteration.

3.4 Interaction Analysis

Interaction analysis is to verify the effective interaction really happen in learning groups. The effectiveness of interaction should be measured by both the outcome of group work and frequency of interactive events. Tutors are able to assess the outcome of group work. But it's hard for them to do assessment of the collaborative activities between group members because of the difficulties to deduce the actual peer interaction based on the interaction logfile. Fortunately, sequential pattern mining techniques have been developed to analyze peer interaction [5; 7]. The result of relevant research shows that the best interaction groups have high frequency of certain sequential behaviors [7]. Using the frequency of these uncovered sequential patterns together with the outcome of group work, the effective interaction groups could be distinguished from the negative ones.

3.5 Learn Group Composition Rules

Group composition rules indicate that which types of learners placed into a group could trigger either strong or weak peer interaction. Each member of the group is represented by a set of personal characteristics which are surveyed in Section 3.1. We firstly need to cluster all learners based on these personal characteristics. Then the resulting clusters are labeled respectively as cluster A, cluster B, etc. According to each group's performance, we can conclude the group composition and its interaction level in a dataset, as illustrated in Table 1. The numbers in the table signify how many students in each group belong to the clusters.

Decision tree learning algorithms (e.g. ID3) are then applied to construct a decision tree for classification based on the dataset. The interaction types construct the leaf node of the decision tree while the clusters of students (constructed based on personal characteristics) construct the inner nodes of the tree. When the decision tree is constructed, group composition rules are simply generated through traversing all paths from the root of the tree to every leaf node.

Table 1. Example of dataset

	Cluster A	Cluster B	…	Interaction type
Group1	1	2	…	strong
Group2	2	1	…	weak

4. CONCLUSION AND FUTURE WORK

This paper proposes a dynamic group composition method to refine collaborative learning group formation and outlines the designed software system. Our future work will be focused on implementation and evaluation of the proposed idea in a collaborative learning context.

5. ACKNOWLEDGMENTS

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