Learning Support through Personalized Review Material Recommendations

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Abstract: Recent enrichment of digital learning environments has made it possible to obtain learning logs (data) on learners' learning behavior. In this situation, it is possible to recommend learning contents which are appropriate for individual learner by analyzing learning data. Our study develops a learning support system which recommends personalized review materials based on the results of quizzes and learning activities recorded by e-textbooks. In this paper, we explain the details of the system and report experimental results.

Keywords: learning support system, review material recommendation, adaptive learning

1. Introduction

The digital learning environment has been enriched with the recent development of information technology. In recent times, online platforms such as MOOCs offer a wide variety of learning content and opportunities for many people to learn. In addition, even at universities, online lectures using electronic devices are becoming more and more common. For example, an e-book system could be used to provide lecture materials, and a learning management system is capable of conducting quizzes and collecting students' reports at the university level. By integrating these systems, we can expect to realize an advanced supporting strategy for enhancing students' learning (Flanagan, 2017).

Similar to traditional learning, online learning methods often include quizzes on content after learning about a topic (section, subsection, or part) to assess students' understanding. These assessments help students to reflect on what they have learned and estimate their learning progress (Khushboo, 2020). One effective way to compensate for the knowledge deficits revealed by the assessment is to recommend learning materials relevant to the content. Studies have been conducted on recommending learning contents (Konstantin, 2018; Ai, 2019). The majority of these studies on recommending learning content assume that students' overall progress is good and focus on recommending what students should do next; they do not take into account the need for review. However, some students fail after learning a topic only once because they do not understand it well enough. Such students need to review material; however, some students are unable to do so due to lack of ability or motivation. For such students, supporting the review process with a learning support system is effective. For example, one possibility is to suggest some specific pages in the textbook that are presumed to be poorly understood.

The purpose of this study is to provide adaptive review support for individual learning comprehension by using a university online system-based lecture as a testing environment. In this study, it is assumed that students learn with e-textbooks and take a quiz at the end of the topic. We propose a learning support system that provides personalized review materials by identifying specific pages in the e-textbook that are presumed to have been met with low comprehension based on individual learning activities including quiz results. In the following section of this paper, we introduce the configuration of the proposed system as well as each method.

2. System

The purpose of this study is to support learning by developing an adaptive recommendation system for review materials. An overview of the system is shown in Figure 1. The system consists of Moodle, a well-known learning management system (Dougiamas, 2004), an e-book system, a database, and a dashboard. The system flow is described as follows. First, students study a certain topic using e-textbooks. When a student uses any of the functions of the e-book system (such as open an e-textbook, go to the next page, highlight, etc.), e-book event logs are automatically recorded in the database. Students then take quizzes to check their proficiency on the topic on Moodle, and the quiz results are stored in the database. Then, based on the data collected from each student's quiz results and e-book event logs, personalized review materials are recommended on the dashboard. In the following sections, we will describe the details of the proposed system.

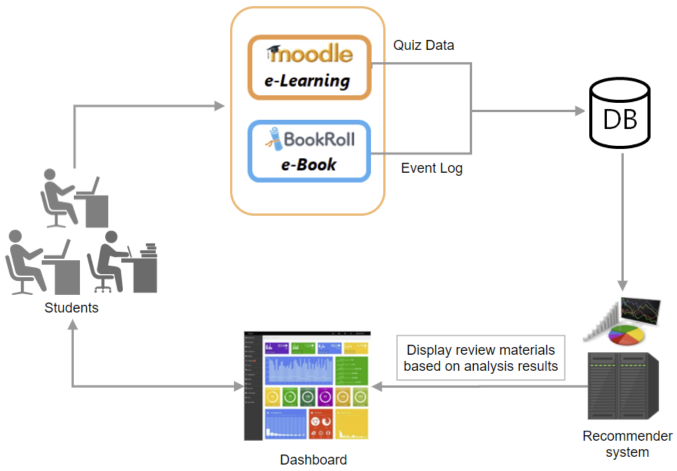


Figure 3. System configuration

2.1 e-book-system

We use an e-book system called BookRoll (Ogata, 2015). After uploading e-textbooks in .PDF format to BookRoll, students can view the e-textbooks via a web browser. BookRoll has various functions such as adding a memo or a marker to a current page, evaluating whether a student understands the current page, and so on. As mentioned above, when a student uses any of the functions of BookRoll, e-book event logs are automatically recorded in the database.

2.2 Recommendation Methodology for Review Materials.

This system assumes that students learn a topic with the e-textbook and then take a quiz to check their proficiency at the end of the topic. It is common for students to fail to reach a target level of understanding after studying a textbook once. Therefore, this system identifies pages in the e-textbook that are poorly understood and presents them as content to be relearned. However, even if only the target page is presented within the scope of the textbook prepared in advance, there is a possibility that the learning may not be sufficient. Thus, our system also recommends websites related to the target page for further understanding. In the following sections, we describe how to identify pages associated with a low level of understanding, and then we describe how to get the URLs of websites related to the target pages.

2.2.1 Use of Quiz Results

One way to identify pages of low comprehension is to extract the specific pages in the e-textbook that are relevant to the content of the quiz that was incorrectly answered. In this case, it is necessary to link the relevant pages of the e-textbook to each question on the quiz. Although it is possible for teachers to register the related pages in advance, it is not practical for teachers to register the related pages every time a quiz is created. Therefore, our system uses an approach (Ishikawa, 2020) that automatically retrieves related pages using text information. The following is a method for retrieving the pages in an electronic textbook that are related to a quiz.

First, we vectorize the question texts and answer texts in a quiz as follows.

1. Extract n words from the quiz questions, answer sentences, and obtain the word set $T_p = \{t_1, t_2, \dots t_i, \dots t_n\}$.
2. Convert each of the n words in T_p to a vector $\boldsymbol{v_{t_i}}$ using Word2Vec (Mikolov, 2013). Since we deal with Japanese texts, we use an existing Word2Vec model created from the Japanese Wikipedia (Suzuki, 2018) and transform n words into 200-dimensional vectors $\boldsymbol{v_{t_i}}$.
3. Add all the vectors generated in the previous step and divide by the number of words n to normalize the data (formula (1)).

$$\boldsymbol{v_q} = \frac{\sum_i \boldsymbol{v_{t_i}}}{\mathrm{n}} \left(t_i \in T_q\right) \quad \dots (1)$$

In this way, we can represent a quiz as a 200-dimensional vector $\boldsymbol{v_q}$.

Next, in the same way, we vectorize the e-textbook page by page, as follows.

1. Extract n words from the text on a page and obtain the word set $T_p = \{t_1, t_2, \dots t_i, \dots t_n\}$.
2. Considering the text on a page as a document, calculate the value of TF-IDF(Ramos, 2003) for each of the n words in the T_p.
3. Each of the n words in a T_p is transformed into a vector $\boldsymbol{v_{t_i}}$ using a 200-dimensional pre-trained Word2Vec model.
4. Add up all the vectors of the previous step. In this case, a weighted average is performed with the TF-IDF value of step2 (formula (2)).

$$\boldsymbol{v_p} = \frac{\sum_i \mathrm{TF-IDF}(t_i)\boldsymbol{v_{t_i}}}{\sum_i \mathrm{TF-IDF}(t_i)} \left(t_i \in T_p\right) \quad \dots (2)$$

In this way, we can represent pages in an e-textbook as a 200-dimensional vector $\boldsymbol{v_p}$.

Finally, the relevant pages of quiz q_i can be extracted from the e-textbook using the following procedure.

1. Compute the cosine similarity between the feature vector of q_i and the feature vector of each page.
2. The pages are ranked in order of cosine similarity, and the page with the higher score is considered to be related to q_i.

2.2.2 Use the Function of the e-book System

There are two response buttons, "got it" and "didn't get it," on the screen of the e-book-system as a function of BookRoll. Each student can evaluate whether or not they have understood the current page by clicking one of the two buttons when viewing e-textbook. The click information of these buttons is stored in the database as a log. This system simply utilizes this log and presents the pages where the "didn't get it" button was pressed as pages with low levels of understanding. In addition, the number of students who clicked the "didn't get it" button when using an e-textbook are tallied. The top four pages with the most clicks of this button are presented as review materials.

2.2.3 Page-wise Website Recommendation

This system also presents URLs of websites related to each page extracted by the method described in 2.3.1 or 2.3.2. Relevant websites can be retrieved by using the text mining method described in (Nakayama 2019, 2020). This method provides an appropriate learning environment that helps learners find appropriate knowledge objects within the vast amount of information on the Internet. Finally, we obtain five URLs for each page and present them.

2.3 Dashboard

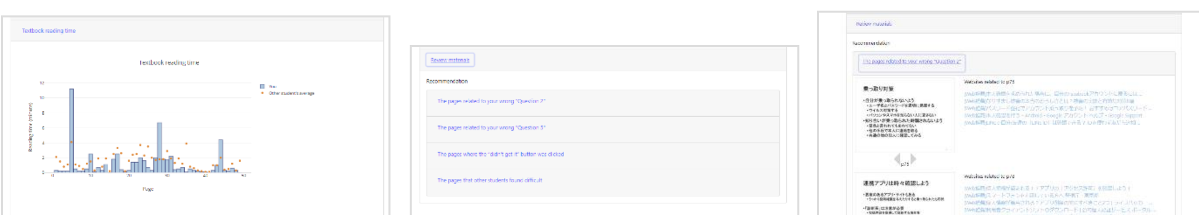
We developed a dashboard for providing review materials. The dashboard can be used by clicking on the link in Moodle. This dashboard provides the following three functions, including the function to provide review materials.

・Reflection on the results of the quiz

・Checking e-textbook reading time
・Provision of review materials

In this way, we developed this dashboard not only to present review materials, but also to help students reflect on their own learning. The dashboard screen is shown in Figure 2. Figure 2-(A) is a web page for selecting the topic students want to review. When the selection is complete, they click a green button. Figure 2-(B) is the screen after the selection. The three function screens are shown in an accordion format and are minimized at first. Figure 2-(C) shows the reflection of the results of the quiz. The user's score and the average score of the other students are displayed in the upper left corner. The overall score distribution is shown as a graph. In addition, users can check the questions, answers, and correctness of the quiz. Figure 2-(D) shows how to check the amount of time students using the dashboard have spent reading the e-textbook. The reading time per page is shown as a graph. The horizontal axis is the page number of the e-textbook, and the vertical axis is the reading time. Figure 2-(E) presents the review materials. This function is initially closed in an accordion form. As mentioned in section 2.3, these materials comprise (1) the top four pages related to the quiz question with the incorrect answer, (2) the pages where the "didn't get it" button was clicked, and (3) the top four pages with the most clicks on the "didn't get it" button. If (1) or (2) is not present for the user, it is not displayed. Figure 2-(F) shows the screen for viewing the review materials. The target page is on the left side, and the URLs of the related websites are shown on the right side of the page. When reviewing a textbook, it may be necessary to check not only the specific page, but also the flow of the textbook before and after the target material. Therefore, we made it possible to display the previous page and the next page by clicking the gray triangle below the target pages. In addition, the image of the page is enlarged when users hover their mouse over it.

(A) Selection screen (B) Screen after the selection (C) Reflection of quiz results



(D) Checking reading time (E) Provision of review materials. (F) Screen for viewing the review materials.

Figure 2. Interface of the Dashboard

3. Experiment

We conducted an experiment to evaluate the usefulness of the proposed system. Participants were students who took a "cyber security" course at Kyushu University in the spring semester of 2020. There were 101 students in this course. The first part of the experiment was a pre-questionnaire to investigate the students' attitudes toward online learning. This questionnaire was answered by 83 students. After the course, we then sent an email to the students to encourage the use of the dashboard for review; 33 of the 101 students used the dashboard. Note that the use of the dashboard was optional, and the usage rate was about 30%, which is high considering the fact that the link click rate on email about higher education is around 7% (Constant Contact, 2020). We further asked system users to answer a questionnaire about their impressions of the dashboard. Altogether, 22 students responded to the questionnaire. Both questionnaires were scored on a 5-point scale. Below, we will report on the trends of students using the system, the results of the system questionnaire, and the usage status of the system.

To first determine what trends students have used the system, we divided 83 students into two groups: system users and others, and we compared the results of the pre-questionnaire. In the pre-questionnaire, students were asked the following three questions about online lectures to see if they felt comfortable with their learning. “PQ1: Are you worried about the learning method?” “PQ2: Is it difficult to understand the content only using the lecture?” and “PQ3: Are you learning properly at your own pace?” If students are confident in their learning, we can assume that PQ1 and PQ2 would be low and PQ3 would be high. The average scores of the two groups for these three questions are shown in Table 1. The Wilcoxon rank sum test (a nonparametric statistical test) was also performed between the two groups. In the test, PQ1 was significantly different ($p<0.01$), while PQ2 ($p=0.135$) and PQ3 ($p=0.243$) were not significantly different. However, as shown in Table 1, system users tended to have higher scores on PQ1 and PQ2 and lower scores on PQ3. Considering the results, system users were relatively confident and system non-users tended to have less confidence in their learning. This may mean that more motivated students used the system.

Table 1. *Pre-questionnaire comparison results*

	PQ1		PQ2		PQ3		Total number of students
	Mean	SD	Mean	SD	Mean	SD	
System Users	2.97	1.17	3.67	0.87	4.20	0.98	33
System non-users	3.83	1.28	3.91	1.19	3.98	1.36	50

Table 2 shows the contents and results of the questionnaire. All questions in Table 2 were to be answered on a 5-point scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Q1 asked about the usefulness of each of the three functions of the system. Of the 22 respondents, respondents had a favorable evaluation of the usefulness of “Reflection on the results of the quiz” (“strongly agree” or “agree”). The evaluation of the usefulness of “Checking e-textbook reading time” function was inconsistent. This function simply showed a comparison between the students’ own reading time and the average time of the other students, but it seems that it was difficult for participants to judge whether it was useful just by looking at it. Of 22 respondents, 16 responded “strongly agree” or “agree” that the “Provision of review materials” function was useful. For Q2, the respondents were asked to look at the review materials presented to them and to rate whether the materials were useful for the review. Of the 22 participants, 19 responded positively. From the results, we can conclude that the proposed method provides useful review materials to some extent. In Q3, we asked if the participants would like to use this kind of dashboard for review in the future, and 20 of the 22 students responded positively. The positive evaluation in Q1 and Q2 may have led to this result.

Table 2. *Questionnaire Results*

	Question items		*Evaluation*				
			1	*2*	*3*	*4*	*5*
Q1	*Were the following three functions of the dashboard useful?*	*Reflection on the results of the quiz*	*1*	*2*	*3*	*5*	*11*
		Checking e-textbook reading time	*1*	*7*	*4*	*8*	*2*
		Provision of review materials.	*1*	*2*	*3*	*6*	*10*
Q2	*Do you think the content presented as review material would be useful for your review?*		*0*	*1*	*2*	*12*	*7*
Q3	*Do you want to use this kind of dashboard in the future?*		*0*	*0*	*2*	*14*	*6*

Finally, we investigated how students used the system. On average, the system users selected 4.8 out of 8 topics in the course to view the review materials. Thus, we can assume that they used the system to some extent. In addition, the analysis of the system usage time showed that shorter users worked with the system for less than 1 minute and longer users worked with the dashboard for approximately 10 minutes. From these results, at least, review activities were triggered by the proposed system, and some students utilized the recommended materials for positive usages. Meanwhile, we have to consider another effective recommendation strategy for taking care of the other students. Given the results of the questionnaire, we think there is ample room for students to accept this system.

4. Conclusion and Future Work

In this paper, we proposed a system for recommending review materials based on the results of quizzes and the functions of e-textbooks. We conducted an experiment using the developed recommender system. As a result of the analysis of the questionnaire, we obtained positive responses about the use of the system. However, a voluntary usage experiment revealed that students who were relatively more anxious about their learning were less likely to use our system. Furthermore, analysis of the use of the system showed that few students were using it for full-scale review. Therefore, it will be necessary to improve the system so that it is properly utilized to support all students, including those who are anxious about their learning. There are several other challenges for the future. First, we are going to expand our recommended review materials to include more than just e-textbooks and websites. Second, a more detailed analysis of the learning behavior of the system users is needed to improve the efficiency of learning improvement. Therefore, we would like to improve the design of the dashboard to be able to track the students' learning behavior in more detail. Third, we would like to investigate how the system can positively affect the learners with a long-term experiment.

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