Automatic Generation of Personalized Review Materials Based on Across-Learning-System Analysis

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Abstract: In this paper, we propose a novel method to make a summary set of lecture slides for supporting students' review study. Quizzes are often conducted in a lecture to check students' understanding level. The aim of our study is to support a student who wrongly answers the quiz. The quiz statement is analyzed to extract nouns in the statement. Then, text mining is performed to find the pages related to the quiz statement in the relevant lecture materials. The proposed SummaryRank algorithm evaluates the topic similarity among pages in material with emphasizing the related page to the quiz statement. In addition, our proposed method considers the preview status of each student, resulting in the generation of adaptive review materials tailored for each student. Through experiments, we confirmed that the proposed method could find appropriate pages with respect to the quiz statements.

Keywords: Automatic generation, Personalized review material, e-Book, e-Learning system

Introduction

In a learning cycle, preview and review processes are very important for students. A preview process, i.e., studying in advance for a class, enables students to understand the class narrative, to become familiar with important keywords, and to discover new terms and concepts. Some studies such as Beichner (1995) report that good preparation prior to lectures leads to improved student performance. A review process, i.e., studying after a class, is also important not only to look back on the things that a student has learned in the lecture, but also to enrich one's understanding of the lecture contents. Therefore, students are often asked to undertake preview and review study.

In terms of efficient study support, systems enabling the automatic creation of summaries of online audio/video presentations(He et al., 1999), spoken lectures(Chen et al., 2011), and sets of lecture slides(Shimada et al., 2015) have been proposed. These systems provide a brief summary of lecture contents so that students can perform efficient previewing and reviewing. Automatic quiz generation systems have also been proposed by many researchers to support students' self-learning and enhance their understanding of lecture contents (Aldabe et al., 2006; Liu et al., 2010; Sathiyamurthy and Geetha, 2012; Liu et al., 2012). Text analysis or natural language processing (NLP) is applied to input text to extract important keywords. Then, a quiz is automatically generated to check the understanding level of students. This system is useful not only for students but also for teachers, since they need not expend any effort in compiling the quiz. To clarify the standpoint of our research, we categorize the automatic quiz generator as a forward type of support system, where text in lecture materials is used as the input to a system, which then produces output in the form of quizzes.

Conversely, in this paper, we proposed a backward type of support system, whereby quiz results are used as input to a system, and then the corresponding pages of lecture materials are automatically salvaged. Such inverse correspondence is very important for the efficient provision of review material for students. The most noteworthy characteristic of the proposed system is that it adapts review material to the requirements of each student based on not only their academic performance but also their preview behavior. To achieve such tailored support, we utilize the 1 e-Book system for the collection of preview behavior performed in the physical space and e-Learning system for the collection of academic performance in the cyber space.

Automatic Generation of Review Material

Figure 1: Overview of proposed review summarization system An overview of the automatic generation of personalized review materials is shown in Figure 1. First, quiz results are analyzed to determine whether or not a student answered correctly. If he/she answered incorrectly, the corresponding quiz statement is used as an input to the proposed system. A text analysis is then performed to find related pages.

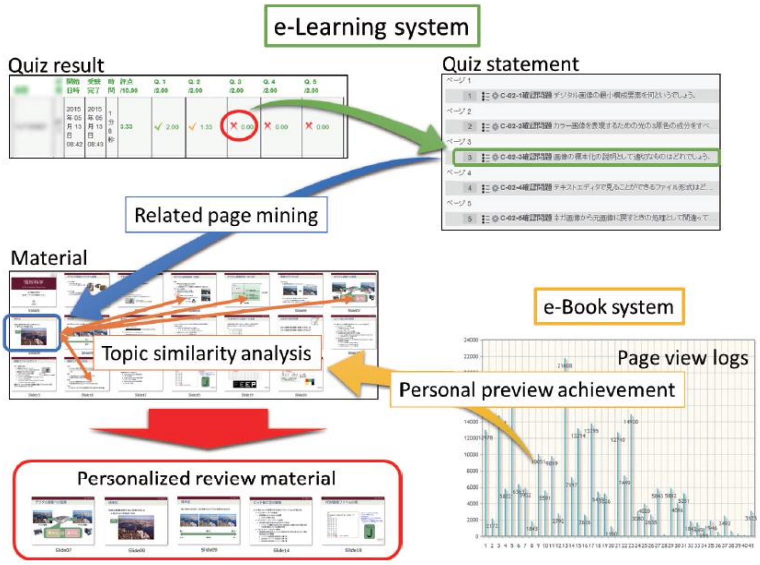

Figure 1: Overview of proposed review summarization system

Second, the lecture material is analyzed for topic similarity. This process is based on the concept that pages containing similar content should be included in the review material. Third, preview achievement is analyzed using page view logs in the e-Book system.

Finally, the related page mining, topic similarity, and preview achievements are holistically evaluated to generate a summary of the material. The details of each process are provided in the following sections.

Related Page Mining

Our strategy assumes that a related page contains the same keyword as the quiz statement. Each quiz statement QS is divided into morphemes. Then, we extract the nouns $n(1, \ldots, n, \ldots, N)$. For each noun n, a normalized histogram hn is created by counting the number of times the noun n is contained in page u, followed by normalization throughout the pages. In other words, each bin bu,n of the histogram hn represents how many times page u contains noun n. Note that the bins are normalized after counting the number of times noun n appears in all the pages.

Figure 2 shows an example of a noun histogram when the following quiz statement is provided.

Quiz: “What is the smallest element constituting a digital image?”

The horizontal axis and vertical axis of Figure 2 denote the page number and normalized histogram value, respectively. Five nouns are extracted from the quiz statement, and there are 41 pages of related material. It seems that the higher frequencies are concentrated around page #3.

To acquire the final mining result, the frequencies of all nouns are summed. We define the normalized value ru as the related score of page u. Figure 3 shows the related scores calculated from the noun histogram shown in Figure 2. The highest related score is observed for page #3, which is the page manually selected by the teacher.

Review Page Summarization

Although the mining method introduced in the above section finds pages that are highly related to a given quiz statement, the relationships among pages are not considered. In other words, a page is individually evaluated whether it contains related nouns or not. To support effective review by students, it is important to provide not only the most related page but also its associated pages. In addition, it is important to customize the review pages according to each student’s particular situation.

In our study, we make the following assumptions to create review material that is adapted for a student’s background.

All students: Pages that include similar topics are helpful in supporting students’ review study.
Individual student: Pages that were not previewed by a student should be important for the student’s review study.

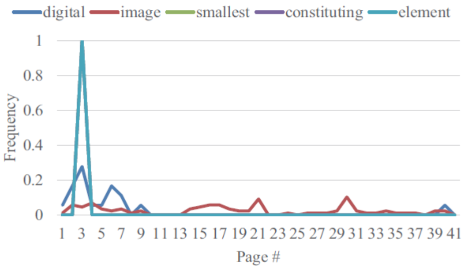

Figure 2: An example of a noun histogram. The horizontal axis and vertical axis denote the page number and normalized histogram value, respectively

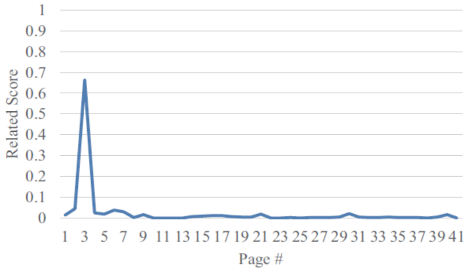

Figure 3: Scores for each page relating to the quiz statement

To generate review material that satisfies the above assumptions, we propose a page-rank-based review summarization method. We call this the SummaryRank (SR) method, which assigns a ranking score to each page. The higher the ranking score of page *u*, the more important the page is for the student. The idea for the proposed SR method is inspired by PageRank(Page et al., 1999) and VisualRank(Jing and Baluja, 2008). When we find that page *u* is related to a given quiz, and that it relates to page *v*, page *v* is also important, since page *u* is important.

SR is iteratively defined by the following formula:

$$SR = \alpha(S * \times SR) + (1 - \alpha)E, \qquad (1)$$

where $S*$ is the column normalized similarity matrix *S*, in which Su,v measures the page similarity between pages *u* and *v*. *E* is a bias vector to impact to the ranking. The details of the methods used to acquire *S* and *E* are given in the following subsections. *SR* is repeatedly updated until it converges. α, $(0 \leq \alpha \leq 1)$ controls the balance between the similarity matrix and the bias vector. According to the literature (Jing and Baluja, 2008), $\alpha >$ 0.8 is often used in practice.

To measure the similarity between all the possible page pairs, we must define a metric. In this study, we simply evaluate the similarity using the L2 norm between two feature vectors:

$$Su,v = ||du - dv| |, \qquad (2)$$

where du and dv are feature vectors represented by a collection of words(Zhang et al., 2010), and Su,v is an element of the similarity matrix *S*. The role of the bias vector is to emphasize a focus page to attain a higher ranking. In our study, a bias vector is generated by considering two aspects.

Relation to quiz: A large bias value should be given to a page if the page has a higher relation to a given quiz.

Preview achievement: A large bias value should be given to a page if the page was not previewed by a student.

Due to the page limitation, we skip the detail calculation of these bias vectors, but they are finally fused to be *E*.

Experiments

We investigated the effectiveness of the proposed method in a series of information science classes. In total, 105 first year students, including both arts and science students, attended the classes, which commenced in April 2015. The classes were conducted over 8 weeks. Every week, prior to the beginning of the lecture, we conducted a short quiz to check the level of understanding. There were 25 quizzes in total over the 8 weeks divided into subsets according to the progress of each lecture series.

Related Page Mining Accuracy and SummaryRank Efficiency

In this section, we report the results of our investigation of related page mining. Teachers provided the one-to- one correspondence between a quiz statement and its related page in advance. We treated this correspondence as Ground Truth, and evaluated the top ranked matching rates. Figure 4 shows the cumulative matching characteristic (CMC) curve, which measures how well the proposed method ranks the desired page with respect to a given quiz statement. The curve denoted "PageMining" represents the related page mining results reported in section. The proposed method showed higher accuracy in locating related pages. The curve denoted "SummaryRank" represents the result when we ignored the bias vector relating to preview achievement, which strongly depends on the individual student. The proposed summary rank algorithm finds pages that include similar topics to the page most closely related to a given quiz statement. Therefore, there is a possibility that the desired page will be ranked after the convergence of the SR algorithm, even if it is not included in the results of related page mining. There were five cases in which the desired pages were not found by related page mining (denoted "PageMining"). After performing SR, the desired pages were salvaged in three of these five cases. In Figure 4, although the rates for the rank-5 pages were slightly lower than those of PageMining, SR achieved a higher recall rate in the rank-10 matching. Based on these results, we found that the proposed SR approach provides better performance in terms of finding pages related to a given quiz statement.

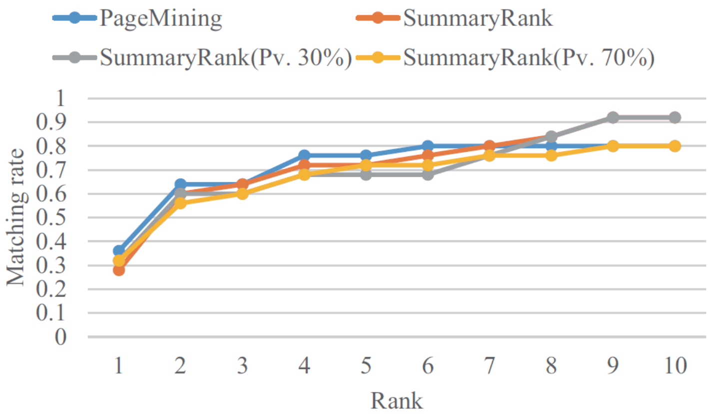

Figure 4: Cumulative Matching Characteristic (CMC) Curve. The “Pv. XX%” means students’ preview achievement rate.

Personalized Review Material

In this section, we investigate the results of review materials, which are realized by introducing the preview status of each student. By analyzing e-Book action logs, we were able to ascertain the page at which a student stopped previewing the material. The bias vector *EP* is calculated by the achievement rate of each student, that is why the review material is personalized. Due to the page limitation, we show a typical result of personalized review material consisting of 10 pages in Figure 5. For comparison, the result of related page mining (SummaryRank is not applied) is shown in the most left column. The remaining columns represent three kinds of summarized review materials. SummaryRank(Pv. 0%), SummaryRank(Pv. 30%), SummaryRank(Pv. 70%) are personalized review materials for students whose preview achievement was 0% (No preview), about 30%, and about 70% respectively. Note that we selected the paged ranked in top-10 (i.e., most reliable 10 pages), then sort the pages by the page numbering. In the figure, each page is surrounded by colored rectangle. The red color denotes the key page matched to Ground Truth. In all review materials, the most important page is contained. The green color represents pages related to the key page. These pages are helpful for students to understand the key page. Finally, the blue color means the pages which were not previewed by the students. Based on the preview achievement, the summarized review materials differ from each other. In the case of SummaryRank(Pv. 0%), the related page are surrounded by blue rectangles because the students did not preview these pages.

Conclusion

In this paper, we proposed a method to create a summary set of lecture slides to support students’ review activity. First, a quiz statement is analyzed to extract the nouns. Then, text mining is performed to find pages in the lecture materials related to the given quiz statement. The proposed SummaryRank algorithm evaluates the topic similarity among the 4 pages found in the previous step. In addition, our proposed method considers the preview status of individual students, enabling the creation of adaptive review material customized for each student. In the experiments, the proposed method could find appropriate pages with respect to the quiz statements. Further, we confirmed that the adaptive review material for each student is automatically generated by referring to the preview logs provided by the e-Book system. In future work, we will provide summarized review material to students and investigate whether or not this material is effective in enhancing understanding of the lecture. Further, a comprehensive support system will be developed by combining the summarization system for preview material proposed by Shimada et al. (2015) and that for review material proposed in this paper.

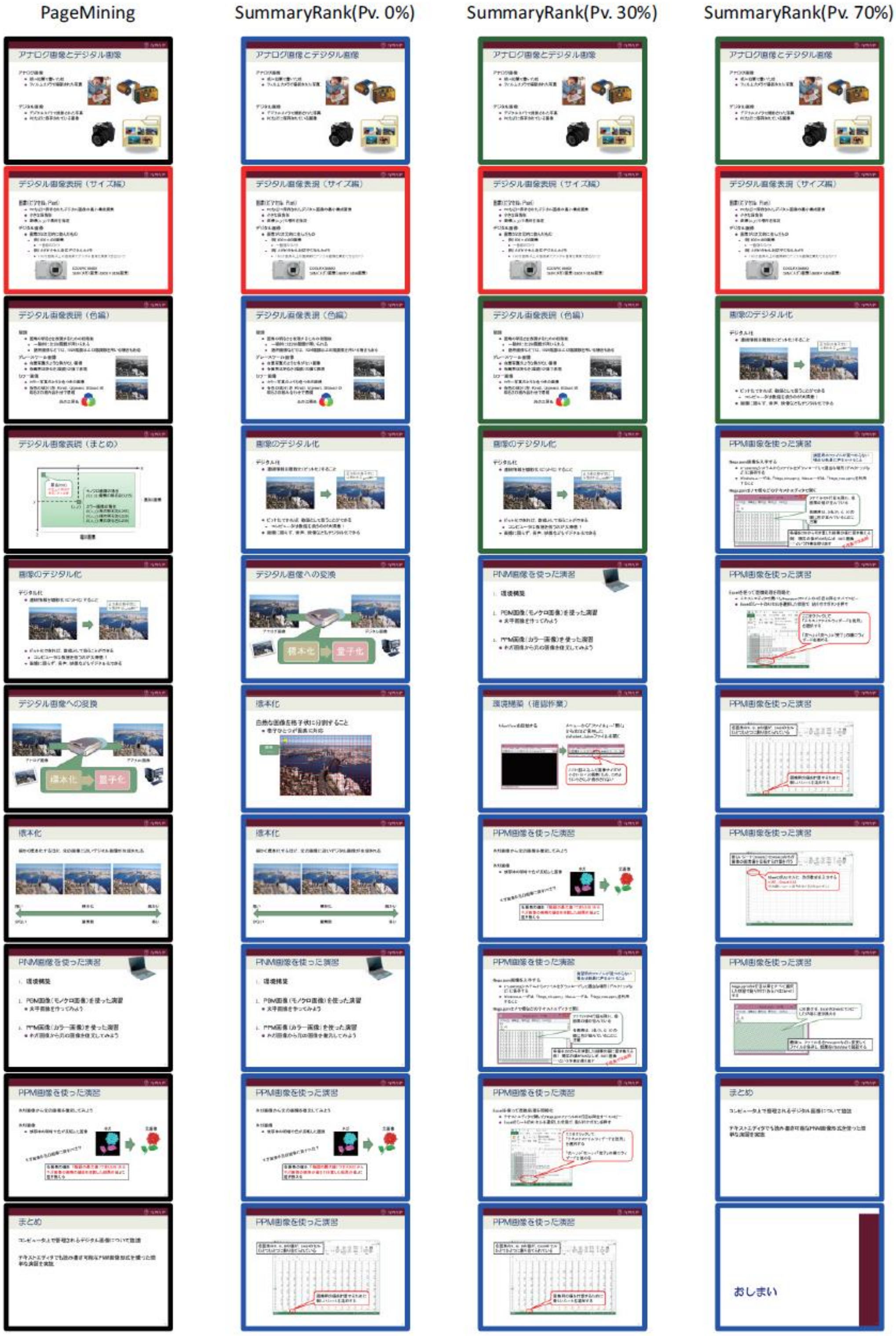

Figure 5: Examples of personalized review material. The most left column is the result of related page mining. The second, third and forth columns are Summary Rank results with respects to preview status of students. The order of each column is sorted by page numbering (it is not the ranking order). The red, green and blue rectangles denote the key page matched to Ground Truth, pages related to the core page and not-reviewed pages respectively.

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