

Enabling Mixed Genetic Algorithm for Automatic Group Formation System

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Abstract. Group formation plays a crucial role in designing collaborative learning activities, as the success of the group largely relies on the makeup of its members. While numerous algorithms exist, many group formation systems tend to adopt a single grouping strategy, such as either heterogeneous or homogeneous grouping, limiting their ability to address diverse student characteristics simultaneously. In this paper, we propose an integrated approach utilizing a mixed genetic algorithm within a data-driven learning platform, which considers both homogeneous and heterogeneous characteristics concurrently. Through an exploratory implementation in a university course, we examined the algorithm’s performance using authentic log data under various grouping strategies in classroom settings. We also highlight the potential of interpretability in group formation results, particularly through the composition panel, enabling teachers to make informed interventions and thereby enhancing overall class performance.

Keywords: Group formation · Genetic algorithm · Grouping strategy · Group composition · Classroom implementation

1 Introduction

When conducting collaborative learning teachers tend to spend considerable time on group formation tasks due to their limited familiarity with students, resulting in biased groupings [15]. Using learning log data available in digital platforms, automated group formation techniques can streamline this process and facilitate optimized group compositions. These algorithms can address multiple student characteristics to allocate them homogeneously or heterogeneously [9]. As the prevalence of automatic group formation in educational settings, evidence from learning outcomes and teacher insights suggests that exclusively homogeneous or heterogeneous groupings for all characteristics can be inadequate. The necessity for a combination of homogeneous and heterogeneous groupings concurrently emerges [7]. Theoretically, advancements in genetic algorithms offer promise in meeting this requirement [12]; however, existing studies lack a user-oriented system tailored for educational practitioners. To narrow the gaps, this paper introduces a mixed genetic algorithm integrated into a widely used learning platform

and presents an exploratory study to implement the system in an authentic university classroom setting.

2 Research background

2.1 Group formation with genetic algorithms

There are various computer-supported techniques for creating suitable groups, and many of them concentrate on a single grouping strategy, such as either heterogeneous or homogeneous grouping, and a specific learner characteristic for group formation [9]. The genetic algorithm emerges as a prominent solution due to its ability to incorporate multiple input variables, ensure balanced group sizes to avoid orphan students, produce diverse groups despite identical input parameters, and utilize fitness values to interpret group compositions efficiently.

The key concept of the genetic algorithm for group formation involves identifying grouping candidates with optimized fitness values through iterations (see Fig. 1). The candidate consists of a set of students allocated in a set of groups (G), and the fitness values are determined by functions based on a 0-1 scaled student characteristic matrix (C) to select the optimal candidate as output. Characteristics of C come from recorded learning behaviors in digital learning platforms, such as reading logs, quiz scores, and peer ratings [6]. Previous functions have focused on either inter-group differences for balanced grouping [10] or intra-group compositions [3]. Moreover, for intra-group focus, the method can handle non-numeric indicators by converting overlapped annotations into sub-characters in the student matrix for active reading contexts [7].

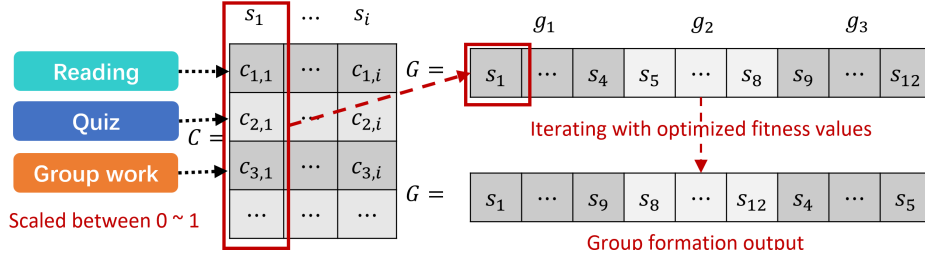


Fig. 1. Characteristic matrix (C) and candidates (G) for the genetic algorithm.

However, as for intra-group compositions, employing a monotonic grouping strategy for all input variables may not suffice. For instance, in active reading classes where students read with different types of markers, [7] shows that groups with heterogeneous difficulty markers facilitate peer assistance, while homogeneous highlighting markers may foster communication based on shared interests. To overcome this gap, [12] introduced a mixed genetic algorithm and evaluated its performance in terms of time cost with varying population sizes. While its empirical study still focuses on evaluating two monotonic strategies, pedagogical implications for the mixed method are still unexplored. Moreover, compared to

controlled experiments that incorporate manually collected data from questionnaires like [12], a user-oriented system is absent for educational practitioners and cases using authentic data. This gap leads to further research to bridge the divide between theoretical advancements in group formation algorithms and their practical implementation.

2.2 Group composition and criteria in learning practice

Besides grouping algorithms, it is also crucial to inspect the characteristics to be taken into account and the appropriate criteria when creating groups with different objectives. Two significant factors to consider are knowledge and engagement, with groups typically being either homogeneous or heterogeneous [9].

Knowledge is often the primary factor to consider, as disparities in knowledge levels provide a basis for peer assistance [5]. Studies like [4] indicate that undergraduate students with complementary incomplete prior knowledge perform better than those with complete knowledge, supporting the heterogeneous strategy. Homogeneous strategy often focuses on non-cognitive issues like personalities or interests, and for less-challenging works [13]. Though we cannot compare high and low for personal traits [12], studies like [2] found that in higher education, homogeneous groups consisting of students with high prior knowledge outperform others in collaborative problem-solving. However, these studies primarily address the effectiveness of individual teams rather than the division of an entire classroom into groups. Consequently, questions remain regarding the overall learning outcomes of the entire class, especially with regard to the equitable treatment of homogeneous low-ability groups that should not be isolated [14].

In cases where cognitive resources are less required, desirable group dynamics also rely on the participation of all members. The engagement levels observed in antecedent learning tasks, such as e-book interactions [1], and individual preparation [8], can mirror the quality of subsequent collaborative learning. During classroom implementations, teachers can intervene during the group orchestration phase to assist groups exhibiting low engagement levels, thereby fostering improved overall performance across the entire class in group learning activities. This intervention strategy can be reinforced through interpretable scaffolding, suggesting avenues for future research.

3 System design

The Learning and Evidence Analytics Framework (LEAF) serves as an overarching technical framework that consolidates multiple learning log data sources, implemented in over 100 schools globally, with more than 1,000 student users of Japanese public schools [11]. Within the LEAF-enhanced environment, Group Learning Orchestration Based on Evidence (GLOBE) provides a framework and instantiated systems to support group learning with data-driven designs across four phases: formation, orchestration, evaluation, and reflection [6]. Data sensors

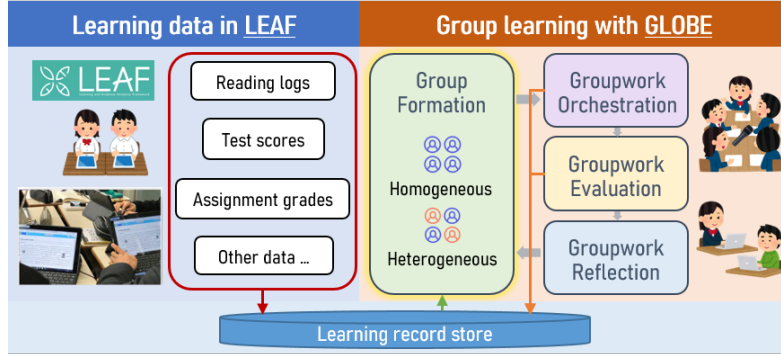


Fig. 2. Iterative use and update of learner model with group work implementations under GLOBE

incorporated in LEAF and other GLOBE modules enrich the group formation module with a diverse data pool (see Figure 2).

Utilizing the fitness function (1) for each group g in the genetic algorithm depicted in Figure 1, where $\bar{x}_{j,g}$ represents the average value of characteristic j within the group, the group formation module enables the adoption of homogeneous or heterogeneous grouping strategies. The final fitness value (F), obtained by summing all F_g values of all groups, enables the determination of homogeneous groups with a small F or heterogeneous groups with a large F .

$$F_g = \sum_{i=1}^S \sum_{j=1}^C (c_{j,i} - \bar{x}_{j,g})^2 \quad (1)$$

The latest version of the group formation system integrates the mixed method from [12], leveling a playground for empirical research with routine data. As described in Equation (2), the mixed method partitions input variables into homogeneous and heterogeneous components, calculating the fitness value for each. The group fitness function F'_g is determined by subtracting the fitness value of the homogeneous part (where smaller values are preferable) from that of the heterogeneous part (where larger values are preferable). A larger resultant value indicates a more favorable grouping candidate.

$$F'_g = \sum_{i=1}^S \left(\sum_{j=1}^{C_{hetero}} (c_{j,i} - \bar{x}_{j,g})^2 - \sum_{k=1}^{C_{homo}} (c_{k,i} - \bar{x}_{k,g})^2 \right) \quad (2)$$

Embedded with the mixed algorithm, the group formation system also features an automatic grouping panel pre-configured with settings on input variables derived from previous evidence for C matrix and grouping strategies, alleviating teachers from the burden of overwhelming parameter adjustments. Additionally, it provides detailed composition panels illustrating group compositions through bars for teachers (see Fig. 5), along with evaluation panels to grade each group and check dynamics through formative peer evaluations [6].

4 System implementation in a university course

As a predominant implementation, the mixed method was employed in a university course on Human Interface in 2023. This case study endeavors to address the following two questions.

- **RQ1:** How does the mixed algorithm perform in an authentic educational setting?
- **RQ2:** How do the created groups perform, and how can the group formation system assist teachers in interpreting their performance?

4.1 Learning context, course design, and data collection

The system was implemented in a 4-week session instructed by the same lecturer on the basic concepts of human interface design. 40 students enrolled in the course, most of them were beyond sophomore. Each week in this session followed the same workflow shown in Fig. 3.

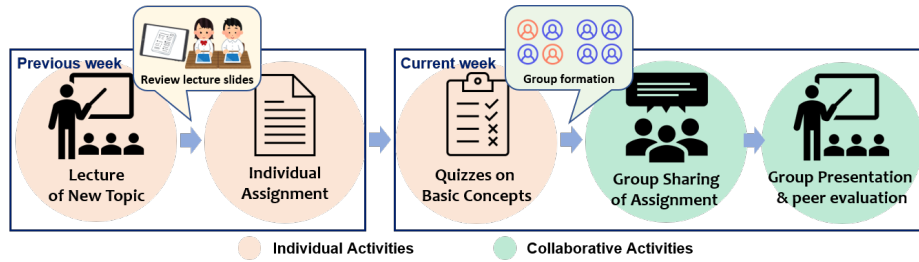


Fig. 3. Workflow of the course.

To examine the impact of the mixed group formation strategy, we implemented two conditions in the final two weeks of the session, as students need to acclimate to the workflow in the preceding weeks and minimize potential learning effects. Condition A utilized homogeneous engagement and heterogeneous knowledge, while Condition B employed heterogeneous engagement and homogeneous knowledge. Each condition consisted of six groups (A1-A6 and B1-B6), with 31 students participating in A and 25 in B due to absences. The tasks involved applying learned concepts to write and present a report, with only subtle differences between weeks. Condition A was based on the lecturer’s experience teaching STEM classes, anticipating that groups with high homogeneous engagement would be self-regulated and active, while low engagement groups might need more teacher intervention. Condition B served as a contrasting condition to evaluate the algorithm’s performance.

The group formation considered engagement and knowledge indicators to construct the matrix C in Fig. 1. The individual reading engagement was operationalized through the total reading time and operation times logged in the e-book containing the lecture slides for each week, scaled into the range of 0-1 using percentage rank transform $((rank - 1) / (n - 1))$. Knowledge was assessed

through five quizzes developed by the lecturer based on the lecture content. All these data points were collected from LEAF systems.

Weekly peer evaluations assessed learning outcomes for presentations based on completion (basic), concept application (knowledge), and additional commentaries (extra). The teacher grading used the same criteria but with separate assessments for each construct.

4.2 Result and discussion

Regarding RQ1, the density plots in the upper part of Fig. 4 illustrate the heterogeneity of each group based on squared difference. Overall, the system effectively generated groups with varying within-group differences based on the selected algorithm. A clear disparity is observed in two engagement indicators between the two conditions. Though the expected lower F values for quiz scores were not achieved, as most students scored above half points, resulting in minimal variance, two typical groups (B2 and B3) had B2 with identical scores. Despite using uniform scales to construct matrix C , the quiz score indicator performed poorly in the algorithm. This finding underscores the challenge of obtaining high-variance indicators for group formation in real-world settings.

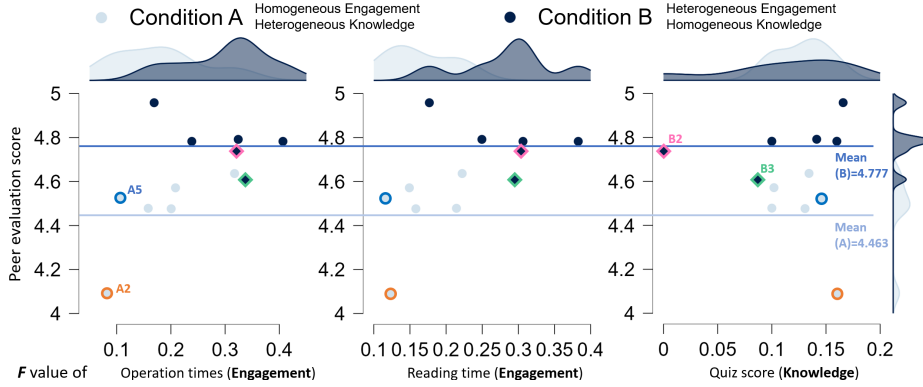


Fig. 4. Interval plots of peer evaluation score.

As for RQ2, we examined peer evaluation scores and teacher's grading. Overall, Condition B outperforms Condition A, indicated by both peer evaluation and teacher grading. We can see Group A2 received the lowest peer rating score in Condition A, with teachers also assigning low ratings in the knowledge construct; and Group B3 obtained the lowest score in Condition B. Regarding teacher grading, all groups across both conditions met the two basic criteria. However, Groups A2 and A5 failed both items in the knowledge construct, and Group B2 failed in item 3 of the knowledge construct.

When comparing the grouping strategies of two conditions, Condition B outperforms Condition A in group presentations, as indicated by both peer evaluation and teacher grading. This finding suggests that the combination of homogeneous engagement and heterogeneous knowledge, inspired by the lecturer, may

not be appropriate for this particular learning context. This observation may be partially attributed to the difficulty of the course material, which requires low cognitive resources to understand, but only engagement in reading the slides. In STEM subjects with higher cognitive load, where the deviation in knowledge proficiency is more pronounced, the Condition A strategy may be more suitable, leading to further research. Therefore, employing a heterogeneous strategy for all groups remains a desirable choice for the current scenario.

To interpret the underperforming groups in Fig. 4, we examined the detailed panel of the system (Fig. 5) to understand their compositions. In Fig. 5, each row represents one student, with the color of the bar changing based on the indicator's value: green signifies high, yellow medium, and red low values. Groups A2 and A5 exhibit high levels of engagement homogeneity despite disparities in engagement levels, while Groups B2 and B3 rank as the top two in knowledge homogeneity in Condition B. These findings suggest a potential relevance between undesirable performance and homogeneous group compositions. Rather than facilitating negotiation with surplus cognitive resources [2], homogeneity hinders the spread of ideas within new social communities, which conflicts with the lecturer's expectations [14]. Through the system, teachers can identify such groups like A2 and allocate additional attention to them during class sessions to ensure the overall performance of the entire class.

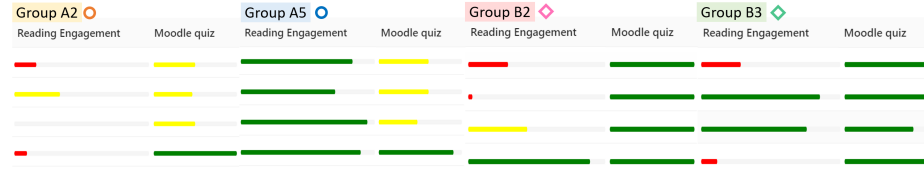


Fig. 5. Interpretation of low-performance groups from the system.

5 Conclusion

In this paper, we introduce a mixed genetic algorithm that incorporates both homogeneous and heterogeneous characteristics simultaneously. We implement this algorithm in a face-to-face university course as part of an exploratory study. Our findings demonstrate that the mixed method can effectively form groups based on the assigned grouping strategy. Based on the group formation system, teachers can examine the composition of these groups, enabling them to intervene promptly to enhance overall classroom performance. Future research could explore grouping strategies across various learning contexts, particularly in STEM subjects with higher cognitive loads of knowledge.

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