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Social Process Awareness: Extracting Learning Process Patterns for Actionable Formative Feedback

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Abstract: Students' formative assessment is essential for promoting self-regulated learning, particularly during long vacations when students manage their own learning without direct teacher support. While traditional formative assessment has been teacher-led, recent studies emphasize the importance of providing feedback that is actionable and formative to students. This study serves as a preliminary analysis toward implementing Social Process Awareness (SPA), a concept designed to help students gain formative insights by comparing their learning processes with peer group trends. Using trace data from the LEAF system, we analyzed patterns that can provide actionable formative feedback. We identified three progress patterns—"Low Engagers," "Early Finishers," and "Consistent Finishers"—as well as three effort patterns—"Proficient Students," "Struggling Students," and "Persistent Students," which were defined based on final answer accuracy and reattempt actions. Results show that "Early Finishers" performed significantly better, whereas "Struggling Students," categorized as a low-effort group, had lower performance. If these findings are visualized on a dashboard, students' formative assessment can be supported with their progress and effort displayed in actionable and formative ways.

Keywords: Learning Analytics, Social Process Awareness, Formative Assessment, Actionable Feedback, Long Vacation Period

1. Introduction

The importance of "formative assessment" that promotes learning by positioning students as active agents has been emphasized (Wiliam, 2017). Conventionally, it has been conducted under teacher-led instruction to enhance teaching strategies. However, it is also important to enable students to evaluate their own learning status rather than relying solely on teacher feedback (Sadler, 2010). In terms of this, the accumulated trace data from widespread devices in schools provide new approaches to formative assessment (Stanja et al., 2023).

Learning Analytics Dashboards (LADs) research targeting students recognized the need to consider the information necessary for providing meaningful feedback to students, rather than merely visualizing the frequency of individual learning activities (Matcha et al., 2020). In practice, the actionable feedback model is emphasizing the importance of being "timely," "individualized," "non-punitive," and "customizable" (Hysong et al., 2006). However, it has been pointed out that many existing LADs induce direct competition among students by visualizing their relative rankings within the class (Jivet et al., 2017). Kuromiya et al. (2024) quantified and examined progress patterns over long period by dividing it into the first and second halves of the long break. However, such insights can be difficult for students to imitate, and they often lack the granularity needed to support improvement before final outcomes are visible. As a result, existing LADs frequently fail to provide actionable formative feedback.

To address this issue, we define a new concept, "Social Process Awareness (SPA)," in which students gain insights by observing the learning processes of their peers. Here, "Social" refers to familiar entities such as classmates, and "Process" denotes the process of learning activities. SPA aims to support individual student "Awareness" by presenting trends (e.g., weekly progress, effort) as feedback in the learning processes of different performance groups within the class. This study serves as a preliminary analysis for implementing SPA, with the broader goal of providing actionable formative feedback to students. Accordingly, our research question is set as follows: ***What learning process patterns can be extracted to provide actionable formative feedback?***

2. Method

2.1 Dataset

In this study, we analyzed data from 108 first-year junior high school students in Japan. Figure 1 presents how the students were supported by the LEAF (Learning Evidence Analytics Framework) system (Ogata et al., 2022) during the long break. The long break lasted from July 21 to August 23, 2023, and assignments were distributed one week before the break began. Students were required to complete the assignments by August 24, and on the same day (August 24), a post-break test based on the given assignments was administered to evaluate their learning outcomes. The LEAF system comprises multiple components: Moodle, a Learning Management System (LMS); BookRoll, a learning material delivery system; a Learning Record Store (LRS) that collects interaction logs from BookRoll; and LOG PALETTE, a tool for visualizing and analyzing the accumulated logs. During the break, teachers at the participating school used BookRoll to distribute assignments. While working on these assignments, students were required to respond to a comprehension check survey embedded in each assignment page on BookRoll. Both engagement data on BookRoll and post-break test results were recorded.

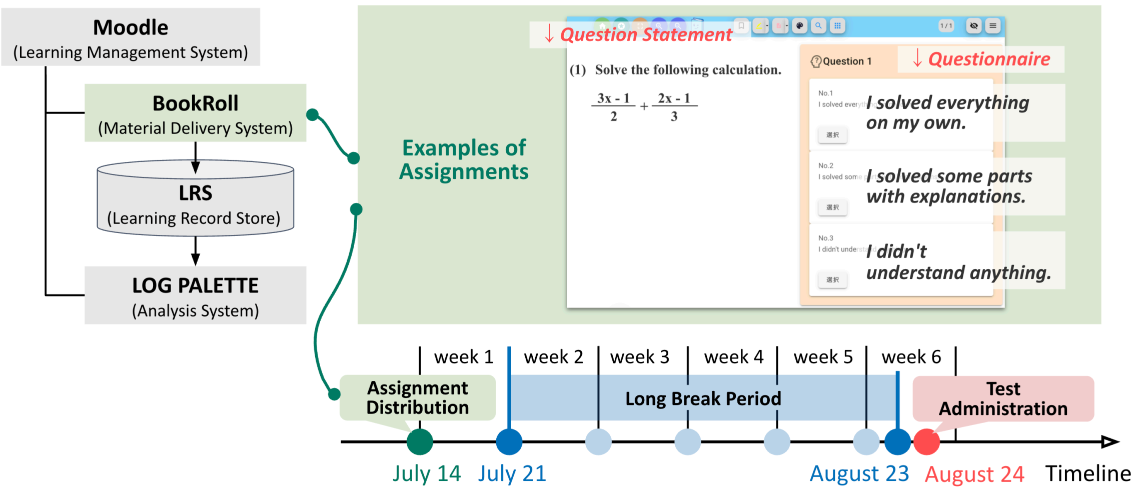

Figure 1. Long Break Assignments in the LEAF System

2.2 Analysis Items

2.2.1 Calculation of Weekly Progress

In this study, we conducted clustering based on weekly progress rates. The calculation process is illustrated in Figure 2.a. For each week after the assignments were distributed, we calculated the proportion of uniquely attempted questions relative to the total number of questions. For example, if an assignment consisted of five questions and a student attempted two questions in week 1, the progress rate for week 1 would be 2/5 = 0.4. If the student attempted one additional new question in week 2, the progress rate for week 2 would be 3/5 = 0.6. If no new questions were attempted in week 3, the progress rate would remain 0.6. If the student attempted another new question in week 4, the progress rate would increase to 4/5 = 0.8. When the progress rate reaches 1.0, it indicates that all assigned questions have been completed. We aggregated this weekly progress rate for each student and applied time-series clustering.

2.2.2 Calculation of Effort

This study defines effort using two key indicators: “reattempt rate” and “final answer accuracy.” These two values were calculated for each student and then clustered. The calculation process is illustrated in Figure 2.b. For reattempt rate, we calculated the number of questions each student reattempted and divided it by the total number of unique questions they worked on. For final answer accuracy, we determined whether the student’s last recorded answer for each question was correct or incorrect and calculated the final accuracy rate accordingly. For example, suppose a student worked on four out of five assigned questions and reattempted three of them. In this case, the reattempt rate would be 3/4 = 0.75. Similarly, if the student answered three out of four attempted questions correctly in their final submission, the final accuracy rate would be 3/4 = 0.75. These two values were computed for all students, followed by clustering analysis.

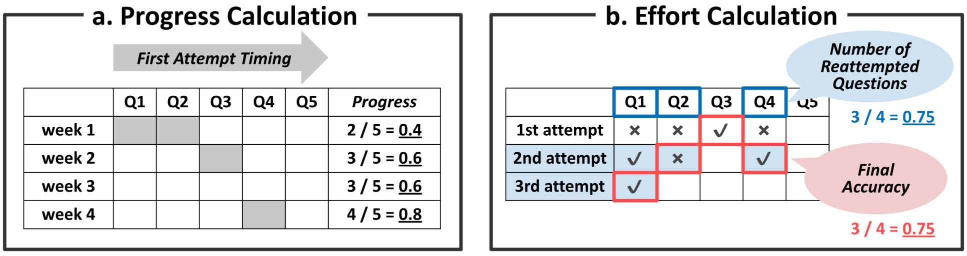

Figure 2. Progress and Effort Calculation

3. Results

3.1 Analysis 1: Extracting Progress Patterns

The results of clustering based on students’ weekly progress rates are presented. The number of clusters was set to three based on the elbow method, and time-series clustering using Euclidean distance was performed. As a result, three patterns were identified (Figure 3):

- ***“Low Engagers”*** who exhibited low progress and did not complete the assignments.
- ***“Early Finishers”*** who completed the assignments at an early stage.
- ***“Consistent Finishers”*** who gradually completed the assignments.

To examine the relationship between these clusters and post-break test performance (scores out of 100), boxplots and ANOVA were conducted. The results indicated a significant difference among the clusters ($F = 8.62$, $p < .001$). Further post-hoc analysis revealed that students classified as “Early Finishers” tended to score significantly higher on the post-break test compared to “Low Engagers” ($p < .01$) and “Consistent Finishers” ($p < .01$).

The patterns clearly highlight variations in weekly progress, offering practical insights that students can use to plan and improve their weekly schedules. In this sense, the patterns serve as actionable and formative feedback for students if presented through dashboards.

3.2 Analysis 2: Extracting Effort Patterns

Next, we present the results of clustering based on students’ effort patterns, defined by two indicators: the number of unique questions reattempted and final accuracy status. The number of clusters was set to three, determined using the elbow method, and K-means clustering was applied. As a result, three patterns were identified (Figure 4):

- ***“Proficient Students***” who achieve high accuracy with few reattempts.
- ***“Struggling Students”*** who achieve low accuracy with few reattempts.

- ***"Persistent Students***" who achieve high accuracy with many reattempts.

Notably, among these students, those in "Persistent Students" who exhibited high final accuracy rates, improved their accuracy by an average of 6% from their initial responses to their final responses. In contrast, other "Proficient Students" and "Struggling Students" showed minimal changes of 0–1%. This suggests that effort through repeated attempts contributes to a deeper understanding of the material.

To examine the relationship between these clusters and post-break test performance (scores out of 100), boxplots and ANOVA were conducted. The results indicated a significant difference among the clusters ($F = 8.30$, $p < .001$). Further post-hoc analysis revealed that students classified in "Struggling Students," which exhibited low accuracy and a low number of reattempts, tended to score significantly lower on the post-break test compared to "Proficient Students" ($p < .001$) and "Persistent Students" ($p < .01$).

The patterns suggest that high performance is associated with making efforts aligned with each student's level of understanding, rather than simply reviewing all questions. By incorporating two indicators—whether students understand the content and whether they are actively trying to improve—the patterns help students formatively assess the amount of effort required. Thus, the patterns serve as actionable and formative feedback for students if presented through dashboards.

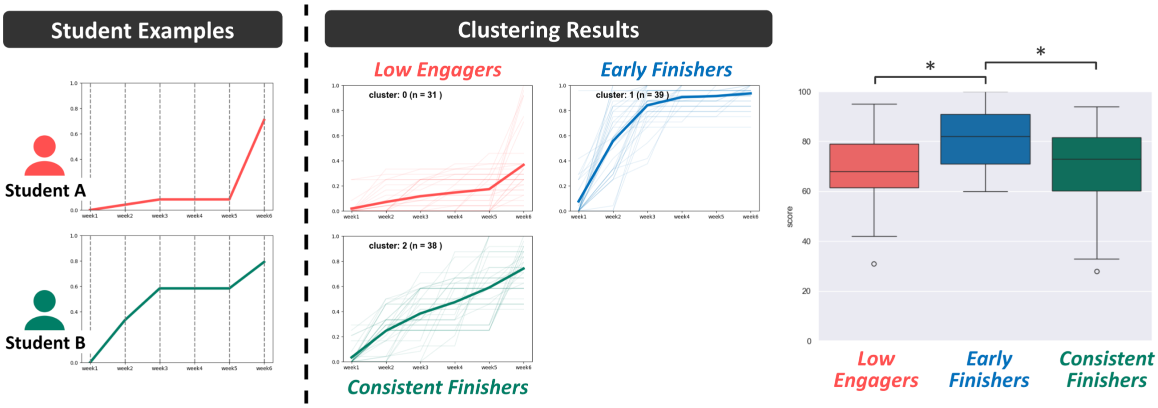

Figure 3. Examples of Student Progress and Clustering Results

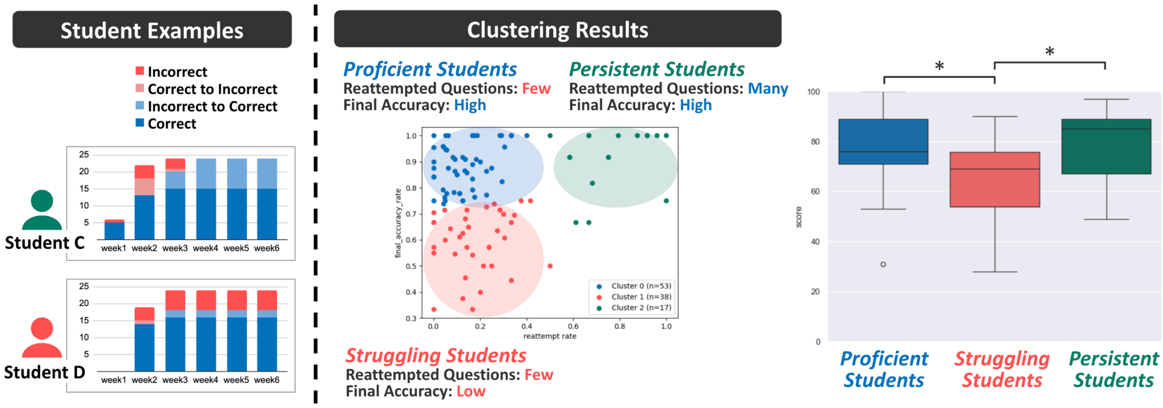

Figure 4. Examples of Student Effort and Clustering Results

4. Discussion and Conclusion

Our analysis results suggest that achieving high performance is not solely about completing assignments (Analysis 1) but also about how students engage with the content (Analysis 2). The findings indicate that efforts to repeatedly attempt questions to improve accuracy contribute significantly to better outcomes. The novelty of this study lies not only in identifying learning patterns, but also in making them actionable and formative for students. We illustrate this through two cases focusing on progress and effort. In Figure 3, Student A ultimately belonged to the "Low Engagers," but differences from other clusters were already observable by week 2. Detecting this early may have helped prompt timely awareness and improvement. In Figure 4, Student D ultimately belonged to the "Struggling Students," with clear signs of diverging effort patterns emerging in the early weeks. Recognizing this could support earlier awareness of the need to address questions they are unable to solve. As such, these progress and effort patterns were extracted to support actionable formative feedback for students in this study. While prior research in stable contexts—such as MOOCs, where teaching styles are standardized through video lectures and quizzes—has shown the value of comparing current students with past successful ones (Davis et al., 2017), this approach is less applicable in schools due to contextual variability from teacher influence and flexible instruction. To address this, the SPA introduced here enables students to gain awareness by comparing their learning processes with peer group trends, offering a more adaptable solution. Future work will implement actionable formative feedback by integrating these findings with predictive models using machine learning.

This study has a limitation that the effort was examined in terms of simple "reattempt actions" and "final accuracy." However, in the learning process, there is a phenomenon known as wheel spinning, where students invest significant time and effort without making progress in mastery (Beck & Gong, 2013). Research has also been conducted on visualizing wheel spinning using learning logs to help students identify such unproductive learning patterns (Yamauchi et al., 2024). Future research may explore more detailed aspects of the learning process, enabling more sophisticated interventions. Finally, we plan to develop a dashboard based on our findings and investigate whether it can effectively support students' formative assessment.

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