Visual Analytics of Student Learning Behaviors on K-12 Mathematics E-learning Platforms

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Abstract

With the increasing popularity of online education, many E-learning platforms have been launched to facilitate the education of K-12 students, where their learning logs such as grades, login time and mouse movement are often recorded. However, it still remains unclear how to make use of these detailed learning behavior data to improve the design of learning resources and gain deep insights into students' thinking and learning styles. In this work, we propose a visual analytics system to analyze student learning behaviors on a K-12 mathematics E-learning platform. It supports both correlation analytics between different attributes and detailed visualization of user mouse movements. Our case studies on a real dataset show that our system can better guide the design of learning materials (e.g., math questions) as well as facilitate quick interpretation of students' problem-solving and learning styles.

Index Terms: Human-centered computing—Visualization—Visualization application domains—Visual analytics

1 Introduction

With the increasing popularity of online education, many E-learning platforms have been launched to facilitate the education of K-12 students. The E-learning platforms are often equipped with various kinds of learning resources such as item banks and videos. When students interact with these learning materials, their learning logs such as grades, login time and mouse trajectories are often recorded.

Previously, many studies have been done on using visual analytics to analyze students' learning behaviors. For example, Vismooc [3] visualized the clickstream of video-watching behavior in MOOCs (Massive Open Online Courses); Viseq [1] analyzed the learning sequence of different learning activities (watching videos, doing exercise, etc.); PeerLens [4] provided a visual interface to facilitate students planning their learning path through online question pools. However, few works have touched upon the analysis of detailed problem-solving steps within questions. It still remains unclear how to make use of these detailed learning behavior data to improve the design of learning resources [2] and gain deep insights into students' thinking and learning styles.

In this work, we propose a visual analytics system to analyze student learning behaviors on a K-12 mathematics E-learning platform. It supports analysis from different levels of detail. On the one hand, it supports a quick overview of student performance and learning behaviors on the whole question set. On the other hand, it utilizes the heat map and the transition map to enable detailed exploration of problem-solving patterns on each question, and provide feedback and guidance to help educators optimize their teaching methods. We also conducted three case studies, which shows that our system can better guide the design of learning materials (e.g., math questions) as well as facilitate quick interpretation of students' problem-solving and learning styles.

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2 Visual Analytics System

The system interface is shown in Fig. 1. It contains four views: (a) Overview of the problem and the heat map showing the problem-solving interaction data; (b) Transition map view revealing the detailed problem-solving steps; (c) Data analytics view displaying the basic correlation between learning attributes and learning performance; (d) Control panel adjusting the size of Region of Interests (ROIs).

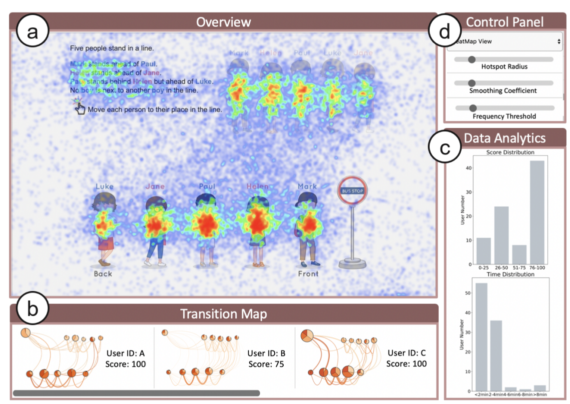

Figure 1: The system interface.

As for the transition map in Fig 2, ROIs that students mostly interact with are extracted and visualized as pie charts, which are connected by arcs according to users mouse action streams to form a transition map. The size of the pie charts represents the number of interactions over the ROIs; the color of arcs and sectors represents the time order of actions. The map reveals students problem-solving steps. We can see that the third and fourth pie on the bottom line are larger than others and the line between them is much thicker: this represents a large amount of transitions between these two ROIs.

3 Case Studies

3.1 Overall Performance Analysis

In this first case study, we use our system to perform a correlation analysis on the students' mean score with the labeled difficulty of

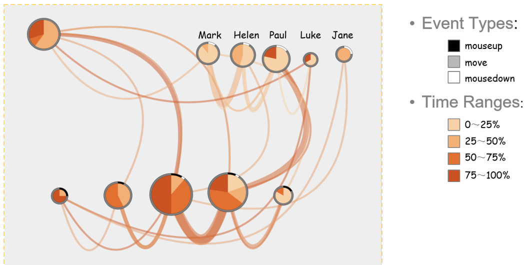

Figure 2: The transition map demonstrating the detailed problem-solving steps with event types and time information.

the questions. Fig. 3 shows the correlation between the predefined difficulty level of each question and the mean score of all students. It is interesting that some questions labeled as ”easy” by instructors actually have lower mean scores (highlighted in the dashed rectangle), indicating that their difficulty levels probably need to be re-evaluated.

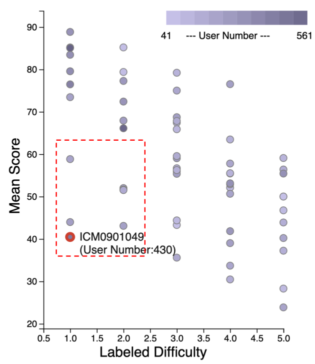

Figure 3: Overview of student performances on all questions.

3.2 Thinking Patterns Identification

The system can also reveal different thinking modes. As shown in Fig. 4a, students are asked to drag the red dot to make a new shaded area of 6 instead of 4. The two sides, left and bottom, are fixed and the red dot only affects the top and right edges. We visualized all the mouse movements through a heat map (Fig. 4c) to identify the thinking patterns of the students. Point 1, 2 and 5 (indicated by arrows on the Figure) are all possible answers. According to the heat map, many students solved the question in the additive way of thinking (Fig. 4b) and preferred to move the point horizontally (passing Point 3 to Point 1) rather than vertically (passing Point 4 to Point 2). A considerable portion of students also solved the question in a subtractive way and pin on Point 5.

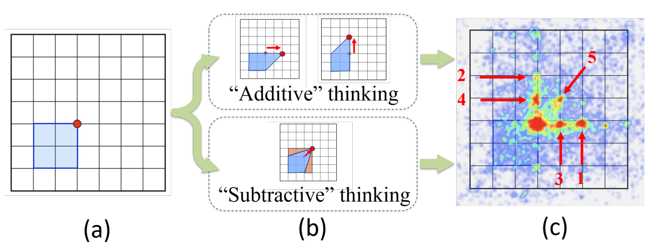

Figure 4: (a) An example math problem: drag the red dot to make the area 6 boxes instead of 4. (b) Different thinking patterns in solving the problem. (c) A heat map showing the problem-solving interaction.

3.3 Problem-solving Steps Reveal

However, for questions like Fig. 5, there is only one unique answer. If only the heat map is used, the key steps to solve a problem cannot be inferred. A transition map can then be used to reveal more details. In Fig. 6, (a) is the transition map of students with wrong answers; (b) is the transition map of students with full marks. We can see that the light area of pies in (a) is decreasing from the left to the right while in (b) it’s increasing. Since the color represents the time order of the sequence, a conclusion can be drawn that the students with full marks tend to order the people from right to left, while students with wrong answers seem to do it in the opposite way.

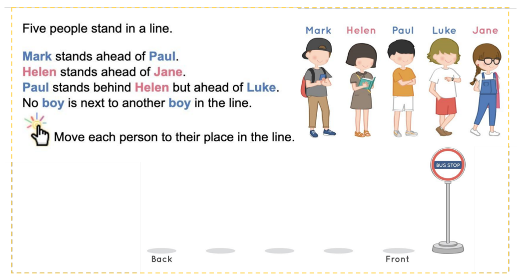

Figure 5: Another example of the math problem.

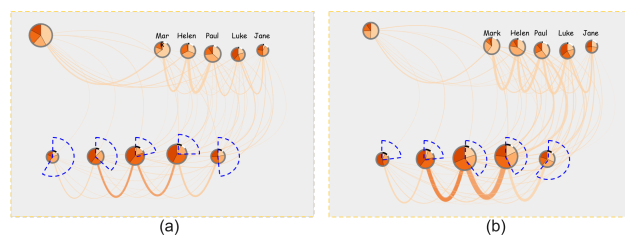

Figure 6: (a) The transition map of students with wrong answers. (b) The transition map of students with full marks.

4 Conclusion and Future Work

In this poster, we proposed a visual analytics system to analyze student learning behaviors on K-12 math E-learning platforms. It enables both correlation analysis of different learning data attributes and visualization of detailed interactions of students. We evaluated the proposed system with real log data from a K-12 math E-learning platform. Our case studies show that the proposed system can help instructors quickly find the possible flaws in the design of learning materials (e.g., which question difficulty levels need to be revised), as well as gain deeper insights into the detailed problem-solving styles of different students. In the future, we plan to further improve the current system by incorporating analysis of more fine-grained problem-solving behaviors and would also like to extend the visual analytics system to other K-12 E-learning platforms.

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