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Exploring the Relationships between Students' Engagement and Academic Performance in the Digital Textbook System

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Abstract: In this paper, we analyzed the relationships between students' engagement and academic performance in the digital textbook system. To measure students' engagement, we first extracted features from the students' digital textbook reading logs (click-streams) that represent their engagement with the contents. Then, we used percentile rank transformation to create normalized engagement scores and an overall engagement score. In the analysis, we first investigated the correlation between engagement scores' and the students' final scores. Second, we modeled students' transition patterns from the engagement to academic performance by using Markov Chains. Third, we analyzed engagement patterns of the students with different academic performance levels. Our results showed that there is a positive moderate correlation between students' academic performance and their engagement with digital textbooks. Our results also revealed that a single engagement score can be used to measure students' engagement with the system, which is easy to understand by non-expert users. We also introduced our dashboard interventions that are developed based on this engagement score.

Keywords: Engagement, academic performance, digital textbook, reading pattern, engagement pattern, markov model

1. Introduction

Students' engagement with the learning environment is closely related to learning outcomes (Hu & Li, 2017; Lu, Huang, Huang, & Yang, 2017). Therefore, regular monitoring of students' engagement is crucial for timely interventions, particularly for at-risk students. However, measuring various dimensions of students' engagement from their learning traces is still challenging task for researchers. In particular, creating engagement scores which are easy to interpret by students and instructors.

In this paper, we used students' digital textbook reading data to create metrics for measuring their engagement with the digital textbook system. We investigated relationships between students' academic performance and their engagement score. We also compared weekly engagement patterns of students with different academic performance levels. Finally, we introduced the dashboard interventions that we developed based on this engagement score for assisting at-risk students.

1.1 Digital Textbook Data Analysis

Digital textbook systems made possible to collect data related to student reading and note-taking behavior that are not possible to capture with paper books (Abaci, Morrone, & Dennis, February 22, 2015). This data previously used to predict students' learning outcomes (Akçapınar, Hasnine, Majumdar, Flanagan, & Ogata, 2019; Hasnine et al., 2018), to analyze students' weekly reading patterns (Akçapınar, Majumdar, Flanagan, & Ogata, 2018), and for the visualization purposes. Junco and Clem (2015) also found that digital textbooks-based interaction data is a stronger predictor of students' learning outcome. Their study also highlighted that students, those who spent longer time in reading textbooks earned higher grades in the course over to those who spent less time.

1.2 Engagement and Learning

Fredricks, Blumenfeld, and Paris (2004) have proposed that engagement is studied as a multifaceted construct, with behavioral, affective, and cognitive dimensions. *Behavioral engagement* refers to students' involvement in academic activities. *Emotional engagement* includes positive and negative reactions to teachers, classmates, academics, and school. *Cognitive engagement* refers to the effort required to master difficult skills and understand complex ideas.

Behavioral engagement is considered crucial for achieving positive academic outcomes and preventing dropping out (Fredricks et al., 2004). In this study, we focused on students' behavioral and cognitive engagement with the digital textbook system and we extracted features from the interaction logs related to students' reading behaviors. In other words, we used learning logs as a proxy to measure students' engagement with the system and analyzed relationships between their engagement and academic performance.

2. Method

2.1 Data Collection

In this study, data was collected from a digital textbook system called BookRoll. The BookRoll allows students to read digital contents. It has a feature like red or yellow markers to highlight some parts of the text. Students' can add memos to remember important points or bookmark pages to access them easily while they are reviewing the content. We analyzed more than 65,000 click-stream data that are collected from 72 students registered in an Elementary Informatics Course at a university. The course was offered to first-year undergraduate university students. Students used the BookRoll system to access course materials that were uploaded by the instructor once a week. Students were given 13 contents in different weeks of the course and their anonymized interactions (e.g. next, previous, jump, highlight, adding memo, etc.) were recorded by the system. Students' academic performance was evaluated based on eight quizzes across the semester and one final exam.

2.2 Preprocessing of Data

At the beginning of data preprocessing, features from the click-stream data were extracted. Extracted features were used to measure students' engagement. In feature selection, students' behavioral (e.g. total number of events, number of times open the system, etc.) and cognitive (e.g. red/yellow marker usage counts, memo counts, etc.) engagement with the system were taken into consideration. A brief description of all features is given in Table 2.

Table 2

Description of Features

Features	**Description**
Total event	Total number of events
Time	Total time spent on the BookRoll system in minutes
Unique Day	Number of different days that student use the system
Long event	Number of events longer than 3 seconds
Short event	Number of events less than or equal to 3 seconds
Next	Number of Next events
Previous	Number of Previous events
Open	Number of times that student open the system
Jump	Number of Jump events
Red marker	Number of red markers added by the student
Yellow marker	Number of yellow markers added by the student
Memo	Number of memos added by the student
Score	Final scores of the students

After extracting features, percentile rank transformation was applied to the raw data to create generalized engagement metrics. Percentile rank transformation was chosen as a method to create generalized engagement score because it can be used in various educational purposes such as comparing students' engagement in different courses, identifying at-risk students, monitoring their engagement, etc. Formula 1 was used to calculate percentile rank (PR) scores where f_b is the number of scores which are less than the score value of the percentile rank, f_w is the number of scores which have the same value as the score value of the percentile rank, and N is the number of scores. The percentile rank measures range from 0 to 1. Single engagement score was also calculated by taking the average of all engagement metrics and compared its performance against the other metrics.

$$PR = \frac{f_b + {}^{1}/_{2}\ f_w}{N} \tag{1}$$

2.3 *Data Analysis*

To analyze the relationship between engagement scores and students' academic performance, correlation analysis was performed. Here, the Pearson correlation coefficient between engagement metrics and students' final scores was calculated. In addition, to analyze the relationship between students' engagement score and their academic performance, Markov Chain analysis was performed. We also visually analyzed long term engagement patterns of students with different level of academic performance.

3. Results and Discussion

3.1 *Correlation Analysis*

Results of the correlation analysis between raw scores, transformed scores, and students' final scores is shown in Fig. 1. In raw data, *total event, total time, unique day, long event, short event, next, previous,* and *open* metrics' correlations with the final score are significant ($p < 0.01$). With the transformed data metrics' expect *jump and red marker* correlation with the final score are significant ($p < 0.01$). As shown the Fig. 1, almost all metrics' correlation increased after the transformation.

(a) Before the transformation

(b) After the transformation

Figure 1. Engagement features correlation with the students' final scores before and after transformation.

In terms of single engagement score that was derived from the other metrics, a moderate (r = 0.59, p = 0.01) positive correlation between the engagement score and final score variable was noted. In Fig.2, with a scatterplot, we summarized the results.

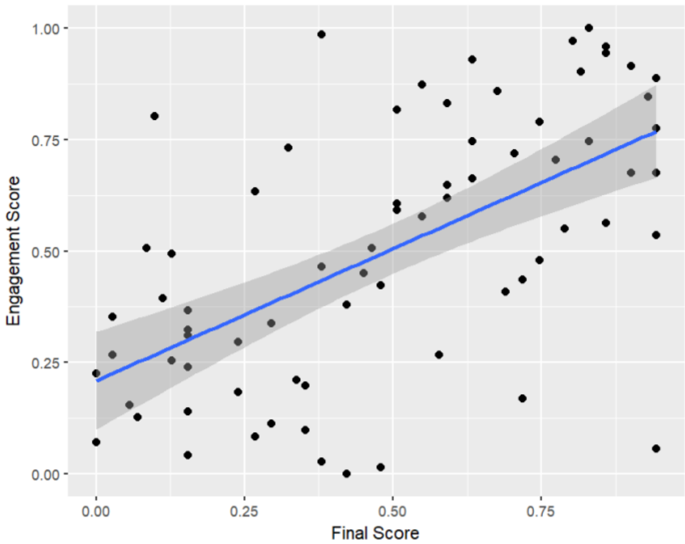

Figure 2. Correlation between Engagement Score and Final Score.

3.2 *Markov Chain Analysis*

We divided students into two groups based on their academic performance and single engagement score. Then, analyzed transitions between the level of engagement and level of academic performance (Fig. 3). We grouped them as *Low Performers* (final score <= .50, n = 36), *Low Engagement* (engagement score <= .50, n = 36), *High Performers* (final score > .50, n = 36), and *High Engagement* (engagement score <= .50, n = 36). According to Fig. 3, low-engaged student's probability to get a low score is 0.83 (83%) while probability to get a high score is 0.17 (17%). A similar pattern is observed for high-engaged students. The probability of getting a high score is 0.83 (83%) while probability to get a low score is 0.17 (17%). In other words, students are most likely to get scores related to their level of engagement.

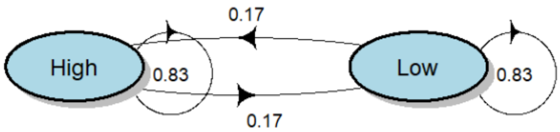

Figure 3. Transitions between engagement level and academic performance.

3.3 *Engagement Pattern Analysis*

To understand students' engagement patterns across the semester, we chose four students with different academic performance levels (two high performers, two low performers) and visually compared their engagement patterns. Visualization of the weekly engagement patterns are shown in Fig. 4. Top two graphs show the weekly engagement of the high performer students while the last two show the low performer students' engagement. In each graph, the grey line shows the class average. High performer students' engagement is higher than the class average across the semester, and their average engagement is higher than 80% of the class. Low performer students, however, have much less activity then class average. For example, students in (c) were only active at the beginning and at the end of the semester. Students in (d) were only active for the first three weeks of the class and there is no activity after that. These graphs can be used to identify at-risk students at the beginning of the semester; however, further investigation is required to see how common these patterns are among other low and high performers.

Figure 4. Students' weekly engagement patterns across the semester.

4. Learning Analytics Dashboard

By using the single engagement score, we developed three interventions for students and implemented them in our learning analytics dashboard (Fig. 5). These interventions are in the form of e-mail feedback, engagement score graph, and weekly engagement graph.

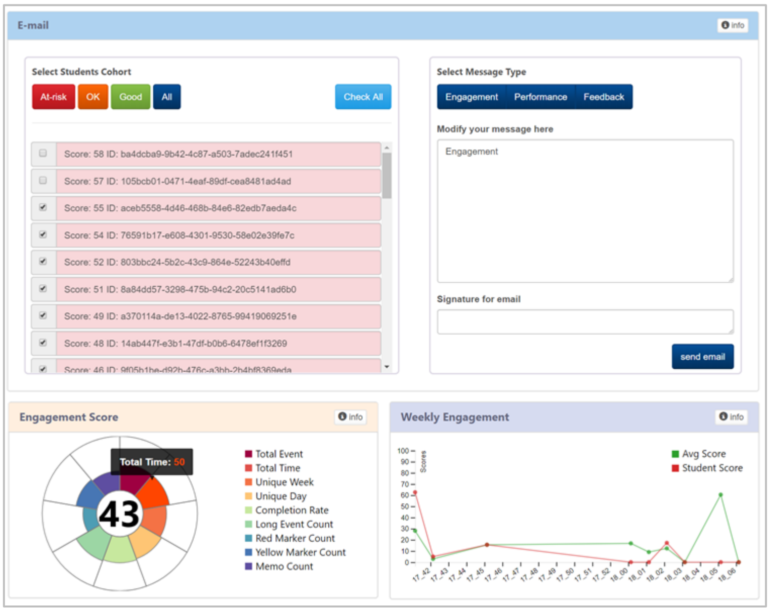

Figure 5. Learning analytics dashboard.

In the e-mail feedback module, instructors can filter and select students based on their engagement scores (e.g. at-risk, ok, good, all) and can send them an e-mail either using predefined templates or adding their own message. Engagement score graph shows students' engagement scores in each metrics (e.g. total time, total event, etc.) and his/her average engagement with the selected content. Weekly engagement graph shows students' average weekly engagement scores and class average. The e-mail feedback module is developed only for instructors, students can only see engagement score graph and weekly engagement graph.

5. Conclusions

In this study, we aimed at analyzing relationships between students' academic performance and their engagement in the digital textbook reader system. We extracted features from students' reading logs to measure their behavioral and cognitive engagement with digital textbooks. Our results revealed that transformed scores' correlation with the final scores is higher than raw engagement scores. Moreover, a single engagement score derived from engagement metrics performed similarly in terms of relationships with the students' performance. A newly generated metric is also easy to understand by non-expert users.

Literature suggests that timely interventions planned based on engagement effective to increase learning outcomes (Arnold & Pistilli, 2012; Tanes, Arnold, King, & Remnet, 2011). Therefore, instructors can use our proposed single engagement score to monitor their students' engagement during the semester and can give them feedback accordingly. Markov model showed that students are most likely to exhibit academic performance close to their engagement level. This model can be used to predict students' academic performance based on their level of engagement. In the future, we will test the effects of these models along with developed dashboard interventions on students' engagement and academic performance. Our future studies will investigate more on various dimensions of engagement (such as emotional engagement) that can be considered while modeling learners' engagement.

Acknowledgements

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