Entwining Individual and Collaborative Activities in Learning-Analytics Informed Collaborative Learning

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Abstract. Learning Analytics (LA) further expands the possibilities of CSCL and collaborative learning. However, there still remain difficulties, such as the cold-start problem in the early phases of group activity, and the challenge of handling learning data of both individual activities and group activities on the same platform. This paper introduces a framework, tools, and course design for Learning Analytics Informed Collaborative Learning. Through continuous activities supported by LA tools with log data from individual and collaborative activities, collaborative learning would overcome those issues.

Keywords: Learning Analytics, Collaborative Learning, Group Formation.

1 Introduction

Learning Analytics (LA), which attempts to "understand and optimize learning and the environments in which it occurs [1]," has advanced, further expanding the possibilities of CSCL and collaborative learning supported by data [2]. However, collaborative learning supported by data has various difficulties. For example, in the early phases of group activity, there is a cold-start problem, where there is not enough data [3]. In addition, the success of group work can be influenced by the students' engagement during individual activities as well as collaborative activities [4]. However, there are few cases that handle learning data on individual activities and group activities on the same platform and can choose the proper one depending on the activities.

To address those issues, this paper introduces a framework and tools for Learning Analytics Informed Collaborative Learning and proposes a course design using log data from individual and collaborative activities.

2 Learning Analytics Tools for Collaborative Learning

2.1 GLOBE framework and LEAF System

Group Learning Orchestration Based on Evidence (GLOBE) is a framework of group learning support with data-driven approaches in the learning analytics-enhanced environment [5]. GLOBE framework consists of the following four phases: group formation, orchestration of group work, evaluation of group work, and reflection after group work. To support each phase of GLOBE, this framework is implemented as several LA modules. These modules constitute part of the LA platform, the Learning and Evidence Analytics Framework (LEAF) [6]. The LEAF system consists of an LMS, an e-Book Reader (BookRoll), and an LA dashboard (Logpalette).

2.2 Learning Log-based Group Formation Module

This function is a core component of GLOBE. Groups are formed using a genetic algorithm using attributes extracted from each student's learning logs. Grouping types include homogeneous grouping, which collects members with similar attributes; heterogeneous grouping, which collects dissimilar members; and random grouping, which can be a solution for the cold-start problem in the early phases of group activity. Input parameters include reading behavior attributes (operation counts, viewing time, marker and memo counts, etc.), past group learning attributes (number of forum posts, interval, sentimental analysis results, teacher's and peer's evaluation), and knowledge attributes.

The effect of grouping types is based on the following theories. According to Knez et al.[7], heterogeneity between group members and their resources is recommended, especially in peer help contexts based on Vygotsky's Zone of proximal development (ZPD) theory [8]. On the other hand, homogeneity in learning engagement is said to produce better quality in team assignments [9]. In addition, this module has a Jig-saw grouping that collects different members for the second time for Jig-saw activities.

2.3 Group Forum Discussion Analysis and Dashboard Module

This function is named GWPulse and is implemented as a module launched from Moodle [10]. GWPulse captures the conversation logs in the Moodle Forum, and feedbacks the results to the students and the teachers. Learning Analytics Dashboard (LAD) in GWPulse shows the average posts count, characters count, posts interval, and "Assistant Needed Level", which is the average of the negativeness score of sentiment analysis for each post. In addition, the features of these analysis results are provided as attributes to the aforementioned group formation function.

3 Learning Analytics Informed Collaborative Learning

3.1 Context and Basic Structure of Classes

The target course is related to computer science at a Japanese university, and about 80 third-year students take the course every year. The first five classes were targeted. Fig.2 shows the basic structure of the classes. It consists of In-class and Out-class activities, each of which further consists of Individual and Collaborative activities.

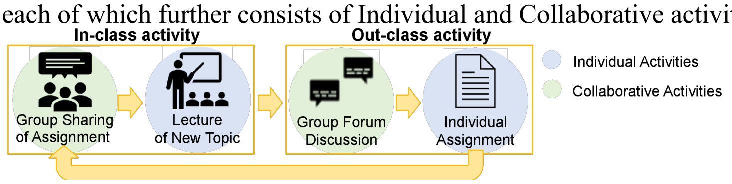

Fig. 1. Basic Structure of Classes with Individual and Collaborative Activities.

3.2 Course Design with Individual and Collaborative Activities

To support the classes described in the previous subsection using Learning Analytics, we used the LA tool introduced in Section 2 as shown in Fig.3.

Prior to each class, groups are formed based on the previous week's learning activity data, and in-class activity begins with group sharing of the previous week's assignments. After that, there will be two types of peer evaluations: one is about the assignment, and the other is about previous week's forum discussion. During that peer evaluation, GWPulse's LAD is used to review the activities in the forum discussion. After that, there will be a lecture on the new topic Out-class activities include reviewing lectures with BookRoll, discussions in forums, and assignments to summarize them. GWPulse also helps students to monitor their own activities and teachers to grasp the situation of this forum discussion. After repeating this three times from the 2nd to the 4th week, students will create a presentation summarizing what they have learned so far as the assignment of the 4th week, and present it in the 5th week.

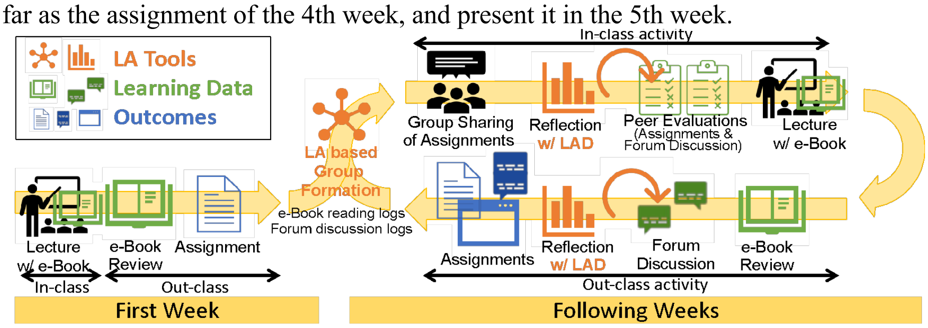

Fig. 2. Course Design for Learning Analytics Informed Collaborative Learning

3.3 Group Formation according to the Activity and Purpose

The group formation function enables grouping according to the activity and purpose by combining the type of grouping and input parameters. Table 1 shows the group formation types, input parameters, and their purposes.

Table 1. Group Formation Types, Input Parameters, and their Purposes.

Weeks	Types	Input Parameters	Group for	Grouping Purposes
2^{nd} week	Random	-	Forum discussion	Begin with a small amount of learning data
3^{rd} week	Jig-saw 1 (Heterogeneous)	Reading attribute (Reading, marker, memo)	Forum discussion	Balance engagement in Individual activities
4^{th} week	Jig-saw 2 (Re-grouping)	-	Forum discussion	Make presentation to different members
5^{th} week	Heterogeneous	Forum discussion attribute	Presentation preparation	Balance engagement in Collaborative activities

For the first grouping, even though there may not be enough data, random grouping enables to form a group in such a phase. The following two groupings took into consideration the balance of students' engagement in the Individual activities so that the forum discussion would go well. The grouping for the fifth week takes into account the balance of students' engagement in the Collaborative activities to ensure every group has active members for group work for presentation preparation.

4 Conclusion and Future Works

This paper discussed how Learning-Analytics Informed Collaborative Learning can be implemented. The proposed implementation addresses the cold-start problem in the early phases and considers suitable learning data from individual and group activities according to the activity and purpose. Future research will verify the appropriation of the proposed design.

Acknowledgments

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