Advanced Tools for Digital Learning Management Systems in University Education

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Abstract. This paper introduces advanced tools in the digital learning management system M2B. The M2B system is used in Kyushu University, Japan, and contains three sub-systems: the e-learning system Moodle, the e-portfolio system Mahara, and the e-book system BookRoll. We developed useful tools to help improve both teaching and learning.

Keywords: Digital learning environment · E-learning system · E-book system · Learning management system · E-portfolio system · M2B · Moodle · Mahara · BookRoll

1 Introduction

Digital learning environments enable teachers to conduct lectures online. Several effective tools are available to support these environments, including learning management systems to track students' activities, e-portfolio systems to encourage student self-reflection, and e-book systems to provide textbooks in digital form. Thanks to learning management systems, collecting large-scale data about education practices has become easier in recent years. For example, learning management systems such as Blackboard and Moodle record clickstream data when users submit reports, access materials, and complete quizzes. This data plays a crucial role in learning analytics and educational data mining.

Learning analytics is a research domain which involves collecting and analyzing data about learners and their environments in order to understand what contexts best facilitate learning and how those contexts might be created [2]. Various studies thus far have focused on learning analytics, including learning activity analysis [15], identifying at-risk students [10,14], understanding learning paths [4], pattern mining [7], performance prediction [3,5], and learning support [13]. One common characteristic of these studies is that they focus on collected learning logs but do not pay much attention to how these logs might be created. To maximize the effectiveness of learning analytics, a learning management system itself has to be well considered and well designed.

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In this paper, we discuss an advanced digital learning environment using examples from Kyushu University, Japan. Kyushu University uses the M2B learning management system, which contains three sub-systems: the e-learning system Moodle, the e-portfolio system Mahara, and the e-book system BookRoll. All students use their own laptops so they can access these systems from anywhere, either on or off campus. Students submit reports, take quizzes, access materials, and reflect on their learning activities using Moodle and Mahara. BookRoll creates reading logs by tracking activities such as when a student opens a material or turns a page. In Kyushu University, additional self-developed plugins are installed in these systems, which enabled us, among other things, to collect real-time responses from students, analyze more precise learning and teaching activities, and give quick feedback to students and teachers. The following sections of this paper present the details of the M2B system and its additional plugins.

2 Advanced Functions in M2B

2.1 M2B

In Kyushu University, the learning management system M2B was introduced in 2014. M2B's three subsystems are Moodle, Mahara, and BookRoll. BookRoll is a self-developed e-book system used for providing digital lecture materials and collecting browsing logs.

Various kinds of educational logs are collected by the M2B system. Basic logs of when students submit reports and complete quizzes, for example, are collected in Moodle and Mahara. BookRoll creates more precise learning logs about when a student opens a material or turns a page, for example.

The collected learning logs are converted into active learner points (ALPs), which are barometers of learning activities. In this study, we utilized three activities in Moodle (quizzes, reports, and logins), four activities in Mahara (highlights, memos, actions, and browsing), and one activity in BookRoll (diary length). Each activity was measured for all students and converted into one of five scores. Please refer to literature [8] for a more detailed explanation of ALPs.

2.2 Clicker Plugin for Collecting Student Responses

A clicker is a well-known device for collecting answers on quizzes and questionnaires from students in real time. We developed a clicker system plugin for Moodle (see the right-hand side of Fig. 1). In our study, we utilized the clicker plugin to collect data on seating location in the classroom in order to perform relationship analytics between learning activities and where students sat. The classroom, which contains about 240 seats, is divided into 12 subareas, and the M2B system keeps track of which students are seated in which area so that we may analyze the correspondence between seating areas and clicker responses.

Figure 2 is the visualized result of seating changes over 14 weeks. The horizontal axis represents the i-th week, and the vertical axis represents the individual

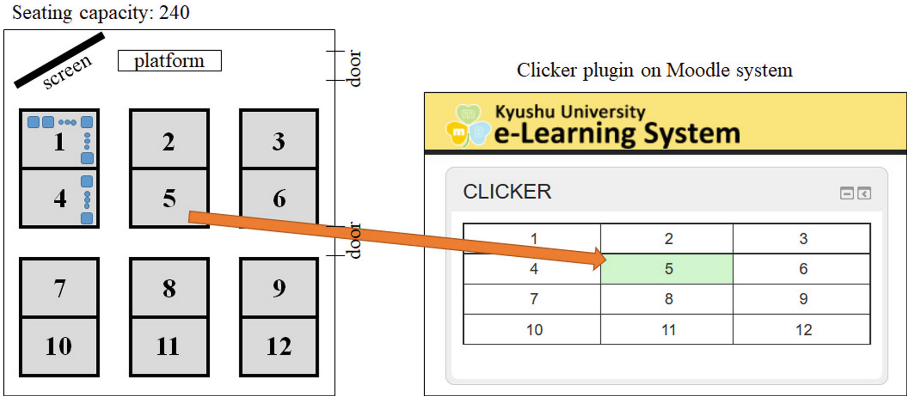

Fig. 1. Left: top view of the classroom. About 240 seats are available in the classroom. The classroom is divided into 12 areas to collect the seat area of students. Right: clicker plugin on Moodle system. Students answer their seat area by clicking the corresponding area number.

student. Therefore, a single row shows the seating changes of a single student. The color of each cell corresponds to the color map on the bottom part of the figure. The gradient from darker to brighter colors represents seating areas #1 through #12. Figure 2 shows that most students did not change seats very much; they sat in the same or nearby seats over several weeks. On the other hand, some students frequently changed seats week by week. Such students were more likely to be absent from class.

We analyzed the relationship between seating areas and ALPs. Through experiments with about 200 students over 14 weeks, we found that seat location has a strong correlation to learning activities. Overall, we can see that the scores of students seated in the front areas (from #1 to #3) are higher than those of students in the back areas (from #10 to #12). This result suggests that students seated in the front of the classroom had higher activity levels than those in the back. For more details on seating area analytics, refer to literature [12].

2.3 Recommending Related Content in Lecture Materials

Recommending related content when presenting lecture materials is effective for promoting deeper understanding in students. We developed a plugin for BookRoll which provides web links to related websites on each page of lecture materials. Figure 3 shows the overview of the recommendation system. The system consists of the e-book system, three databases, and a program which recommends related content. Each database stores the e-textbooks used in lectures, their recommended supplementary teaching materials (STMs), and e-book activity logs. The system flow is as follows: First, teachers register e-textbooks in the database via BookRoll. Next, the recommendation system analyzes the e-textbooks and identifies STMs corresponding to each page. That related

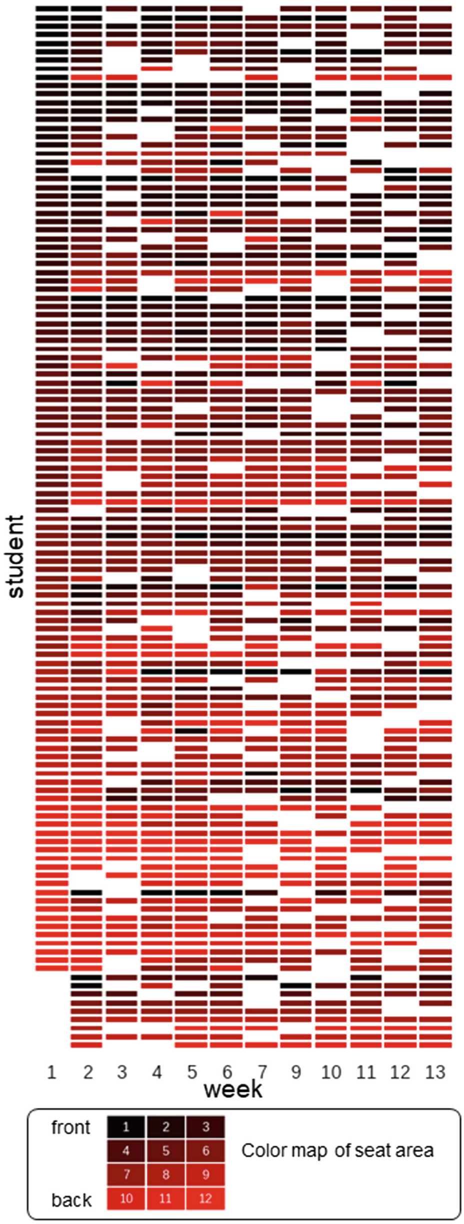

Fig. 2. Area transition over 12 weeks. The 8th week and 14 week are removed because of examination weeks. The row corresponds to each student. From top to down, and from 1st week to 13 week, the seat area is sorted by the area number.

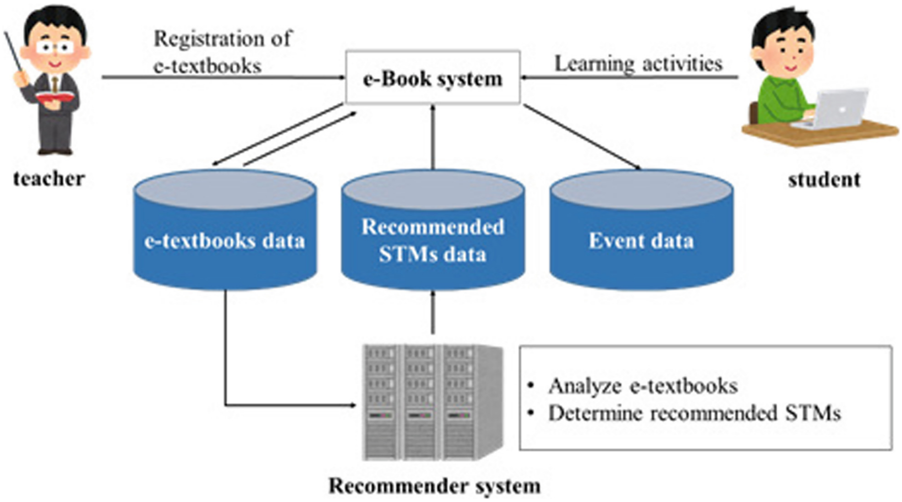

Fig. 3. Overview of recommendation system

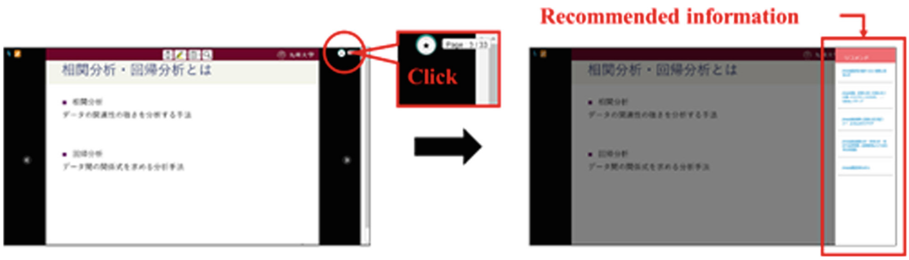

Fig. 4. Overview of recommendation system

content is then stored in the database. When a teacher conducts a lecture using BookRoll and students open the e-textbook during the lecture, the students can access the STMs as necessary (Fig. 4).

The web links are automatically generated by analyzing the contents of the lecture materials. A text mining approach discovers important keywords throughout the lecture as well as page-specific keywords. In each page of lecture material, the most important keywords are used for web searching, matching keywords to the titles of retrieved websites. Good matches are automatically registered as web links directly on the corresponding pages of lecture material. We conducted preliminary experiments using the recommendation plugin and got positive responses from students.

Figure 5 shows the number of clicks on the recommended STM links for each page of the e-textbook. It is apparent that there were numerous clicks on and around page 32 of the e-textbook. During the lecture, the contents of page 32 and its surrounding pages were not explained. Instead, students were given time to browse the pages themselves. It can be assumed that the reason the number of clicks increased here is that students learned by exploring the recommended STMs rather than the lecture itself. In addition, since there were many clicks on pages that contain exercises or pages with difficult contents, it can be assumed that recommending supplementary information on each page is useful for supporting learning. For more details on recommending related content, refer to literature [6].

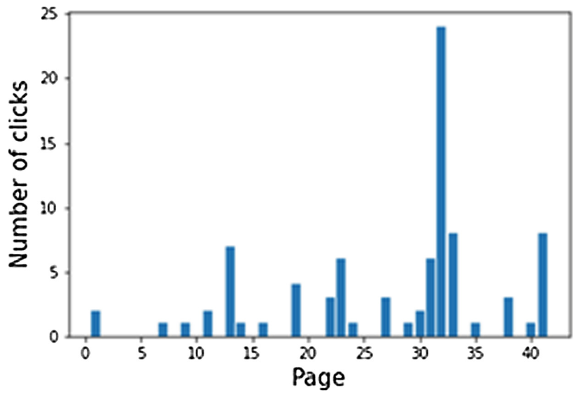

Fig. 5. Number of clicks on recommended information about each page

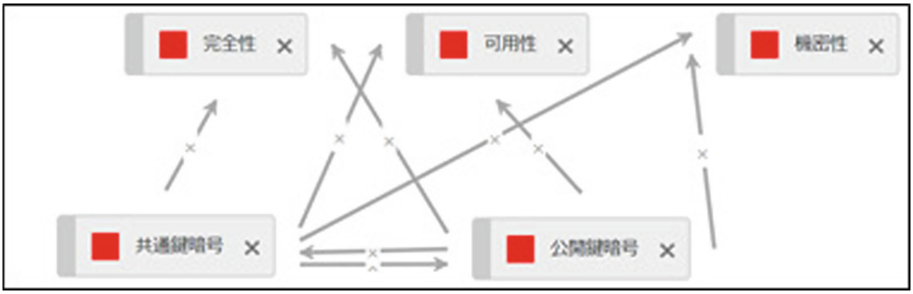

Fig. 6. Example of BR-Map

2.4 Concept Maps for Learning Reflection

Tools which assist cognitive learning? in particular, concept maps and knowledge maps? enhance awareness and comprehension of important concepts, ideas, and relationships. Integrating a concept map creation tool driven by student input can promote learning and support learning analytics in investigating the process of comprehension. Our study aims to develop a visualization tool which aggregates input logs and constructs concept maps in order to make teachers and students aware of potential areas for improvement. We developed a concept map

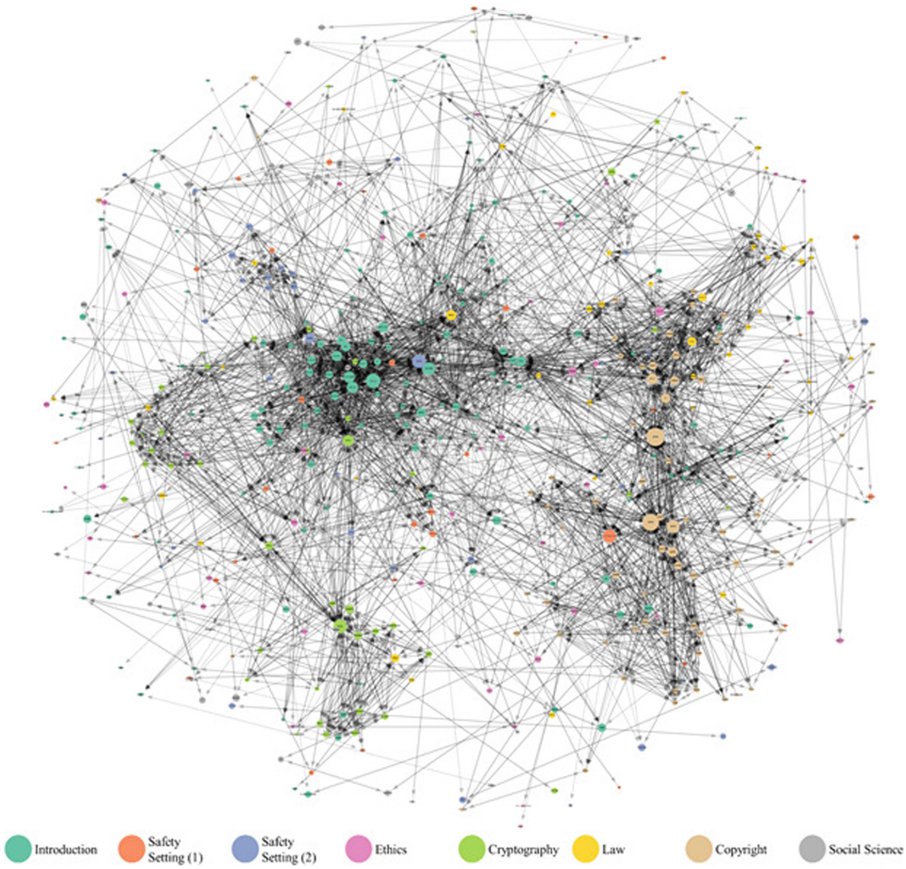

Fig. 7. The integrated knowledge map of all nodes

tool called BR-Map which integrates with BookRoll to support the generation of concept maps.

In our study, BR-Map [16] used logs from BookRoll to create concept maps in this way: First, a learner reads an e-book and highlights words or sentences which he or she finds interesting, important, or difficult. The highlighted words and sentences become candidates for nodes in the BR-Map. Finally, the learner creates their own concept map by arranging the nodes on a canvas and drawing links between nodes as shown in Fig. 6.

The words in the nodes of the BR-Map are automatically extracted from the e-book by referring to the words the learner highlighted. Ideally, each node should have one keyword representing a single knowledge point. However, some nodes have a sentence (or a set of words) because the learner highlighted a complete phrase. For example, one learner highlighted the sentence "Cybersecurity is the protection of computer systems," and another highlighted the keyword "Cyber-

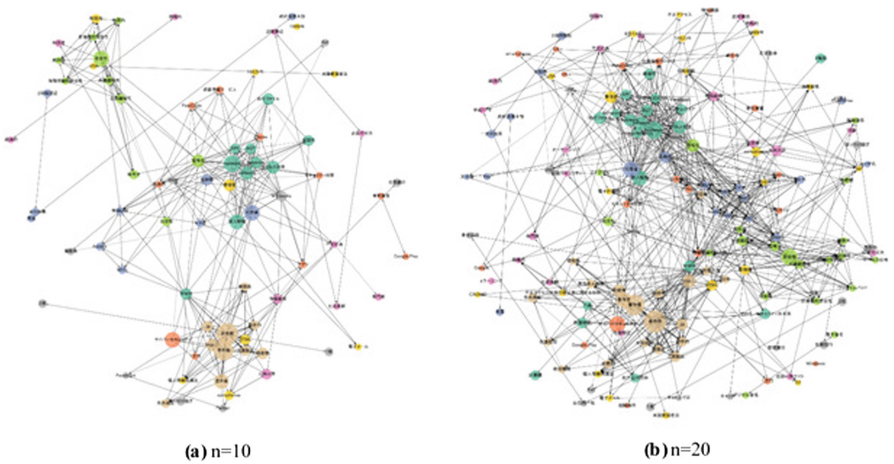

Fig. 8. The integrated knowledge maps of the top n important nodes at each lecture

security." These highlights are differentiated as separate nodes on the concept map. Therefore, we have to perform a text mining process to identify shared keywords in sentences. There are two steps to determining nodes in the concept map. For a detailed methodology of concept map analysis, refer to literature [9].

In our experiments, students drew their concept maps after eight weeks of lectures. We performed an integrated analysis of the concept maps to explore which keywords (nodes) many students had interest in. The concept map (see Fig. 7) shows the relationships between the contents of each lecture. There is a trade-off between readability of the content and the number of nodes. In order to evaluate the level of readability, we presented five kinds of concept maps, which are visualized as different numbers of important nodes (Figs. 7 and 8). The size of the node is proportionate to its level of importance. A larger-sized node represents an important node, which means that many learners drew links to or from the node. Additionally, the node's color corresponds to the lecture in which that word was frequently used. Furthermore, the thickness of the lines connecting the nodes represents the number of links that the learners drew. The thicker the line, the more times learners drew it. We found that important keywords are bridged not only within a lecture but also across lectures.

2.5 Real-Time Visualization of E-Book Reading Logs

Real-time feedback helps teachers know where student's attention is during lectures. We utilized Moodle and BookRoll to collect real-time data regarding learning activities during lectures. We developed a real-time analytics graph using student's BookRoll activity logs which performed analytics in real time and displayed how many students were following the teacher's explanation, which helped the teacher control his or her lecture speed.

During the lecture, as the teacher explained the content of the materials, students browsed the materials on their laptops. In our university, students are asked to open and browse the same page as the teacher and to highlight or add notes on the important points. During the lecture, learning logs were sequentially collected and stored. The analyzed results were immediately displayed on the web interface, as shown in Fig. 6, and updated every minute. Therefore, the teacher was able to monitor the latest student activity. The visualization included real-time information regarding how many students were following the lecture, how many students were browsing previous pages, and so on. The teacher adaptively controlled the speed of the lecture according to what he or she saw on the graph. For example, if many students were not following the lecture and were still on the previous page, the teacher slowed down the lecture. For detailed information about this graph's implementation, refer to literature [11] (Fig. 9).

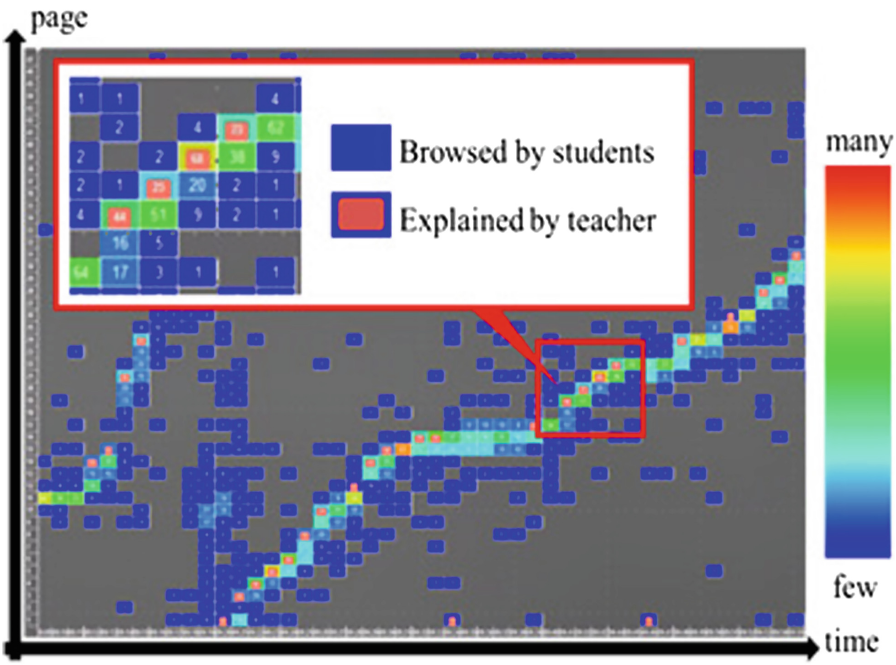

Fig. 9. Real-time heat map of browsed pages. The horizontal axis is the time of day and the vertical axis is the page number. A column corresponds to the distribution of the number of students browsing each page. The page explained by the teacher is highlighted by a red colored rectangle. The heat map is automatically updated minute-by-minute.

3 Conclusion

In this paper, we described the advanced digital learning environment M2B as used in Kyushu University, Japan. We developed and implemented four useful tools in this system: a clicker plugin to monitor how student seating areas affect learning, a recommendation tool for integrating supplementary content into e-books, a concept map tool to visualize each student's chosen focus areas, and a real-time graph of student's browsing activities. We will continue to develop new tools for the purpose of improving education in digital learning environments. The latest information on our research is available on our website [1].

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