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Norum, Reilly	Worcester Polytechnic Institute	
Lee, Ji-Eun	Worcester Polytechnic Institute	
Ottmar, Erin	Worcester Polytechnic Institute	

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Student Profiling on Behavioral Patterns in an Online Mathematics Game: Clustering Using K-Means

Reilly Norum, renorum@wpi.edu
Ji-Eun Lee, jlee13@wpi.edu
Erin Ottmar, erottmar@wpi.edu
Worcester Polytechnic Institute

Abstract: This preliminary study examined whether distinct student profiles (N = 760) emerged based on their behavioral patterns in an online algebraic learning game. We applied k-means clustering analysis to clickstream data collected in the game and then examined how students' behavioral patterns varied across the clusters using data visualization. The results identified four groups of students based on their in-game behaviors, showing that there was a large variation in their behavioral patterns for engaging with the game.

Introduction

With the rapid development of game technology, there has been an increasing interest in the use of online educational games in mathematics learning. Previous studies have reported that well-designed online games are effective in improving students' mathematical knowledge, skills, and engagement (Chang et al., 2016). However, due to the greater flexibility and interactivity of online educational games compared to other types of educational technology tools, their effects largely depend on many factors, in particular, student behavioral patterns in games (Martin et al., 2015). Thus, it is important to understand how individual students behave differently in the game and how their different behavioral types relate to learning outcomes in order to provide more personalized learning environments (Vandewaetere et al., 2011).

Our team has developed an online mathematics learning game to help middle-school students' algebraic learning. Our previous work has shown that the game is effective in enhancing students' algebraic understanding, but the efficacy varies depending on students' behavioral patterns in the game (Authors, in review). In this study, we aim to replicate the findings of our previous work with a larger dataset that includes a more diverse sample in terms of instructional level and race/ethnicity. Our study addresses the following research questions: 1. How many different clusters emerge based on students' behavioral patterns in the game? 2. How do the students' behavioral patterns vary across the clusters?

Method

The game was developed based on perceptual learning theories to help students' algebraic learning. The goal of the game is to transform the expression into the mathematically equivalent, but perceptually different, target goal using various gesture actions. The system allows students to dynamically manipulate and transform numbers and mathematical symbols on the screen so that students can identify algebraic structures easily and think flexibly. Our sample consisted of 760 (55% male, 45% female) 7th-grade students from ten middle schools located in the Southern U.S. The students played the game individually for nine 30-minutes intervention sessions. For cluster analysis, we included four variables of in-game behaviors that correlated to learning outcomes identified in our earlier work (Authors, in review). These variables were the total number of problems completed, the average number of resets, the proportion of reattempts (i.e., revisiting the completed problem again), and the average pause time (i.e., the amount of time spent before making the first action).

Results

The elbow method was used to determine the optimal number of clusters, suggesting four clusters. The k-means cluster algorithm divided the entire sample into four clusters of students based on their behavioral patterns: Cluster 1 (n = 188, 24.7%), Cluster 2 (n = 186, 24.5%), Cluster 3 (n = 76, 10%), and Cluster 4 (n = 310, 40.8%). Figure 2 shows the box plots of four variables of student behavioral patterns by cluster.

The clusters were labeled based on the most dominant characteristics that appeared for each cluster: Slow Progressors (Cluster 1) included students who completed the least number of problems, with the lowest values for the proportion of reattempts and the average number of resets. Fast Progressors (Cluster 2) included students who completed the largest number of problems but the low values of the average number of resets, the proportion of reattempts, and average pause time. These students sped through the game, completing as many problems as possible, rather than taking time to think about their first step. Slow-Steady Progressors (Cluster 3) included students who had the highest proportion of reattempts and the average number of resets. This cluster seemed to carefully progress through the problems, resetting and retrying problems along the way. Intermediate Progressors (Cluster 4) included students who showed middle values for all variables.

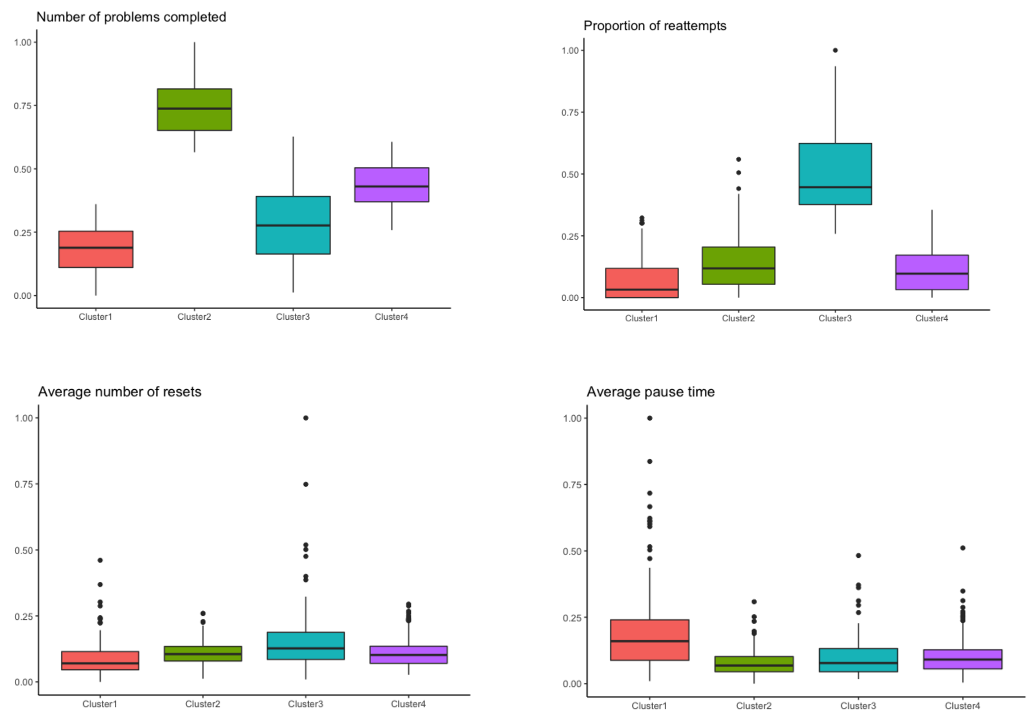

Figure 2

Cluster results depicting the distribution of variables of behavioral patterns for four clusters (Note: Red: Cluster 1- Slow Progressors. Green: Cluster 2- Fast Progressors. Turquoise: Cluster 3- Slow-Steady Progressors. Purple: Cluster 4- Intermediate Progressors)

Discussion

This preliminary study examined whether distinct student profiles emerged based on their behavioral patterns in an online algebraic learning game. The results of the k-means clustering analysis identified four distinct groups of students based on their in-game behaviors, showing that there was a large variation in their behavioral patterns for engaging with the game. These student profiles identified from the cluster analysis can serve as a basis for building an adaptive learning environment (Vandewaetere et al., 2011). Further research should be done to investigate how these different behavioral patterns correlate to mathematics performance.

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