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A Study of Student Behavior in Classroom Response Systems

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Abstract: The Classroom Response System (CRS) is a useful tool for enhancing interactivity between teachers and students in the classroom. Through its use of smart devices and PCs, CRS is expected to effective at aiding both classroom interaction and learning. However, these devices can be used for more than CRS; they may also serve as entertainment tools. This study investigates the behavior of students who use CRS on such devices. Specifically, it analyzes log data of student behavior, focusing on student responses and their behavior of switching application programs on CRS. The results of analysis show a trend that students who immediately switch applications after answering a question on CRS have a low correct answer rate.

Keywords: Classroom Response System, Clicker, Smart Devices, Student Behavior

1. Introduction

The Classroom Response System (CRS) is a well-known tool for enhancing interactivity between teachers and students in the classroom. In recent years, many studies have used Clicker. Because Clicker makes the communication between students and teachers more interactive in the classroom, its use in pedagogy has spread recently in various fields of education. (Crews, T. B. et al., 2011; Raes, A., et al., 2013; Kulesza A. E. et al., 2014; Han, J. H. et al., 2013). However, Clicker cannot improve the interaction between a teacher and an individual student due to its system architecture, as described below.

- Clicker has only one-way messaging from a student terminal to a teacher PC on the system.
- Generally, students' wireless terminals are composed only of buttons.
  - ✓ The message is only the information that the student has clicked the button. The student cannot send a teacher a message or question.
  - ✓ The teacher cannot provide teaching materials that include text, images, sounds, and video, to an individual student. In addition, teacher cannot send a message to an individual student.

To resolve these problems, researchers have developed CRSs that use various devices such as cell phones, smart phones, tablets, and PCs, as the student terminals. For example, Robbins, S. (2011) used ClassQue, a PC application, in courses on MATLAB programming, Java programming, computer organization, and operating systems. ClassQue has several unique functions such as seating charts, review messages, and comment sharing in a group. Especially in recent years, the number of studies using smart devices (e.g., cell phones, smart phones, tablets) has been increasing. Andergassen, M. et al. (2012, 2013) developed browser-based mobile clickers called Learn@WU. Nielsen et al. (2012) presented their project that is developing a Student Response System (SRS) co-funded by the European Commission. Dunn, P. K. et al. (2012) implemented a low-cost, mobile-phone-based CRS named VotApedia. They evaluated the system by collecting data specifically related to interacting with the user interface, the in-class delivery, and instructor perceptions of student engagement. The author of this paper is also developing a web-based CRS that has the functions for real-time interactions using HTML 5 and WebSocket that are new technologies for the Web (Mizutani, K., 2013).

On the other hand, smart devices can run not only CRS but other software applications as well, and thus, they can serve various functions, such as providing entertainment. The GSM Association's

(2013) international survey on children's use of mobile phones revealed that most children access the internet and download applications, and entertainment is the most popular among the child users.

For this reason, the devices used in classrooms often have limitations on which software programs or device functions can be accessed. Yet because smart devices offer useful software for learning, it is not an easy task to decide the policies of such limitations. Not only the limitations of the devices but the functions of CRS and its practical implementation must be considered to improve student understanding.

In this paper, as the first step toward finding behavior patterns that represent the relations between students' understanding and their using events on CRS, investigates the relations between the events of student responses and user behavior events, namely, window switching of applications on PCs. It is thought that the correct answer rates of students who lack sufficient understanding will be lower than those of students who understand well. One hypothesis is that the number of times these students switch windows will be relatively high because they will switch to a web browser to search for answers to the questions. Also, if the students are not interested in listening to the teacher's lecture, they might answer the questions randomly or without putting much thought into their choices, then switch quickly to entertainment contents on their smart device.

If there is indeed a relationship between students' responses and their behavior of window switching, the findings may be used to identify students who are in need of learning support. Therefore, this paper seeks to identify these relationships by using the originally developed CRS.

2. Methods

2.1 Developing a Real-time Classroom Response System, "Response Analyst"

For the purpose of this study, an original CRS called "Response Analyst" was developed because the existing systems, including CRS products, have the following problems.

- The interaction on CRS is not in real-time.
  - ✓ Every student behavior on the CRS has to be in real-time and logged with precision. Otherwise, the data on the students' behavior will be inaccurate.
- The existing systems lack functions for providing teaching materials to each student.
  - ✓ Student terminals often consist of only buttons; they cannot display the teaching materials.
  - ✓ Even if the student terminal has a screen, it often shows only text, not multi-media content.
- The existing systems cannot monitor the events of switching windows on a PC.
  - ✓ This is an important function for this study. Student behavior events such as receiving teaching material, starting thinking, answering, switching windows, etc. have to be recorded.

To implement these functions, Response Analyst has been developed as an application for PCs instead of smart devices. It might have been developed as a software program for smart devices such as smart phones or tablets, but it is difficult to monitor the events of student behaviors, especially switching windows (or applications), on the security models of the smart devices. Therefore, this study hypothesizes that student behavior does not differ between PCs and smart devices.

Response Analyst has a Server-Client model architecture. Its server program communicates to the teachers' client program and the students' client program. To realize real-time processing, the communication has been defined as original protocols.

Figure 1 shows examples of the user interfaces of the teachers' client program (A) and students' client program (B). When students click the answer button, their response is immediately reported to the teachers' program. The teacher can check each student's answers or view a graph that summarizes all the students' answers on the external screen, such as a projector (Figure 1, A-2).

2.2 The basic sequence of Response Analyst and the design for logging student behaviors.

Figure 2 shows the basic sequence of each of the programs of Response Analyst. The messages between Teachers' Program and Students' Program are communicated keeping TCP/IP connections for real-time processing, because establishing the connections of each messaging worsens the system's real-time processing. However, for precisely logging the events of student behaviors, the delay of the TCP/IP communications should be considered. Also, the time stamp of the events might differ by device because a device's clock may not be correct.

This study focuses on student behaviors on the student devices. Of particular importance is the behavior of the students between receiving a question and answering it on their student devices. Therefore, Response Analyst logs the events on both the server and each student device. As shown in Figure 2, the client program logs section data, which are a set of the events between the user receiving a question and answering it. When the student program is closed, the section data are sent to the server in a lump.

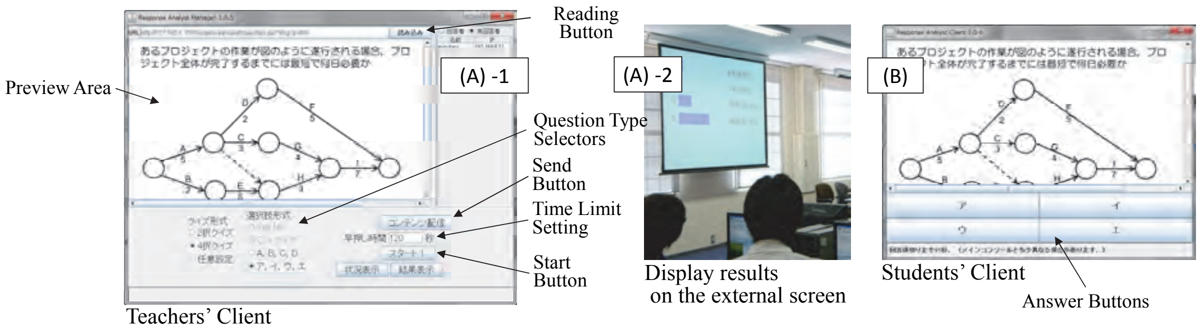

Figure 1. Example screenshots of Response Analyst.

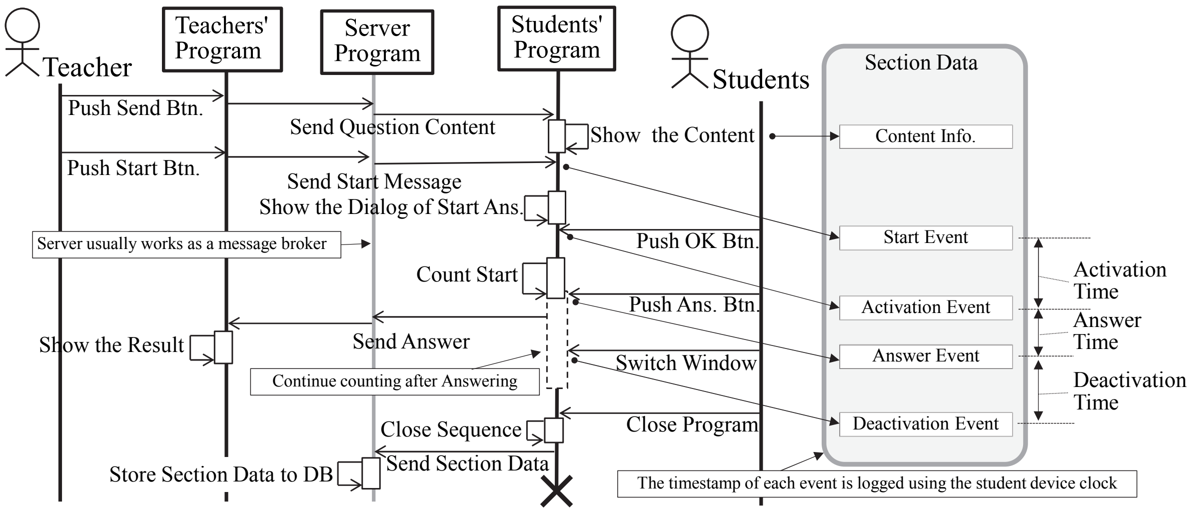

Figure 2. The basic sequence of Response Analyst and the abstract of event logging.

2.3 Log analysis

The section data include the timestamp that is based on incorrect clock on the student device. To reduce the inaccuracy of the timestamp, the section data are analyzed using the time that is the span of one event from the event of receiving the message to start answering. Specifically, as the preprocessing of the log analysis, the time span data is calculated as follows and as shown in Figure 2.

- Answer Time: The time between the start of answering and the user's click on the answer button
- Activation Time: The time between the start of answering and the activation of the window of the student client
- Deactivation Time: The time between user's click on the answer button and the deactivation of the window of the student client

Moreover, because the limit time for each question is different, the time span data are normalized by using the limit time of each question.

To determine the relations between these events, the time span data are analyzed as follows.

- The difference of the answer events between correct and incorrect answers
  - ✓ First, to roughly gauge the trend of the difference in correct and incorrect answers, the mean values of the Activation Time and Deactivation Time are compared by a t-test.
- Making clusters of the students' behavior
  - ✓ To reveal the differences in student behavior, after the average values of Correct Rate, Answer Time, Activation Time, and Deactivation Time are calculated for each student, K-means Clustering is applied to the average values.

3. Results

3.1 Practical use of Response Analyst

Response Analyst was used in a class designed for students to learn the basis of knowledge of information technology. The course syllabus includes solving the past versions of the Information Technology Passport Examination (IT Passport Exam), one of the Information Technology Engineers Examinations in Japan. The IT Passport Exam consists of multiple-choice questions. Examinees select one answer from among four choices in response to each question.

In the class, students were given questions from past issues of the IT Passport Exam by Response Analyst. The teacher explained the issues to the students while referring to the results of the answers in Response Analyst. When sending questions, the teacher set the limit time for a question based on their own judgment. A total of 1,863 section data were logged in the class. This included the logs of 53 students who attended the class, 50 questions from past versions of the IT Passport Exam, and activation/deactivation events.

3.2 Analysis Results

3.2.1 The difference of the answer events between correct and incorrect answers

Table 1 shows the results of a t-test comparing the correct and incorrect answers, answer time, activation time, and deactivation time. These results exclude the section data in which the deactivate time is over 1, because this shows that the student changed the window after the time limit was over. Of course, the data received after the limit time are also important. However, because the purpose of this study is to identify behavior patterns in the course of using Response Analyst, the events that fall within the limit time are more important than those occurring after it. The results of the logarithmic transformation of the activation time and deactivation time were used in a t-test, because the distribution of activation time and deactivation time seems normal.

In each of the results, if the value of the f-test is > 0.05, the value of the t-test shows the results of the t-test assuming equal variances (Student's t-test). If the value of the f-test is < 0.05, the value of the t-test shows the results of the t-test assuming unequal variances (Welch's t-test).

3.3 Making clusters of the students' behavior

K-means Clustering that is a cluster analysis method in which the value of K is the number of the clusters. Before the K-means Clustering, the data of the students who had given only a few answers were excluded. The average number of times a student answered is 25.00 times. The maximum and minimum are 51 times and 1 time, respectively. Because the standard deviation is 13.74, the minimum threshold is defined as 11.26. Eleven students' data that are less than the threshold were excluded from the target of K-means Clustering.

In this study, the optimal K value was calculated using the reconstruction error that is the sum of the mean squared error between all data in the cluster and the centroid of the cluster, in each K value (Alpaydin, E. 2004). As the result of the reconstruction error, it is assumed the optimal value of K is 4 or 5. Then, Table 2 shows the detailed results for each cluster with K values 4 and 5. The clusters are ordered by their average correct answer rate.

Table 1: Results of a t-test about the difference between correct and incorrect answers.

		Mean	Median	SD	f-Test (*P*, two-tail)	t-Test (*P*, two-tail)
Answering Time	Correct	0.423	0.390	0.245	0.385	0.364
	Incorrect	0.403	0.375	0.249		
Activation Time	Correct	0.117	0.064	0.132	0.027*	0.407*
	Incorrect	0.133	0.076	0.157		
Deactivation time	Correct	0.133	0.057	0.163	0.769*	0.006*
	Incorrect	0.106	0.046	0.147		

*The results using the values by logarithmic transformation.

Table 2: The clustering results and mean values for each student.

k	Cluster No.	Count	Average Correct Rate	Average Time		
				Answer	Activation	Deactivation
4	1	12	0.412	0.519	0.148	0.580
	2	11	0.419	0.442	0.167	0.290
	3	6	0.523	0.572	0.127	0.930
	4	13	0.716	0.507	0.115	0.757
5	1	16	0.364	0.459	0.149	0.399
	2	5	0.528	0.562	0.116	0.964
	3	11	0.559	0.536	0.130	0.725
	4	6	0.682	0.498	0.158	0.470
	5	4	0.823	0.515	0.133	0.890

4. Consideration

Table 1 shows the results of the t-test for the difference of the average of correct and incorrect answers. In regard to answering time, the mean value between correct and incorrect answers is not significantly different at the significance level of 5% because the t-test result is 0.364. Similarly, for activation time, there is no significant difference because the t-test result is 0.407. On other hand, the t-test result of deactivation time is 0.006, showing that the mean values of deactivation time are significantly difference between correct answers and incorrect answers. The mean value of the incorrect answer of deactivation time is 0.106, which is smaller than the mean value of the correct answer. The results point to a trend in which the answer is incorrect when the behavior of switching program windows after answering occurs earlier.

Similarly, a trend is also revealed by the results of the K-means Clustering, as shown in Table 2. A comparison of the smallest and largest clusters in terms of the average of correct rate in each k value shows that the deactivation time of the smallest cluster is shorter than that of the largest cluster. For example, when k is 5, the deactivation time of the smallest cluster in the correct rate (No. 1) is 0.399, and for the largest cluster (No. 5), it is 0.890. To validate the difference of these two clusters, a t-test about the deactivation time data was tried. The result was $P < 0.000$, it showed a significant difference at the significance level of 5%.

These results point to the following:

- Because the mean values of deactivation time are significantly different between correct and incorrect answers, when the deactivation time of answering behavior is smaller, the answer might be incorrect.
- The students with low correct answer rates immediately switch program windows after answering questions on CRS, in contrast to the students with high correct answer rates. When a student's deactivation time is short, his or her correct answer rate might be low.
- Predicting incorrect answers based on answer time and activation time is difficult. This study identified the significant differences between these times and students' answer behaviors.
- It may be possible to use deactivation time as a means of identifying students who need help from the teacher. To realize this, CRS on smart devices should have a function for catching the event of switching applications. However, the necessity of this function has not generally been discussed so far.

This finding presents the possibility to realize a learning support function that automatically detects the state of a student. For example, it is able to realize a function that detects a student who is low correct rate and switch quickly to other window after answering on CRS, calls the student attention and notices the detection to a teacher. The author of this paper also plan to implement the automatic learning support function to the original CRS of oneself and to evaluate the instructional effects.

5. Conclusions

The purpose of this study is to investigate the behavior of students who use CRS on smart devices. This paper describes the results of an analysis of log data on student behavior, focusing on student responses and the behavior of switching applications on CRS.

An original CRS "Response Analyst" was used in a class aimed at teaching the basis of knowledge of information technology. The log data were analyzed using the statistical methods of t-test and K-means Clustering. The results revealed a trend that the correct answer rate of students who immediately changed applications after answering questions on CRS was low. However, this trend was not found out from the time of answering the questions to the time of activation events, that is, switching application windows. The results of the K-means Clustering showed a relationship between students who have a low correct answer rate and short deactivation time after answering. This finding presents the possibility that CRS can identify students who may need help from the teacher.

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