

Analysis of Preview Behavior in E-Book System

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Abstract: This paper proposes a method to analyze preview behaviors of students using a learning management system (LMS) and an e-book system. We collected a large number of operation logs from e-books to analyze the process of learning. In addition, we conducted a quiz to test the level of understanding. This study especially focuses on an analysis of the relationship between learning behavior in preview and its effectiveness in the corresponding quiz. We apply a machine learning and classification methodology for behavior analysis. Experimental results report that students who undertake good preview achieve better scores in quizzes.

Keywords: Preview, learning behavior analysis, action logs, slide features

1. Introduction

The growth of information and communication technology (ICT) has produced great changes in education. For instance, ubiquitous learning or mobile learning is a well-known new learning paradigm that enables people to learn anytime and anywhere they want, using electronic devices such as PCs, tablets, smartphones, and so on. Furthermore, the use of learning management system (LMS) has become widespread in academic institutions. These ICT-based learning systems provide not only convenient and effective educational environments, but also various kinds of learning logs for students, such as when and where they use the system, what they learn, and so on.

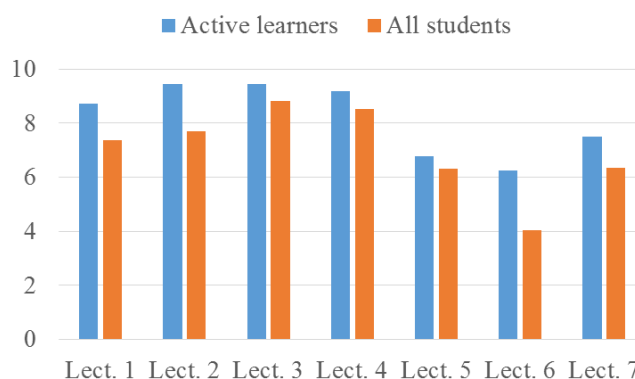


Figure 1. Average quiz scores

These learning logs are very useful for enabling educators to understand the learning activities of students (Yin et al., 2014). For example, teachers can observe a relationship between learning activities and examination scores through the analysis of logs of an e-book system and LMS. We preliminarily investigated the relationship between learning behavior acquired by the e-book system and quiz scores on LMS. Figure 1 presents the scores for several quizzes. Each quiz contained three to five questions related to information science, and was conducted prior to the beginning of the lecture. In the figure, the label of “active learners” indicates students who prepared for the lecture. In all quizzes, the average scores of active learners were higher than the average scores of all students.

In addition, learning logs offer great potential for analyzing the process of learning activities. In other words, it is also possible to analyze how a student learns new things, i.e. learning behavior, quality of learning, etc. Teachers would like to know the learning behavior of students, especially in

informal education (Wu et al., 2012) and/or flipped education (Ronchetti, 2010, Foertsch et al., 2002) where a self-activity is required to the student off-site a classroom. If teachers perceive students' learning behavior, they can provide detailed assistance to individual student, reflect on their own educational style and so on. As part of learning behavior analysis, we focus on the learning style of students who use e-books. In this paper, we propose a methodology to analyze how active learners browse lecture materials during their preview.

We utilized learning logs from a LMS and e-book. Analysis of the learning logs revealed a trend whereby students who undertook good preview achieved better scores on the quizzes. Conversely, students whose preview was poor achieved worse scores on the quizzes.

The paper is organized as follows. Section 2 gives a brief overview of our idea and strategy. The details of our proposed strategy and methodologies are explained in Section 3. Section 4 presents the results of our learning behavior analysis and Section 5 concludes.

2. Overview of Proposed Approach

The aim of this study is to analyze learning behaviors in preview, and to investigate the effectiveness of preview in helping students to understand the contents of lecture materials. We utilize an e-book system and a LMS to collect various kinds of logs such as action logs from e-books, quiz scores, etc. The e-book system contains slide materials that are used for lectures. Students may use the e-book system to browse the materials anytime they want. Teachers encourage students to utilize the materials for preview before the lecture starts. We can therefore acquire an understanding of learning behavior, such as how much time each student spends on preview, how much time is spent browsing each page of slides, and so on, from the action logs of the e-books,. The outcomes of this preview are then investigated by the LMS, wherein students take a brief quiz prior to the beginning of the lecture.

We also focus on the process of preview. More precisely, we analyze whether or not a student

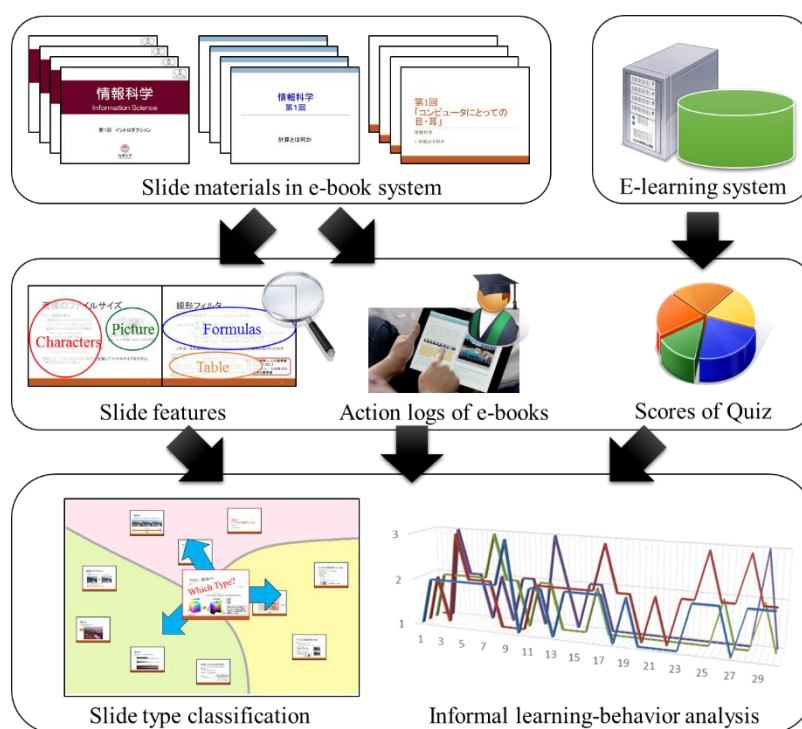


Figure 2. Overview of the proposed approach

spends an appropriate amount of time browsing each page of slides during the preview period. Our assumption is that students who get better scores in the quizzes (i.e., active learners) spend an appropriate amount of time on each page of slides. In other words, each page of slides has a predetermined preview time, and active learners spend the anticipated amount of time browsing the

page. To do this, we have to estimate the expected viewing time for each page of slides. Therefore, we extract slide features from each page to measure the contents.

Figure 2 shows the overview of our strategy. Preview processes are collected via action logs from e-books. In addition, the outcomes of preview are collected via the quiz scores using the LMS. Slide contents, such as characters, pictures, mathematical formulas, tables, and so on, are extracted and represented as slide features by visual image processing. Generally, a presentation slide set contains not only text (e.g., slide title, main slide text/bullets), but also other contents such as mathematical formulas, colorful figures, tables, and so on. Therefore, extracting textual features is not sufficiently informative, and we must consider other features that represent this additional content. That's why we focus on visual features, in which even the text regions are considered as visual information. Finally, these logs and features are applied to slide classification and analysis of learning behavior.

3. Visual Feature Extraction and Classification

Liew et al. proposed a slide image retrieval system in which slide features are extracted by image processing (Min et al., 2008). A similar system was also proposed by Boer et al. They regarded a Web page as an image, and utilized image analysis features for Web page classification (Boer et al., 2010). Our idea was inspired by these related works.

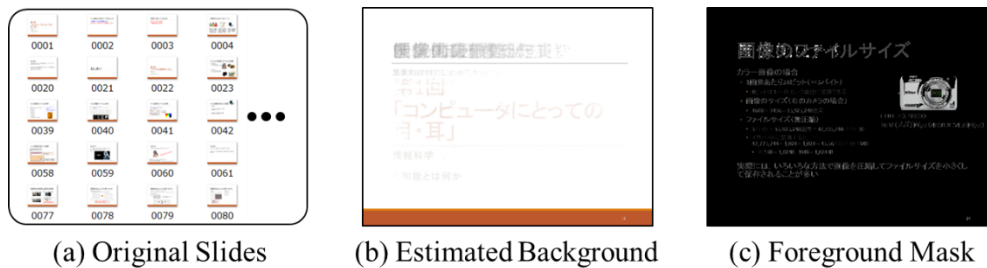


Figure 3. Background estimation and foreground mask



Figure 4. Slide features

3.1 Background Separation and Foreground Mask

Before extracting the slide contents, the background used in the slides has to be estimated. Usually, we can take advantage of the fact that presentation slides have a consistent background throughout the presentation set. Therefore, we apply a background modeling strategy (Zivkovic et al., 2006), which is often used for video surveillance, by using the slide set shown in Figure 3(a).

This background modeling provides an estimate of the dominant RGB value for the background color (see Figure 3(b)). Consequently, we can acquire a foreground mask slide by subtracting the background from the original slide, as shown in Figure 3(c).

3.2 Slide Attributes

Once background separation is complete, we have a set of foreground mask slide images I from which we can extract representative features. We assume that the volume and visibility of a slide affects the learning time of the students, and extract the following three kinds of visual features related to our assumption.

3.2.1 Content Volume

The foreground mask (Figure 3(c)) of each slide image is first binarized by thresholding the color intensity values. As shown in Figure 4(a), the contents of the slide are extracted as white pixels. We calculate the content volume by counting the number of white pixels. We then divide the slide image into 5×5 nonoverlapping subregions to preserve rough content location information.

3.2.2 Visual Saliency

A “Saliency Map” was proposed to find a topographically arranged map that represents the visual saliency of a corresponding visual image (Itti et al., 1998). The saliency map is acquired by combining inputs from several feature maps, intensity, orientation, and color, which display substantial local contrast at several spatial scales in the area.

We apply the strategy to each slide image and acquire salient regions as shown in Figure 4(b). Then, we divide the slide image into 5×5 nonoverlapping subregions and calculate the content volume, and then binarize the map and count the number of white pixels.

3.2.3 Color Histogram

An RGB color histogram is produced from each slide image. Each color channel is discretized into eight bins and concatenated as a 24-bin color histogram (Figure 4(c)). A bin corresponds to part of the color intensity spectrum.

For each slide, we acquire a $(25 + 25 + 24 =)$ 74-dimensional feature vector that characterizes the slide image.

3.3 Slide Classification

A classifier is designed to classify a slide into a corresponding group (class). The slide features extracted from each slide are first trained by a machine learning methodology. In our study, we defined three groups as follows.

- Group 1 Short browsing, less than 5 sec.
- Group 2 Normal browsing, between 5 sec and 20 sec.
- Group 3 Long browsing, more than 20 sec.

Before the training process, all the training samples, i.e., slide images used for training, are categorized into one of these groups according to the e-book learning logs. For further details, see the Experimental Results section. We use a support vector machine (SVM) (Cortes et al., 1995), which is a well-known machine learning method, to generate a classifier.

4. Experimental Results

4.1 E-books and Action Logs

We analyzed the learning logs from an “information science” class. In total, 135 students attended the class, which commenced in October 2014. All the lecture materials were prepared as digital textbooks using the BookLooper system (KCCS, url). Students browsed the materials using their PCs, tablets, and/or smartphones. The materials consisted of three item groups: A (A-01, ..., A-11), B (B-01, ..., B-

15), and C (C-01, ..., C-08). Each item contained several pages of slides. The total number of slides is summarized in Table 1.

Table 1: The total number of slides in each item group.

Item Group	A	B	C	Total
# of slides	452	538	231	1221

Students use their e-books not only while attending a class but also outside of class hours. In our study, we focus on analyzing the effectiveness of preview, especially in learning behavior before the classroom lecture. In other words, we wish to analyze how effectively students learn the materials before the lecture. The target logs for our experiments were collected from the beginning of October to the end of November (All students agreed to our privacy policy for utilizing the logs. The privacy policy was approved by the ethics committee of our university.). We obtained about 187,000 action logs with time stamps such as “go forward”, “go backward”, “put memos”, and so on. Then, we calculated the time spent browsing each slide from these logs. Note that we analyzed action logs that were collected during the week before each lecture, although logs for all learning materials were available over the entire period. Figure 5 illustrates the analysis of the target logs.

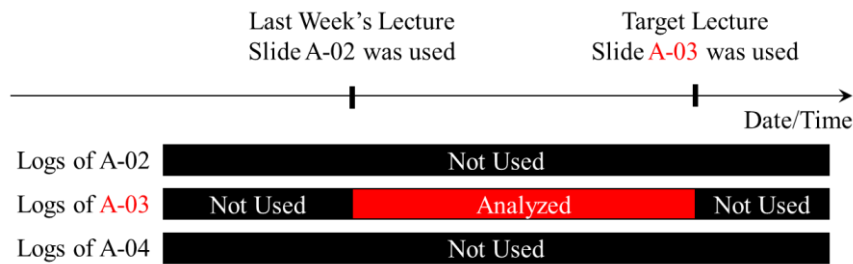


Figure 5. An example of the analysis of an action log period

4.2 Training and Classification of Slide Type

First, an SVM was trained to classify the slides into three groups as explained in Section 3.3. The browsing time of each group was based on the actual browsing times calculated from the action logs. To account for the diversity of students, we selected the action logs of high-grade students whose quiz scores were ranked in the top 25% in the class (Prior to the beginning of each lecture, we conducted a quiz to test the effectiveness of preview.). A total of 263 slides with action logs (average 87 slides for each group) were acquired from the high-grade students.

Then, we classified all 1221 slides into one of the three groups using the trained SVM. Figure 6 shows examples of slides classified into “Short browsing”, “Normal browsing”, and “Long Browsing”, respectively. It can be seen that Figure 6(a), contains slides with relatively simple contents, e.g., title slide, introduction, etc., while Figure 6(c) contains slides that have more visual contents, including colorful figures, tables, mathematical formulas, and so on, than the other groups.

4.3 Estimation of Browsing Time

Slide classification results can be utilized to estimate the browsing time for each item, i.e., A-01, ..., C-08. For example, Figure 7 shows the classification results for three items, which contain about 30 pages of slides. The classification results are different for each of the three items. In this study, we assumed that each group requires an adequate browsing time per page as follows.

- Group 1 5 sec/slide.
- Group 2 20 sec/slide.
- Group 3 60 sec/slide.



(a) Slides classified into Group 1

(b) Slides classified into Group 2



(c) Slides classified into Group 3

Figure 6. Classification results

Based on these assumptions, we can easily calculate the estimated browsing time for each item, as summarized in Table 2. We can see that the browsing time differs even if the items contain the same number of slides. This is because browsing time is affected by the contents of the slides.

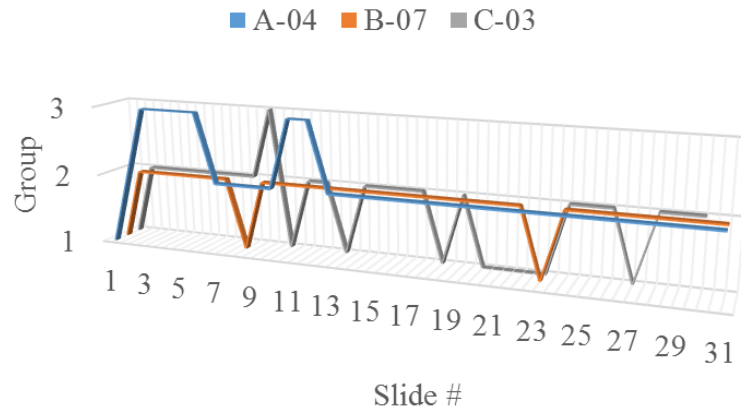


Figure 7. Classification results for three items containing about 30 pages of slides.

Table 2: Estimated browsing time for three items, A-04, B-07, and C-03. We assumed that 5 sec, 20 sec, and 60 sec, respectively, were required for browsing the slides in each group.

Item	Group 1	Group 2	Group 3	Estimated browsing time
A-04	1	24	6	14 min 05 sec
B-07	3	28	0	11 min 10 sec
C-03	9	20	1	8 min 25 sec

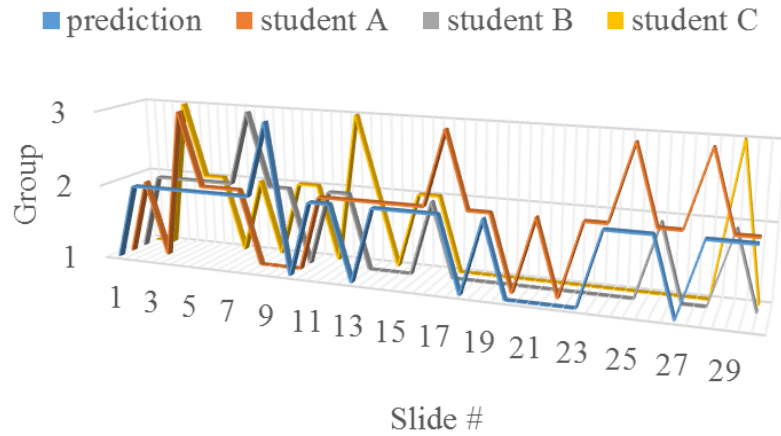


Figure 8. Browsing time for item “C-03”. The sequence labeled “prediction” represents the classification result for C-03 slides. The other three sequences are based on the action logs acquired from e-books.

Table 3: Relationships among quiz scores, preview time, and poor browsing.

Item	Score	Learning time	# of poor browsing
Student A	7.5	10 min 45 sec	12/30
Student B	8.75	12 min 24 sec	10/30
Student C	0	5 min 43 sec	18/30

4.4 Analysis of Preview Efficiency

We analyzed the effectiveness of preview. First, we compared the estimated browsing time and actual browsing time of several students for each slide. Figure 8 illustrates the case for item C-03. The sequence labeled “prediction” represents the estimated time using our proposed method, which is the same as that for “C-03” in Figure 7. The other sequences represent the actual browsing time of three students. Their browsing time was calculated from the logs of their e-books. Therefore, the three sequences reflect the time actually spent on preview before the lecture.

Prior to the beginning of the lecture, the teacher conducted a quiz based on the contents of item C-03. Scores were scaled from 0 to 10 points. The average scores of all students and of students who undertook preview were 4.03 points and 6.25 points, respectively. Overall, the scores of active learners were superior to those of the other students, as would be expected. However, there were some students whose scores were poor, even though they undertook preview. Table 3 shows the quiz scores, preview time, and instances of poor browsing of the three students whose browsing performance is shown in Figure 8. “Student A” and “Student B” achieved better than average scores, but “Student C” failed the quiz (scoring 0 points), even though he undertook preview before the lecture.

We analyzed the learning behavior of “Student C” and found that he spent about 6 min on preview (i.e., browsing the material). Meanwhile, the expected time as predicted by our proposed method was about 8 min. Not only was the preview time of “Student C” shorter than that of other two students, it was shorter than the expected time (i.e., 8 min). We investigated the time spent on each page of slides, and whether it met the expected time. Slides were counted as “poor browsing” if the learning time spent on the slide was less than the expected time defined in Section 3.3. The right-hand column in Table 3 denotes the number of instances of poor browsing by the three students. Compared with “Student A” and “Student B”, “Student C” had a larger number of instances of poor browsing, which might have caused the worse quiz score. Conversely, the other two students spent the appropriate amount of time on their preview, which led to better quiz scores.

In this way, the proposed analysis strategy enables us to investigate the effect of preview behavior more precisely than by just comparing the students' quiz scores or learning time.

5. Conclusion

We proposed a learning behavior analysis strategy using learning logs collected by a LMS and an e-book system. We focused on a lecture in which a teacher used slide-based materials. Students had free access to the slides anytime and anywhere. Our hypothesis was that a student who spent an appropriate amount of time on preview would achieve better quiz scores. To investigate the hypothesis, we analyze the contents of the slides and learning logs using image processing and machine learning approaches.

In our approach, each page of slides was regarded as an image, and several features were extracted to represent slide features. Then, a machine learning-based classification was performed to arrive at an estimated time for preview. As a result of our experiments, we found that students who did not spend an appropriate amount of time on preview tended to obtain worse quiz scores. It was difficult to reach any definite conclusions simply by using the logs to check whether the student had done any preview. Meaningful findings were enabled by analysis of the learning activity process, how much time the student spent browsing each slide, and whether the time spent was deemed sufficient, based on estimated times.

In this study, we utilized slide classification results to predict the time spent on preview. In future work, we will explore other possible methods of slide classification. For example, we could develop a support system that tells students how much time they should spend browsing a slide. Another possibility is slide summarization based on browsing time. If a student has little time for preview, some important slides will automatically be selected according to the predicted browsing time required for each slide. The entire strategy is also applicable to other learning behavior analyses, such as mobile learning, flipped education, and so on.

Acknowledgements

The research results have been achieved by “Research and Development on Fundamental and Utilization Technologies for Social Big Data” (178A03), the Commissioned Research of the National Institute of Information and Communications Technology (NICT), Japan.

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