Online Change Detection for Monitoring Individual Student Behavior via Clickstream Data on E-book System

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ABSTRACT

We propose a new change detection method using clickstream data collected through an e-Book system. Most of the prior work has focused on the batch processing of clickstream data. In contrast, the proposed method is designed for online processing, with the model parameters for change detection updated sequentially based on observations of new click events. More specifically, our method generates a model for an individual student and performs minute-by-minute change detection based on click events during a classroom lecture. We collected clickstream data from four face-to-face lectures, and conducted experiments to demonstrate how the proposed method discovered change points and how such change points correlated with the students' performances.

CCS CONCEPTS

• **Applied computing → Interactive learning environments**; *Computer-assisted instruction*; • **Computer systems organization** → Real-time system architecture;

KEYWORDS

Learning analytics, Change detection, Clickstream, Online processing

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1 INTRODUCTION

Understanding the behaviors of students is a crucial issue in the learning analytics (LA) and educational data mining (EDM) research domain. Clickstream data represent one of the most valuable sources of information for analyzing the activities of students. One of the major prior studies focused on clickstream data in the context of massive open online courses (MOOCs). For example, clickstream data collected in MOOCs were utilized to predict the performance[1], completion[2], and clustering behaviors[8], as well as to investigate the learning path[3]. Clickstream data collected from a learning management system and/or an e-Book system are also useful for analyzing the engagement of students during courses. A recent study found that student engagement was positively related to the course outcome, and a statistical change detection technique was applied to clickstream data to discover the change points during courses[5]. They analyzed when students changed their previewing and reviewing behaviors, and how these changes were related to performance.

In terms of analytics for the type of clickstream data, the previously mentioned studies could be classified as the batch type or offline type. In other words, clickstream data were first stored, and then the analytics were performed in a batch process. Such batch processing is a reasonable method to understand students' behaviors after finishing courses. On the other hand, real-time or online processing is another important method for grasping students' activities during lectures. For example, the clickstream data from programming courses were analyzed in real time to grasp classroom situations and discover students having difficulties[4]. The e-Book-generated clickstream data were sequentially analyzed to determine whether students were following the teacher's explanation[6]. Real-time analytics have great potential to immediately determine the behaviors of students and inform teachers about students having difficulties. Teachers could change their lecture plan if real-time feedback becomes available.

In this paper, we will discuss an online change detection method using clickstream data to grasp student situations during lectures. The final goal of our study is to realize a system of real-time analytics for a learning management system. This paper focuses on the change detection methodology for sequential processing rather

Table 1: Correlation between quiz scores and number of events (clicks)

	class	class 2	class 3	class 4
corr. coef.	0.049	-0.036	0.008	0.035

than batch processing. The prior method proposed in [5] is the most related to our work, but it was based on the large-scale batch processing of data collected over a 10-week period. The clickstream data were aggregated into a daily time scale, and change detection was performed over 10 weeks. In contrast, our change detection is performed on a minute-by-minute time scale. Moreover, we assume that this method will be used for an online system. Thus, our proposed method does not use any future data to estimate the model parameters for change detection. The parameters can be estimated and updated sequentially based on observations of new click events. observations.

According to the report in [5], students in the decreased group (i.e., those where the number of click events decreased after the detected change points) passed the course with a lower probability than those in the increased group. If this rule is applicable to a classroom lecture, the simplest way is to detect the students with fewer clicks to discover the students at risk. Again, note that [5] applied change detection over a 10-week (long term) period. Meanwhile, our study focused on a lecture period, which is usually 90 min. Figure 1 shows a scatter plot of the quiz scores and number of click events from four classes. The data descriptions are provided in Table 2, and a detailed explanation of the dataset is given later in this paper. Here, we can see that there is no correlation between them (see Table 1). Some students generated many click events but received lower scores, and vice versa. Therefore, a sophisticated change detection methodology is required to discover the students having difficulty during a classroom lecture. More specifically, a methodology to model the normal states of individual students is necessary, and change detection should be performed by investigating whether or not the current situation of an individual student is within the model assumption. To realize a new change detection method, we propose a combination of Poisson model-based anormal scoring and page difference-based anormal scoring, to classify individual students into the normal or anormal state.

The contributions of this paper can be summarized as follows.

(1) Change detection was sequentially applied to the clickstream data acquired via an e-Book system sequentially.
(2) Change detection was performed by a Poisson model whose parameters were adaptively updated based on observations.
(3) Change detection was applied during four classroom lectures, with approximately 136,000 click events generated by a total of 743 students.
(4) Change detection could discover students whose quiz scores were lower than the average.

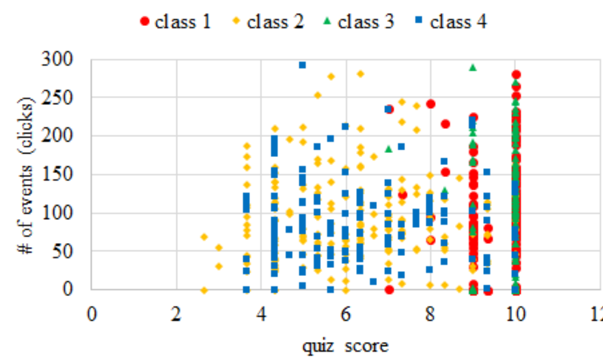

Figure 1: Scatter plot of quiz scores and number of events (clicks) in each class.

2 ONLINE CHANGE DETECTION FROM CLICKSTREAM DATA

2.1 Poisson Model

We modeled the number of click events using the Poisson model. Our proposed method assumes that the model parameters are sequentially updated based on observations. Therefore, we introduce the notation t to indicate discrete time-points. In addition, Poisson models are created for individual students, where i indicates a student. The Poisson model can be represented by

$$P(k_{i,t}) = \frac{\lambda_{i,t}^{k_{i,t}} \exp^{-\lambda_{i,t}}}{k_{i,t}!}, \tag{1}$$

where k is the number of events. In our implementation, the value of k is approximately calculated using the click events observed in the past T period.

$$k_{i,t} = \frac{\sum_{\tau=t-T+1}^{t} x_{i,\tau}}{T}, \tag{2}$$

where $x_{i,t}$ is the number of click events generated by student i at time t.

Strictly speaking, the parameter estimation for the Poisson model should be performed using a sufficient number of observations. However, in order to use the model online, we have to somehow estimate and update the parameters based on only a few observations. Inspired by [7], in which Gaussian mixture model parameters were sequentially updated, the parameter $\lambda_{i,t}$ can be updated as follows.

$$\lambda_{i,t+1} = \rho x_{i,t} + (1-\rho)\lambda_{i,t} \tag{3}$$

Here, ρ is a learning ratio that reflects the latest observation in the current model.

$P(k_{i,t})$ provides the probability of the observation of $k_{i,t}$ click events. The lower probability should be considered as the anormal state of the clickstream. We represent the anormal score based on the Poisson model using the following formula.

$$E_{i,t} = 1 - P(k_{i,t}) \tag{4}$$

Table 2: Description of clickstream data for each class

	class	class 2	class 3	class 4
# of students	205	202	168	168
ave. of quiz score	9.68	6.23	9.80	6.35
sd. of quiz score	0.58	1.81	0.45	1.77
# of events(clicks)	30,820	48,107	18,702	39,029
ave. of events(clicks)	102.6	100.8	81.3	111.9
sd. of events(clicks)	102.7	78.5	87.8	193.4

Table 3: Parameter settings

parameter	range
ρ	$(0.3, 0.5, 0.7)$
$T(min.)$	$(3, 5, 7)$
g	$(0.4, 0.5, 0.6)$
s	$(0, 5, 10, 15, 20)$
α	$(0.5, 1)$
th	$(0.7, 0.9)$
cnt	$(1, \ldots, 20)$

2.2 Page Difference

It is meaningful to compare the pages for a student and the teacher because a large gap indicates a situation where the student is having some difficulty. Let $p_{i,t}$ and $p_{L,t}$ be the page numbers browsed by student i and teacher L. The page difference $d_{i,t}$ is calculated by

$$d_{i,t} = \left|p_{i,t} - p_{L,t}\right|. \quad (5)$$

We apply a sigmoid function to acquire a normalized anormal score, which is calculated by the following formula.

$$D_{i,t} = \frac{1}{1 + \exp(-g(d_{i,t} - s))} \quad (6)$$

where g determines the slope or gain of the sigmoid function, and s is a shift parameter.

2.3 Change Detection

Up to now, we have two kinds of anormal scores. We combine these two anormal scores, $E_{i,t}$ and $D_{i,t}$, into $S_{i,t}$ using a simple blending manner:

$$S_{i,t} = \alpha E_{i,t} + (1 - \alpha) D_{i,t}, \quad (7)$$

where α is a weight coefficient used to adjust the contributions of the two scores.

To determine whether student i at time t is in the "normal" or "anormal" state, we introduce a hard threshold th. Let $A_{i,t}$ be a binary state: 1 for the anormal state, and 0 for the normal state. Then, the determination is performed as follows:

$$A_{i,t} = \begin{cases} 1 & (S_{i,t} \geq th) \\ 0 & (otherwise) \end{cases} \quad (8)$$

We can easily acquire the sum of students detected as being in the "anormal state" at time t by integrating $A_{i,t}$ over students ($\sum_i A_{i,t}$). On the other hand, if we integrate $A_{i,t}$ over time, i.e., $\sum_t A_{i,t}$, we can find how many times student i was detected as being in the "anormal state" during the lecture period.

3 DATASET

We collected clickstream datasets from four 90 min classes conducted in a university (for a double blind review, we omit the specific name when submitting the paper). The click events were recorded via the e-Book system. All of the students had personal laptops and used them to access the e-Book system during the lecture. The teacher also used the e-Book system and explained the contents of the lecture material during a 90 min lecture. The students opened the e-Book and followed the explanation while creating bookmarks, highlighting texts, and memos if necessary. The click events on the e-Book system were recorded and logged with the student ID, material ID, type of operation, and timestamp.

At the end of each class, the students answered quiz questions in the e-Learning system. We used their quiz scores to evaluate the accuracy of the proposed change detection. Table 2 lists the detailed class information: the number of students, average and standard deviations of quiz scores, number of events on the e-Book system, and their average and standard deviations.

4 EXPERIMENTAL RESULTS

4.1 Quantitative Evaluation

We first investigated the effectiveness of the proposed change detection methodology using a quantitative evaluation. Ideally, we would have liked to evaluate $A_{i,t}$ independently of whether or not the judgment (i.e., anormal or normal) was correct. However, it was very difficult to formulate reasonable criteria for the evaluation. Instead, we focused on student outcomes in terms of the quiz scores for each class. We assumed that a student who was frequently detected as being in an "anormal state" would receive lower quiz scores than other students. In fact, $\sum_t A_{i,t}$ indicated the number of anormal detections of student i over time. Thus, we introduced a predefined threshold cnt to determine whether student i belonged to the "anormal" group. More specifically, we let N_a be the number of students belonging to the anormal group, and Q_a be the average quiz score of N_a students. If Q_a was lower than the average quiz score of all the students, we determined that the change detection worked well.

The change detection results, i.e., how many students belonged to the anormal group, were affected by the parameter settings of the proposed method. Therefore, we varied the parameters within the ranges empirically, and found that the proposed method generally worked well (i.e., it was insensitive to specific parameters). Table 3 gives a summary of the parameter settings. In the following, we present the case where $\alpha = 0.5$ and $\alpha = 1$ for "ours" and "ours w/o page_diff," respectively. In total, there were 5,400 parameter combinations for each case. We investigated the ratio of successful change detection cases, where Q_a was lower than the average quiz score of all the students. We performed random student selections and calculated their average quiz score. For the comparison baseline, the random selection was repeated 1 million times and we calculated the ratio of the average score of the selected students against the average of all the students. If the ratio of the proposed method was higher than that for the random selection, the proposed method could successfully detect anormal students.

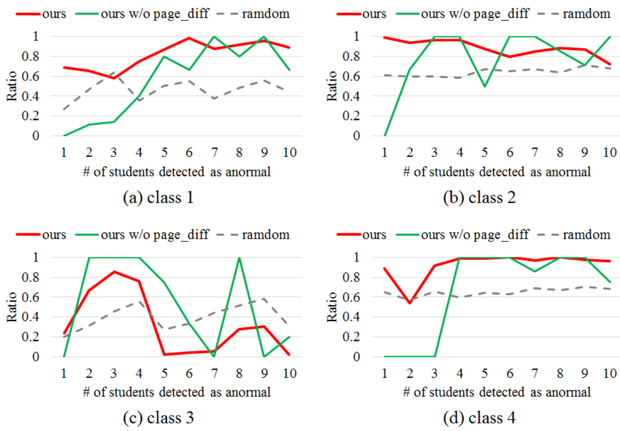

Figure 2: Ratios for successful change detection cases of N_a, where Q_a was lower than the average quiz score of all the students. (ours: results when $\alpha = 0.5$, ours w/o page_diff: results when $\alpha = 1$, random: results of random selection after 1 million times).

Figure 2 shows the ratio of successful selections. The horizontal axis indicates the number of students belonging to the anormal group, and the vertical axis is the ratio (where higher is better). The characteristics of class 1 were a high average quiz score and low standard deviation compared with class 2 and class 4 (see Table 2). Even though the distribution of the quiz scores was narrow, the proposed method ("ours") could successfully detect anormal students as the members of the anormal group increased. When we ignored the page difference term ($\alpha = 1$, indicated by "ours w/o page_diff"), the ratio became lower than "ours." This result showed that the page difference was useful information to realize a correct determination. The proposed method worked well when the average quiz score was lower and the scores were widely distributed such as with classes 2 and 4. The result for class 3 was quite different from those of the other classes. The characteristics of class 3 were very high quiz scores and a narrow distribution. Furthermore, the number of click events was less than for the other classes. We theorize that the lecture contents were easy for the students in class 3. In such a situation, the proposed change detection did not work well because the anormal situation was inherently rare. Overall, the proposed method could successfully detect (select) anormal students and outperformed the random selection baseline. Moreover, the proposed method could provide good performance with a wide range of parameter settings.

4.2 Change Detection over Time

Next, we fixed the parameter settings as those for one of the successful cases based on the previously mentioned experimental results, and investigated how the change detection occurred over time. Figure 3 depicts the change detection result for class 4. The horizontal axis and vertical axis represent the time and students, respectively. The students are arranged in decreasing order based on their quiz scores. We set the change detection period at $t \in [11, 54]$ because

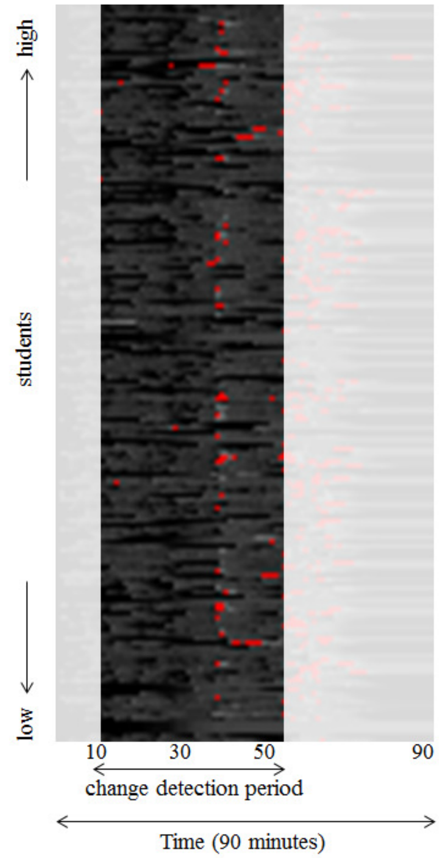

Figure 3: Anormal score of students over time, with brighter colors reflecting larger value of $A_{i,t}$. The red color indicates the change detection results.

the proposed method needed to initialize $\lambda_{i,t}$. In addition, the latter part of the lecture was meaningless because the class activity switched from lecture to exercise. Based on the assumption that the proposed method was useful for the lecture period, we set the change detection period, and the other period is masked in white in Figure 3 (and also in Figure 4).

In Figure 3, the brighter color reflects a larger value for the anormal score $A_{i,t}$, and the red color indicates the change detection result. At the beginning of the detection period ($t \in [11, 35]$), few students were detected as being in the anormal state. At approximately $T = 40$, many students were detected as being in the anormal state. We investigated the reason by checking the lecture contents and event logs around this time. We found that there were two main topics ("research ethics" and "information ethics") in class 4, and the topic switched from the first to the second at time $t = 39$. The second topic suddenly appeared without any heading to indicate the change in topic. Then, the teacher continued the explanation in a matter-of-fact way. We suppose that most students were confused by the topic change, and could not immediately adapt to the new topic. In fact, there were many page click events (moves

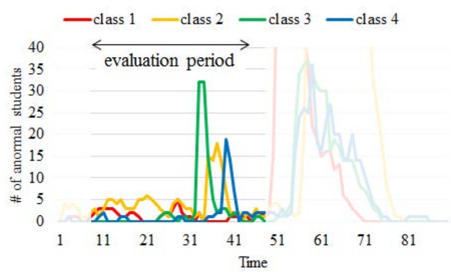

Figure 4: Number of anormal students over time.

to previous/next pages), which implicitly suggests the students' confusion.

Figure 4 shows time-series graphs that indicate the number of students detected as being in the anormal state over time. During the first part of each of the four lectures, the number of detections was almost always less than five. After a lapse of approximately 30 min, the number of detections gradually increased. We theorize that this could have been the result of multiple factors and a combination of factors such as a drop in concentration, change in topic, and increased difficulty understanding the content. We believe that the proposed method has the potential to provide the teacher with change detection results in real time, which will become useful information allowing them to determine the classroom situation.

5 CONCLUSION

We proposed an online change detection method for clickstream data based on the combination of click events and page differences. The number of click events that occurred during a lecture was modeled using a Poisson model. The model parameter was updated based on observations, which contributed to the realization of online change detection. The anormal score based on the Poisson model was calculated using the occurrence probability of click events during the latest period. In addition, the proposed method evaluated the page difference between the teacher and students, in order to grasp an anormal state in the students. Then, the combined anormal scores were used for the final judgment of whether or not a student was in the anormal state.

We conducted experiments with clickstream datasets collected from four classes. First, we compared the change detection performance with a random selection of students, and found that the proposed method provided better performance than the baseline. Second, we evaluated the change detection results from the qualitative viewpoint: what occurred at the change detection point in the lecture. In most lectures, the change detection occurred approximately 30-40 min from the beginning of the lecture. We theorized that the reasons included a lack of concentration, change in lecture topic, and difficulty understanding the topic. The important point was the ability of the proposed method to determine the change in the students' situations from the clickstream data. Furthermore, the proposed method was designed to work online (in real time), which makes it possible to inform the teacher about the real-time situation through a learning management system. If a teacher could receive such real-time information about their class, they could adaptively change the lecture plan according to the situation. Therefore, the proposed method holds the promise of realizing adaptive teaching based on real-time analytics for clickstream data.

In our future work, we will continue to evaluate the effectiveness of the proposed method with other classes. In addition, we will improve the methodology to enhance the change detection accuracy.

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REFERENCES

[1] C. G. Brinton and M. Chiang. 2015. MOOC performance prediction via clickstream data and social learning networks. In *2015 IEEE Conference on Computer Communications (INFOCOM)*. 2299–2307.

[2] Scott Crossley, Luc Paquette, Mihai Dascalu, Danielle S. McNamara, and Ryan S. Baker. 2016. Combining Click-stream Data with NLP Tools to Better Understand MOOC Completion. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*. 6–14.

[3] Dan Davis, Guanliang Chen, Claudia Hauff, and Geert-Jan Houben. 2016. Gauging MOOC Learners' Adherence to the Designed Learning Path. In *Proceedings of the 9th International Conference on Educational Data Mining, EDM 2016*. 54–61.

[4] Xinyu Fu, Atsushi Shimada, Hiroaki Ogata, Yuta Taniguchi, and Daiki Suehiro. 2017. Real-time Learning Analytics for C Programming Language Courses. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*. 280–288.

[5] Jihyun Park, Kameryn Denaro, Fernando Rodriguez, Padhraic Smyth, and Mark Warschauer. 2017. Detecting Changes in Student Behavior from Clickstream Data. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*. 21–30.

[6] A. Shimada, K. Mouri, and H. Ogata. 2017. Real-Time Learning Analytics of e-Book Operation Logs for On-site Lecture Support. In *2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT)*. 274–275.

[7] C. Stauffer and W. E. L. Grimson. 1999. Adaptive background mixture models for real-time tracking. In *Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149)*, Vol. 2.

[8] Gang Wang, Xinyi Zhang, Shiliang Tang, Haitao Zheng, and Ben Y. Zhao. 2016. Unsupervised Clickstream Clustering for User Behavior Analysis. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. 225–236.