Analyzing Frequent Sequential Patterns of Learning Behaviors in Concept Mapping

Shang Wang
School of Computing, Informatics, and Decision Systems Engineering
Arizona State University, Tempe AZ, USA
swang158@asu.edu

Erin Walker
School of Computing, Informatics, and Decision Systems Engineering
Arizona State University, Tempe AZ, USA
Erin.A.Walker@asu.edu

Ruth Wylie
Mary Lou Fulton Teachers College
Arizona State University, Tempe AZ, USA
Ruth.Wylie@asu.edu

ABSTRACT

Computer-based concept mapping learning environments can produce large amounts of data on student interactions. The ability to automatically extract common interaction patterns and distinguish between effective and ineffective interactions creates opportunities for researchers to calibrate feedback and assistance to better support student learning. In this paper, we present an exploratory workflow that assesses and compares student learning behaviors with concept maps. This workflow employs a sequential pattern mining technique to classify interaction patterns among students and determine specific behavior patterns that lead to better learning outcomes.

Keywords

Data mining, sequential pattern mining, student behavior, concept mapping.

1. INTRODUCTION

Concept maps are visual representations of knowledge, with concept nodes representing concepts in the knowledge structure and links denoting relationships among concepts. Concept mapping has been widely used as an active learning tool in educational contexts and research has shown the positive effect of concept mapping in helping students organizing and summarizing knowledge [1][2]. One of the main disadvantages of concept mapping is the complexity of the task. Learners who lack expertise often feel overwhelmed and de-motivated [3].

To facilitate students in concept map construction, we designed a personalized and interactive concept mapping learning environment integrated within a digital textbook. Students are able to create maps directly from the textbook, which allows them to better relate concepts with the textbook content. The system offers a hyperlinking navigation feature where, after creating the concept map from the textbook, students are able to click on the concept nodes and navigate to where these nodes were added from the textbook. We hypothesize that this feature supports learning by offering flexibility in comparing and finding connections between concepts that are located in different pages,

To examine the effect of interactive concept mapping learning environments, we have conducted a week-long study with 32 high school students using the system as a substitute for a paper-and-pencil based concept mapping activity while they learn about their current science textbook chapter. Students in the study were randomly assigned into two conditions: A hyperlinking condition, where nodes in the concept maps were hyperlinked with the textbook, and a non-hyperlinking condition. Pre and post tests were given before and after the study to measure learning outcomes.

This paper explores the use of data mining methods to systematically build and analyze models of student behaviors as they interact with our concept map environment. This paper approaches student modeling by analyzing similar and different behavior patterns between various types of student groups.

2. WORKFLOW METHOD

2.1 Data Inputs

The raw data are xml files, where each item in corresponds to a specific action performed by students on the system. There are 8 fields of information being logged in each student action.

1. *Student ID*, identifying the student interacting with the system.
2. *Session ID*, denoting the session of the study.
3. *Time*, recording the time stamp of the action.
4. *Time zone,* indicating the time zone of the system.
5. *Selection*, representing where student is interacting with. For example, concept map view, textbook view, etc.
6. *Action*, denoting the specific student action. For example, adding a concept node from the textbook, navigating to a new page, linking two concepts, hyperlinking navigation, etc.
7. *Input*, representing the input of the action. For example, an input for adding a concept from the textbook would be "root" and an input for navigating to a new page would be "page 5".
8. *Page number*, indicating the text page when the action is performed.

These raw data are generated in real-time and are sent to a server after each session for further analysis.

Apart from the log files, we also use pre and post test results and final concept maps for analysis. Pre and post tests consist of 30 multiple choice questions. The test results can be used to classify students into high and low performance groups and help us determine specific behavior sequences that distinguish the better groups from the weaker ones. Similarly, the concepts created by students enable us to understand how different behavior patterns affect concept mapping.

2.2 Workflow Model

Action abstraction is the first step of our workflow, in which we categorize a specific sequence of low granularity actions into aggregated actions that indicate specific learning behaviors. This step filters out irrelevant information and combines qualitatively similar actions (Table 1). For example, a student might flip 10 pages in the textbook quickly when searching for certain sections in the textbook. Instead of analyzing these 10 navigation actions separately, we consider them as one aggregated action called "Quick Search" (QS).

Aggregated Behavior	**Log Action**
Quick Search (QS)	Students flip several pages quickly to go to a specific page
Long Stay (LS)	Students don't perform any actions for a long period of time
Read and Add (RA)	Students read the textbook and add a concept node into the concept map
Read and Link (RL)	Students read the textbook and link two concepts in the concept map
Add and Link (AD)	Students add a concept node to the concept map and quickly link it to another node
Read and Delete Node (RD)	Students read the textbook and delete a node from the concept map
Hyperlinking Navigation (HN)	Students click on a concept node to navigate to the page where it's created
Back and Forth (BF)d	Student navigate between a few pages back and forth within a short period of time

Table 1. Student actions and aggregated behaviors

We classify all the student actions into 8 aggregated student behaviors, which are easier for sequential pattern mining and student modelling. For example, a back and forth (BF) behavior could be an indication that the student is comparing two linked concepts in the concept map. A long stay (LS) behavior might suggest that the student is spending a lot of effort reading the textbook or distracted and not motivated.

After this classification, we apply sequential pattern mining techniques to extract interesting behavior patterns. Research in the literature has applied sequential pattern mining techniques to a variety of educational data. Perera and colleagues showed the importance of leadership and group interactions towards learning success using k-means clustering to find groups of similar teams and similar individuals, and employing a modified version of the Generalized Sequential Pattern (GSP) mining algorithm to extract student behavior patterns [4]. Martinez *et al*. applied clustering and sequential pattern mining techniques to determine the sequences of actions that characterize high-achieving and low-achieving learners [5].

In our workflow, we plan to use sequential mining techniques to identify the frequent sequential patterns from the two conditions for further analysis.

2.3 Workflow Outputs

The first output from the workflow model is a list of sequential patterns extracted from the log files depending on the *minsup*. These patterns represent frequent student behaviors that occurred during the concept mapping task. After extracting frequent behavior patterns, we further cluster these patterns based on different student groups.

1. *Hyperlinking and No-hyperlinking:* Comparing sequential patterns between hyperlinking and non-hyperlinking conditions suggests how hyperlinking navigation affects student behaviors.
2. *High performance and low performance*: Comparing frequent patterns in these two conditions identifies certain behavior patterns that distinguish better learning groups than the lower ones.
3. *Better concept maps and weaker concept maps*: Comparing sequential patterns in these two conditions would help us understand how behavior patterns affect the final concept maps created by students.

3. DISCUSSION

We present a workflow that first creates aggregated behaviors from the log files and then applies sequential pattern mining to extract behavior patterns from various conditions. Comparisons of student behaviors between the hyperlinking and non-hyperlinking condition would help us understand how the hyperlinking feature affects student navigation. Questions like does the navigational flexibility in the hyperlinking condition yield more comparison between concepts located in different pages in the textbook would be interesting to explore. Comparisons of student behaviors between different types of student groups would help us examine specific behavior patterns that lead to high learning outcomes and better concept maps, which provides opportunities for researchers to develop feedback or scaffolding methods to support these behaviors. This work opens doors for teachers or automated systems to intervene and provide feedback more appropriately. It also enables researchers to develop concept mapping learning environment that offers automation to replace the ineffective behaviors while preserving and supporting behaviors that yield better learning outcomes.

4. ACKNOWLEDGMENTS

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