Towards Understanding Learning Behavior Patterns in Social Adaptive Personalized E-Learning Systems

Research in Progress

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ABSTRACT

Implicit user modeling has always long since played an important role in supporting personalized web-based e-learning environments and is increasingly important in other learning environments such as serious games. Its main concern is to unobtrusively and ubiquitously learn from a learner's previous experiences and characteristics, in order to adapt the services to their personal needs. An empirical investigation for understanding learning behavior patterns forms the basis for establishing stronger implicit user modeling mechanisms and this study aims to get a better insight into types of learning behavior. The proposed usage of data mining and visualization elicited some interesting *learning behavior patterns*. We analyzed these from two perspectives: *action frequency* and *action sequences*, based on an expert-designed classification of behavior patterns that helped rank the various action categories according to significance from a user's perspective. The initial results of the study are promising and suggest possible directions for further improving implicit user modeling.

Keywords

Adaptive hypermedia, implicit user modeling, learning behavior pattern, educational data mining, data, e-learning, games.

INTRODUCTION

Adaptive Educational Hypermedia (AEH) is one of the most popular research areas of Adaptive Hypermedia System (AHS) (Brusilovsky, 1996). It combines AHS and Intelligent Tutoring Systems (ITS), with the aim of breaking away from the "one-size-fits-all" mentality (Brusilovsky, 2012), engaging learner interaction as well as enabling e-learning systems to adapt to different learners' specific needs in a given context, and thereby provide a personalized learning experience for each learner. The issue of personalization is not only relevant for hypermedia but also for other e-learning media such as Serious Games, which are often engaging and motivating. The trend towards personalization in Serious Games is a surprisingly recent one (Peirce, Conlan, and Wade). The process of creating and maintaining the leaner's specific needs is known as user modeling (Brusilovsky and Millán, 2007), which either explicitly gather or implicitly obtain learner information during user-system interaction. Using an implicit approach, an AEH system can track learning behaviors unobtrusively and ubiquitously, infer unobservable information about the learner from observable information, and update a learner's user model. A range of educational benefits brought about by implicit user modeling is thoroughly discussed in the literature (e.g., Drachsler, Hummel and Koper, 2008; Farzan and Brusilovsky, 2006; Germanakos, Papatheocharous, Belk and Samaras, 2012; Mulwa, Lawless, Sharp, Arnedillo-Sanchez and Wade, 2010; Paredes and Rodriguez, 2004). Implicit user modeling is, by its nature, analyzing a sequence of specific actions, to discover and infer new knowledge based on a learner's usage data, to establish a personalized pattern, or patterns, of successful learning experiences. However, limited research is available on such learning behaviors and learning activity patterns in AEH systems.

Data mining or knowledge discovery in databases (KDD) is a process of analyzing and extracting knowledge from data contained within a database (Roiger and Geatz, 2003). Researchers have started exploring various KDD methods to improve e-learning systems (e.g., Jovanovic, Vukicevic, Milovanovic and Minovic, 2012; Khribi, Jemni and Nasraoui, 2008; Li and

Zhang, 2010) since 2006 when the first few publications on educational data mining (EDM) appeared (Winters, 2006). Evidently, EDM has great potential and it is particularly useful for the improvement of e-learning systems, but most researchers focused on the development of data mining algorithms rather than empirical analyses of e-learning systems (Hung and Zhang, 2008). Typical patterns of accessing an AEH system and the interaction information contained in these patterns can be logged in a database via implicit user modeling. In this context, EDM is able to recognize regularities in learner trails as learning behavior patterns and to integrate them into the user model. The structured descriptions of these regularities, as the output of EDM, can be used for explaining the original data and to make predictions.

One of the key questions in EDM is to find out which learning data needs to be analyzed and what learning behavior patterns can be captured, in order to implement and enhance adaptive educational services (Frias-Martinez, Chen and Liu, 2006). This could be achieved by using data visualization techniques. The objective of the analysis and visualization of data is to highlight useful information and support decision-making. Statistics and visualization are the two main techniques that have been most widely used to analyze students' online course activities and usage information (Romero and Ventura, 2010). In conjunction with data mining, data visualization refers to data presentation, and thereby new patterns can be discovered more easily, and it can also provide a clearer understanding of the discovered patterns (Shaw, Subramaniam, Tan and Welge, 2001; Turban, Aronson, Liang and Sharda, 2007). To represent learning behavior data and explore the learning behavior patterns, we utilized the combination of data mining methods and data visualization tools, so that we could be directly involved in the data mining process, gain insight into the data and come up with new discoveries (based on Keim, 2002).

This paper presents our recent attempt to discover learning behavior patterns in AEH systems, in order to provide suggestions on further development and improvement of implicit user modeling. The novel contributions of this study are: 1) conducting an empirical investigative study using data mining methods and visualization tools to understand learning behavior data and explore learning behavior patterns in AEH systems; and 2) identifying possible directions to improve implicit user modeling for AEH systems. This paper is organized as follows. Firstly, we introduce *Topolor*, a social adaptive personalized e-learning system (Shi, Al Qudah and Cristea, 2013) as the experimental environment, focusing on its learning behavior tracking mechanisms. Secondly, we present the experimental setup including participant information. Thirdly, we elaborate on the analysis of the experimental results using data mining methods and visualization tools. Finally, we conclude and discuss our discoveries, and suggest future research directions.

TOPOLOR

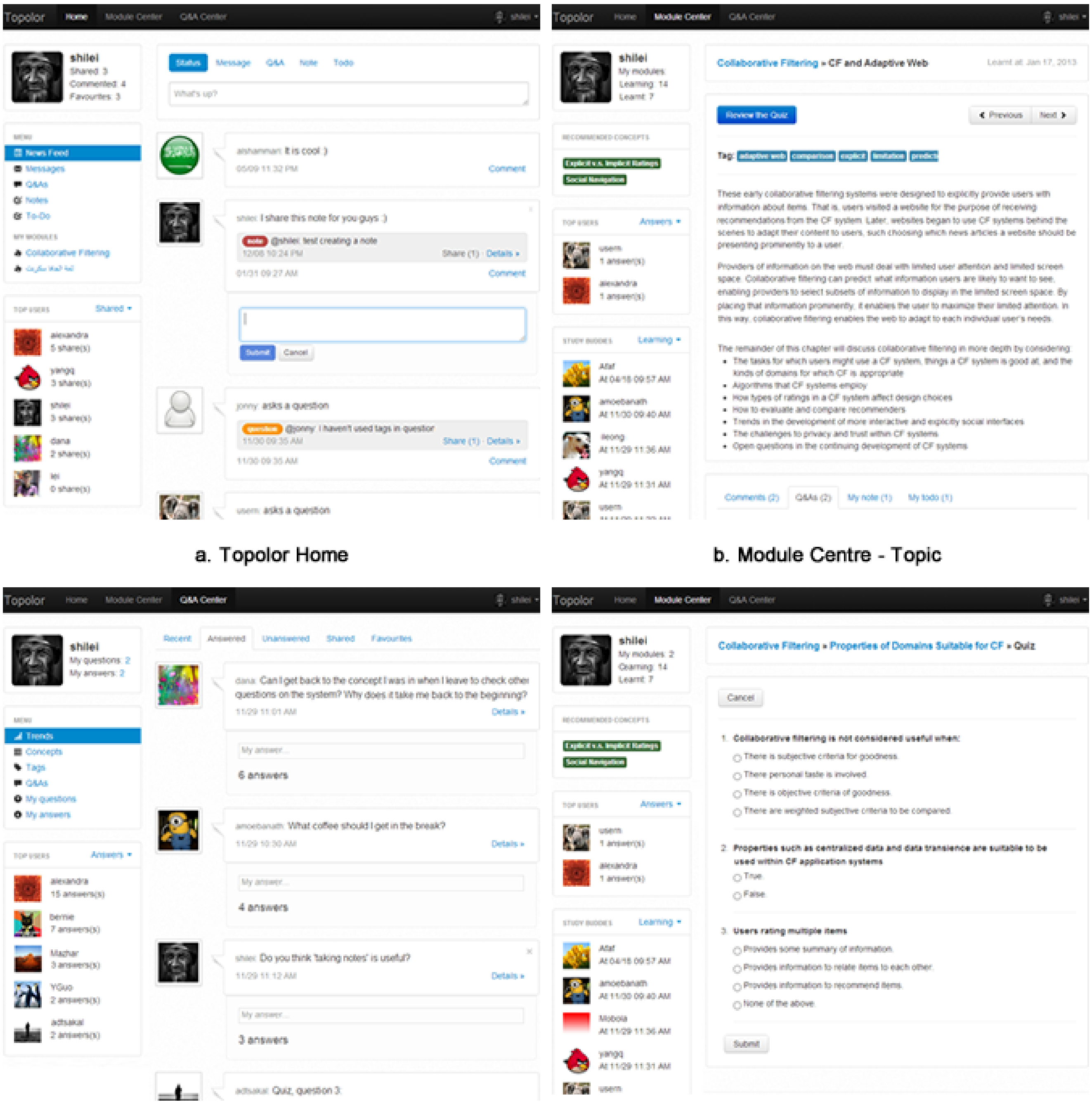
Topolor is featured as a social adaptive personalized e-learning system (Shi, Al Qudah, Qaffas and Cristea, 2013a). It is built on Yii[1] and Bootstrap[2], and hosted on Github[3] for open source sharing and version control. The first version of Topolor (Shi, Gkotsis, Stepanyan, Al Qudah and Cristea, 2013) was launched in November 2012, and has been used as an online learning environment for MSc level students in the Department of Computer Science, at the University of Warwick. We have conducted an experiment to evaluate the social interaction features in Topolor (Shi, Stepanyan, Al Qudah and Cristea 2013; Shi, et al, 2013b). The evaluation results showed high system usability from a student's perspective. The registration for using the system has been recently opened to the general public, with the expectation to collect a larger cohort of user feedback and usage data for system improvement and further research. Topolor's design is based on the hypothesis that *extensive social features, personalized recommendations and Facebook-like appearance of a system, anticipated to make the environment more familiar to students, will subsequently increase the usefulness and usability of the system*. Topolor is under iterative development, and its latest version can be downloaded for free from Github (https://github.com/aslanshek/topolor). As shown in Figure 1, Topolor mainly consists of three sub-systems. Their features are briefly described below.

- *Topolor Home* (Figure 1a) provides a chronological list of the learning statuses posted by individual learners. It also provides access to a set of interaction tools that encourage informal communication and collaboration such as commenting on, sharing and favoring of learning statuses.
- *Module Center* (Figure 1b and 1d) offers a warehouse of online courses, as well as provides adaptive learning topic recommendations, learning peer recommendations and interaction tools that encourage personalized social learning, such as sending messages to recommended peers. Besides, learners can take either tests for whole modules, or quizzes for single learning topics.

1 http://yiiframework.com
2 http://twitter.github.com/bootstrap
3 https://github.com

- *Q&A Center* (Figure 1c) maintains several lists of questions & answers related to learning topics, as well as providing adaptive question recommendation, learning topic recommendation, expert peer adaptation and social interaction tools for discussions and practices.

In Topolor, the user-system interaction information logging mechanism can be switched *on* for experimental purposes or *off* for normal use. When it is switched on, Topolor is able to track every single action, for example, clicking on a button, of learners with a timestamp and store it in the database. The log data tuple is *<user_id, controller, action, type, request, create_at>*. A typical value of the tuple is *<12, "concept", "view", "GET", "id=20", "2012-11-29 10:20:30">*, meaning at 10:20:30, November 29th 2012, the learner (id=12) accessed a topic page, which taught the learning concept with id 20. Note to address student privacy concerns there is no way to identify who 'learner 12' is in reality; as such the data is anonymous.



a. Topolor Home

b. Module Centre - Topic

c. Q&A Centre

d. Module Centre - Quiz for a Topic

Figure 1 User Interface of Topolor

EXPERIMENTAL SETUP

The experimental study was conducted with the help of 21 students from the Department of Computer Science at the University of Warwick, who were registered for a fourth year MSc level module called ‘Dynamic Web-Based Systems’. The students were asked to learn an online course on “collaborative filtering” using the system. Before accessing the online course, a ‘to-do list’ was handed out to the students, to make sure they have a reminder of all actions at their disposal. The order of doing the actions, as well as if to undertake or repeat any actions was up to them. The online course lasted for 2 hours. During the 2 hours session, a logging mechanism kept track of each of the student’s actions.

RESULTS AND ANALYSIS

After the learning session, we analyzed the learner actions extracted from the log data stored in the database. The log data contained all the information about a user’s system interaction over the 2 hours experimental session. The goal of this experimental study was to discover the following two types of learning behavior patterns within the log data:

- *Action frequency* – action frequency represents the frequency with which a student performed a type of action during the two hours session. It might reveal the students’ different participation and engagement level. It might also suggest the likeness and perceived ease of use of the provided features.
- *Action sequence*– an action sequence is a chronologically ordered set of actions. It would be useful to observe a list of action sequences, in order to investigate their similarities and differences for different students. We were hoping to find individual action sequence patterns as well as common action sequence patterns.

Out of these 21 students, 4 students had performed less than 10 actions, and 1 student had performed only the social interaction actions. After the exclusion of these 5 students, the remaining 16 students’ actions, adding to a total sum of 2175 actions (with an average of 136 actions and a standard deviation of 71 actions per student) were analyzed.

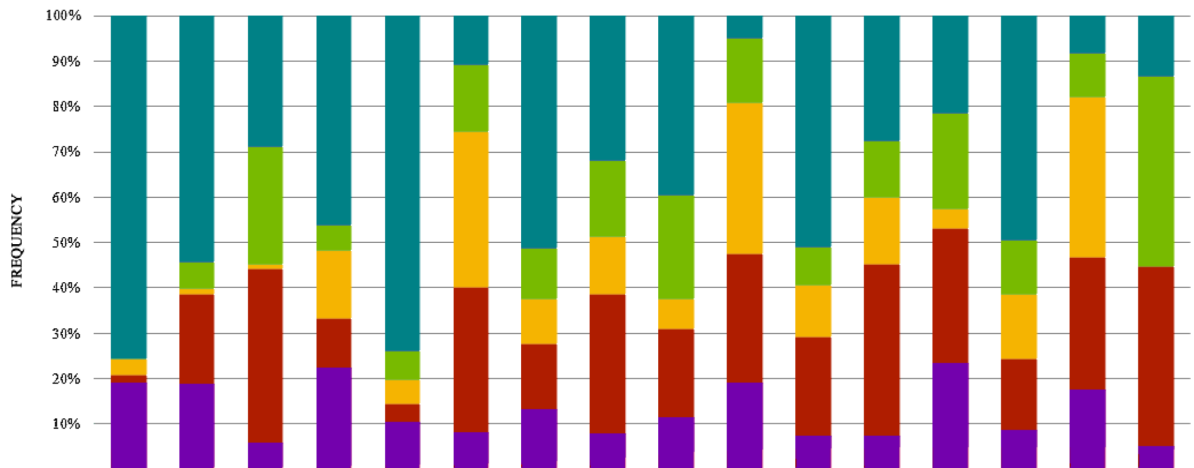
In total, 41 different types of raw actions were identified from the log data. To simplify the visualization, observation and analysis, the actions extracted from the log data were annotated following an expert designed higher-level categorization dividing actions into: a) **assessment**, b) **auxiliary**, c) **social interaction**, d) **navigation**, and e) **reading**, as shown in Table 1.

Category	Actions
Assessment	Create a quiz, submit a quiz, review a quiz;
Auxiliary	Create / view / update / delete a note, filter notes, view the note list; Create / view / update / delete a to-do, filter to-dos, view the to-do list; Claim “I’ve learnt the topic”;
Social Interaction	Create / view / update / delete a question, filter questions, view the question list; Create / update / delete an answer to a question; Create / view / update / delete a learning status, view the status list; Comment on / favorite / share a learning status; Send a message, view the message list; Comment on / favorite a topic;
Navigation	View the module list; View the topic list, filter topics;
Reading	View a topic page.

Table 1 Learner Actions Tracked and Logged

Action frequency

The *100% stacked column chart*, shown in Figure 2, displays the proportion of each categorized actions performed by each student. The cumulative proportion of each categorized action totaled 100%. The stacked columns were applied to all students and horizontally listed in the chart. The chart was used to analyze **action frequency** patterns of the students. Each column represents a 2 hours session and the colored blocks mean the specific categorized actions taken by the student. We can see from Figure 2, that the most frequent actions were **social interaction** actions (i.e., question & answer, message, share, comment, etc.), followed by **reading** actions (i.e., viewing a topic page). This was to be expected, as the students were to focus on learning topics (**reading** actions) – as the core objective of using the e-learning system, and interacting (**social interaction** actions) with each other when learning a topic. All students took **navigation** actions, because they were recommended related topics and they could also find interesting topics using filtering tools, so that they could switch between different topics. Not all students took **assessment** actions (i.e., quiz), or the **auxiliary** actions (i.e., note, to-do, etc.). This might be because they were considered minor features.



Student	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16
Social Interaction	123	92	57	80	219	13	46	64	24	3	90	41	10	79	5	5
Auxiliary	0	10	52	10	19	18	10	34	14	9	15	19	10	19	6	16
Assessment	6	2	2	26	16	42	9	26	4	21	20	22	2	23	22	0
Reading	3	34	76	19	12	39	13	62	12	18	39	57	14	25	18	15
Navigation	31	32	12	39	31	10	12	16	7	12	13	11	11	14	11	2
Total actions	163	170	199	174	297	122	90	202	61	63	177	150	47	160	62	38

ACTION

Figure 2 Action Frequency of Each Student

Another interesting observation from Figure 2 is the difference between each student's participation and engagement. During the same 2 hours session, the action frequencies of different students were very different, from the maximum 297 actions to the minimum 38 actions. We examined the correlation of the number of total actions and the proportion of the 5 categories of actions, but unfortunately there was no significant correlation between them. However, we found some (positive and negative) correlations between the proportions of the categorized actions. For instance, as shown in Figure 3, the proportions of **auxiliary** actions and **reading** actions were positively correlated (the strongest positive correlation that we found). We assume the reason was that if the students viewed more topic pages (**reading** action), they would have more chance to, e.g., claim 'I've learnt the topic' (**auxiliary** action). The negative correlation that we found included those between **auxiliary** actions and **social interaction** actions, **auxiliary** actions and **navigation** actions, etc. However, the negative correlations were relatively weak. Besides, the positive correlation between the proportions of **auxiliary** actions and **reading** actions is also consistent to the observation from Figure 4 that represents the high proportion of claimed learnt topics among all the viewed topic pages (184/212, i.e., 87%). This suggests that the students liked directly manipulating their user models. Therefore, it may be necessary to support this service more fully. For example, providing a button and allowing the students to click on it to proactively state their feelings about the topics' and quizzes' difficulties, or claim their confidence of the topics and questions so that they can be recommended as expert learning peers to be contacted and discussed with.

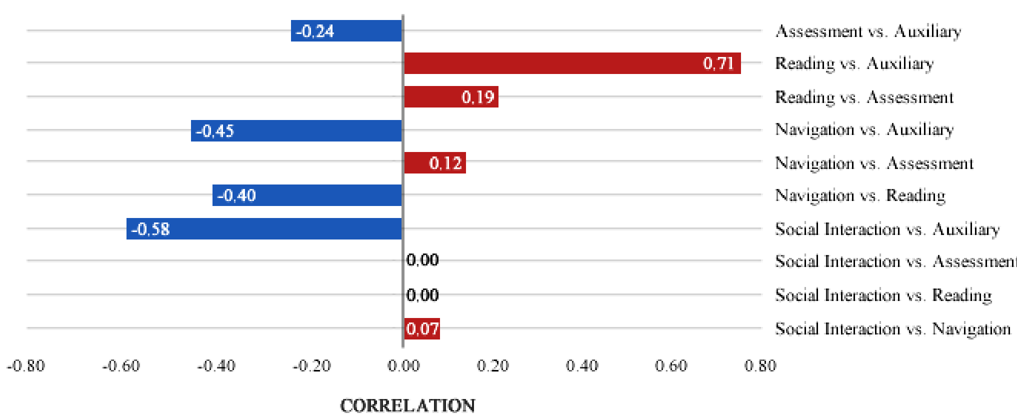


Figure 3 Correlation of Action Proportion

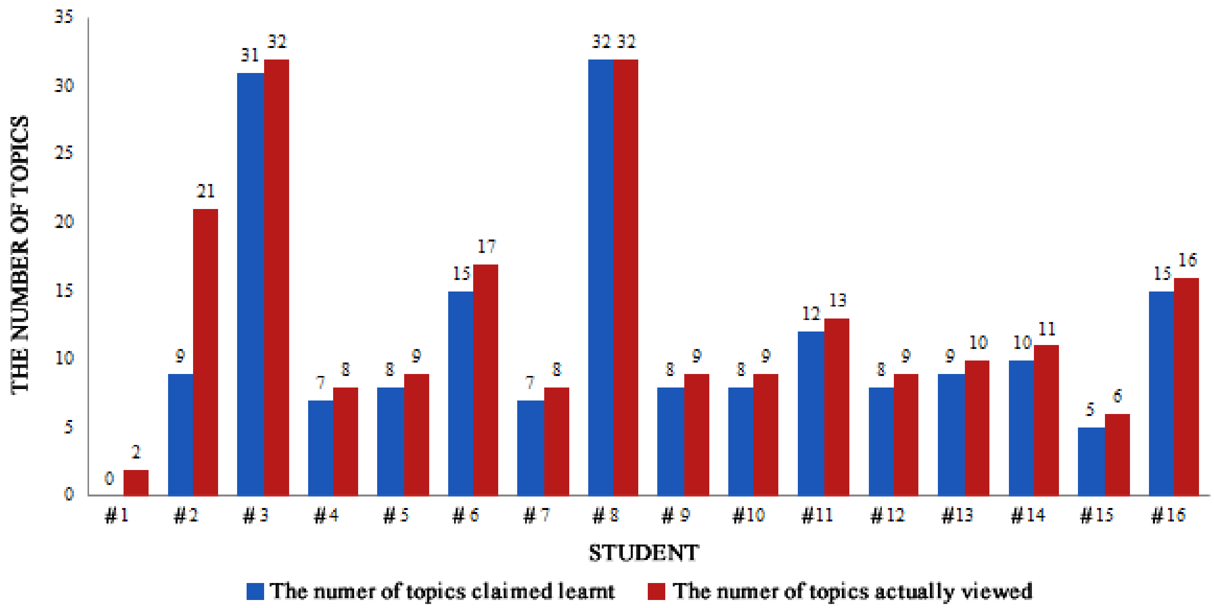


Figure 4 the Comparison between the Number of Topics Claimed Learnt and the Number of Topics Page viewed

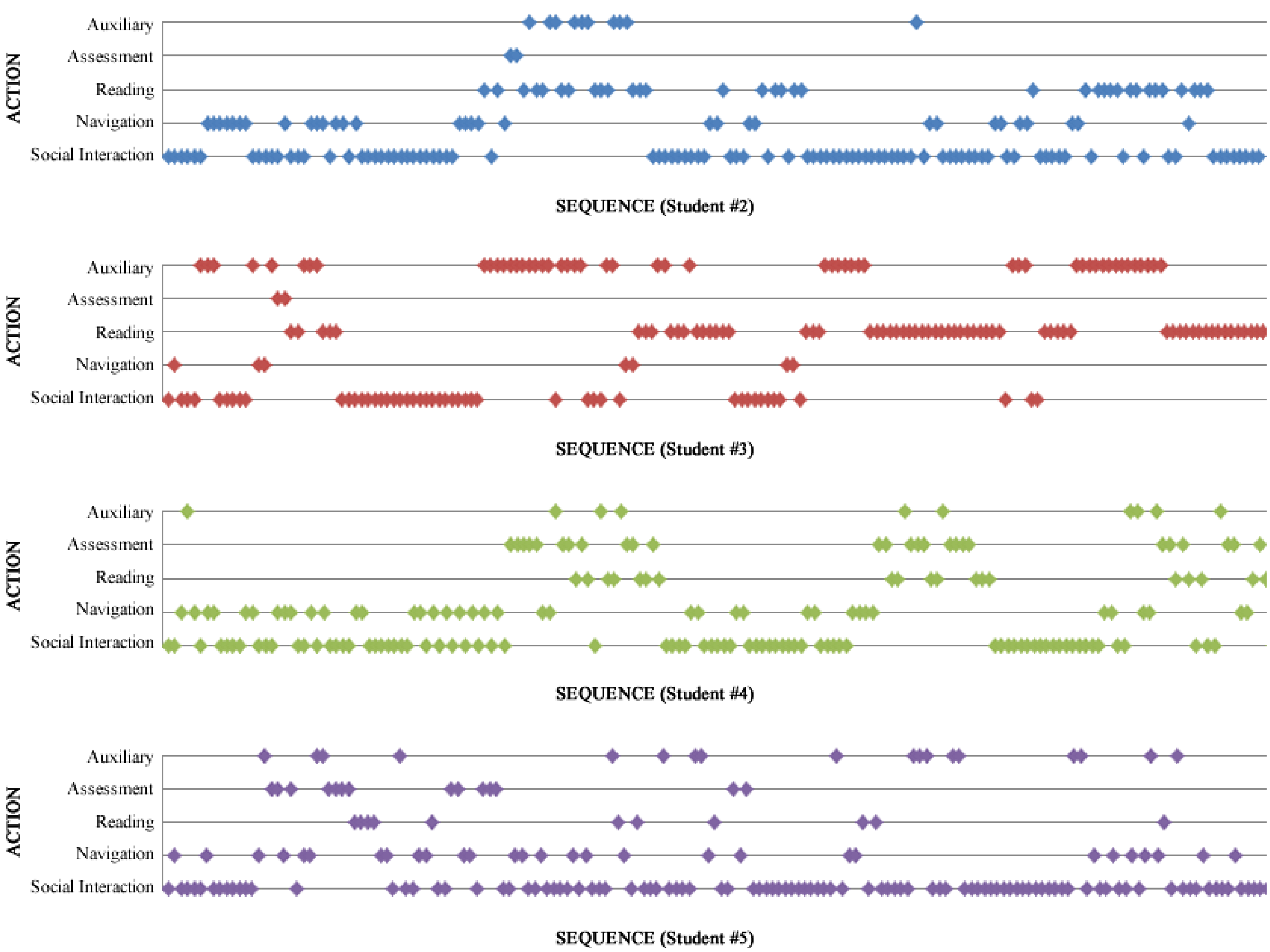


Figure 5 the List of Action Sequences (partially) (chronological order against action category)

Action sequence

The *Marked scatter chart*, as shown in Figure 5, was used to represent and compare *action switches* and *action sequences* of different students. *X-axis* presents the chronological order in which the actions were performed, and *Y-axis* presents the categorization of actions. We drew all the actions performed by a student in a row to be composed of an *action sequence* where each plot represented a single action. We then vertically listed all the *action sequences* in one chart for observation and comparison, in order to find *action sequence* patterns of the students. Due to space limitations, here we randomly present 4 students' *action sequences*, and for each sequences, we only present the first 180 actions performed by the students.

The overall observation of Figure 5 reveals some common patterns from different students. For instance, all of the students started with performing **social interaction** actions; the students liked to concentrate on performing **social interaction** actions for a while; they switched between **social interaction** actions and **navigation** actions and between **assessment** actions and **reading** actions quite often; the performances of **auxiliary** actions varied between different students; there were a lot of exploratory actions in some periods and the rich feature set provided by Topolor was fully exploited. Besides, there were also some different patterns between different students. For example, student #2 tried to perform some **auxiliary** actions, and then s/he stopped using these features. Student #3 could focus on viewing topics (**reading** actions), after s/he spent some time to exploit all the features provided. Student #4 switched between **social interaction** actions and **navigation** actions more often than others, with forays into **reading** and **auxiliary** actions. Student #5 could not concentrate on viewing topics (**reading** actions), whilst curious to explore all the provided features instead, though focused more on the **social interaction** actions.

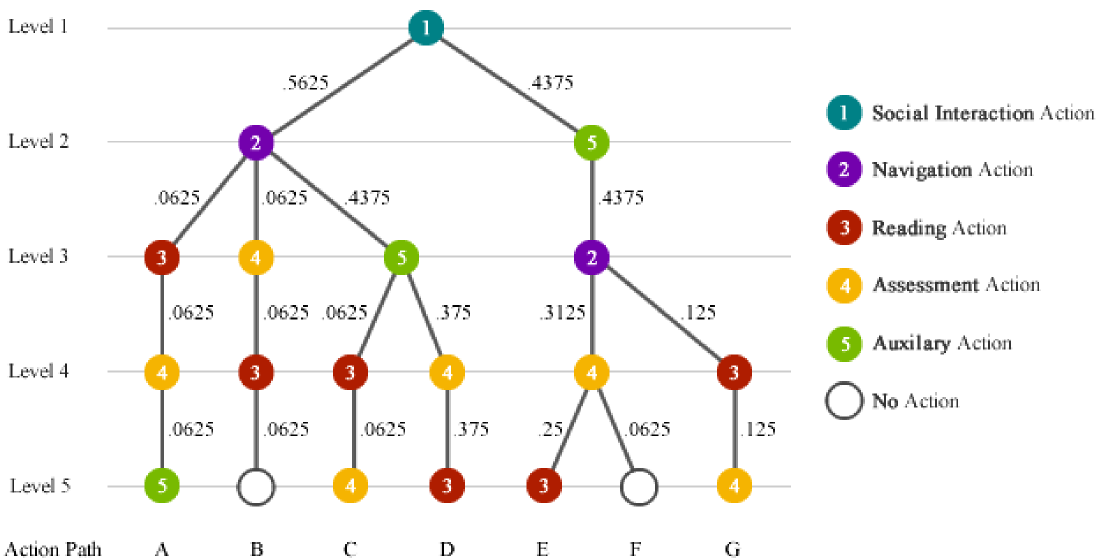


Figure 6 the Directed Acyclic Graph (DAG) of possible action paths

For further investigation, we summarized these *action sequences* into a *Directed Acyclic Graph* (DAG). As shown in Figure 6, the DAG consisted of colored nodes representing the grouped repetitive actions belonging to the same categorization, and the edges representing routing relationships. Lower-level actions were performed after higher-level actions (e.g., action 5 in level-2 were performed after action 1 in level-1). The numbers labeled on the edges represent the probabilities that the actions in the lower-level end of the edges performed while routing from the entry point (e.g., the probability of performing actions in the order of 1-5-2-3 was 0.125). From Figure 6, we have following observations for common learning behavior patterns:

- **Social interaction** actions were the entry points (occurred at level-1) for all the possible action paths. The second performed actions were **navigation** actions or **auxiliary** actions. The former occurred with the probability of 0.5625, and the latter occurred with the probability of 0.4375.
- **Navigation** actions were performed relatively earlier than other actions (only occurred at level-2 and level-3), and they had more following routes if they occurred in level-2. We assume that as routers, **navigation** actions played an important role during the learning process. Students exploited the features in Topolor by firstly performing **navigation** actions. Besides, student might like the filtering tools provided by Topolor, as they used them to find interesting topics and questions & answers before they accessed detail pages and performed further actions.

- **Auxiliary** actions were relatively dispersed (occurred from an early level – level-2 to the last level – level-5). We assume that different students had different demands from **auxiliary** tools, so it would be necessary to enhance the personalization and adaptation features for these tools.
- **Reading** actions were performed relatively later (the majority occurred at level-4 and level-5). It might be because the topic learning pages were not attractive enough; especially the reading contents themselves had no interactional features, such as a manipulatable chart.
- **Assessment** actions were also performed relatively later (the majority occurred at level-4 and level-5). The reason for this might be that the **assessment** actions should be performed right before or right after performing **reading** actions. Some **assessment** actions were performed before **reading** actions, because the students could take a pre-test for the whole module before they started to learn a topic in the module.

Table 2 summarized the 7 action paths, of the DAG, descending by probabilities, leading to the following observations:

- The most performed action path was D: 1-2-5-4-3 (0.375), followed by E: 1-5-2-4-3 (0.25) and then G: 1-5-2-3-4 (0.125).
- Most of the action paths (5 out of 7) routed all the categorizations of actions.
- The action paths could end after performing **reading** actions or **assessment** actions.
- There was 6.25% chance that **reading** actions were never preformed, and the same with **auxiliary** actions.

Label	Action path	Probability
D	1-2-5-4-3	.375
E	1-5-2-4-3	.25
G	1-5-2-3-4	.125
A	1-2-3-4-5	.0625
B	1-2-4-3	.0625
C	1-2-5-3-4	.0625
F	1-5-2-4	.0625

Table 2 the Possible Action Paths (1: Social Interaction; 2: Navigation; 3: Reading; 4: Assessment; 5: Auxiliary)

The above observations suggest some potential improvement of implicit user modeling. For instance, if the students are following the same action path, it might be useful to cluster them into the same group, because they might have similar cognitive styles of learning or similar preferences of using an e-learning system. As some action paths had more probabilities to be performed, the system may recommend related tools (e.g., by making them to be more attractive) for the students to use, when the system detects they have already performed the actions following an action path.

DISCUSSION

This paper describes the process of analyzing the visualized learning behavior data, which can suggest the improvement of e-learning systems (from a system designers' perspective). At the same time, these visualizations might also be helpful for online course authors, teachers and students. For instance, as an author, s/he might need to consider adjusting the course structure, if s/he found the frequency of **navigation** actions performed by the students was too high. As a teacher, s/he might need to consider providing more interpretations for a particular topic, if s/he found the students performed too many **social interaction** actions on that topic. As a student, s/he might need to consider taking more quizzes, if s/he found the **reading actions** s/he had performed were much more than that of **assessment** actions. This points to the demands of learning behavior data visualizations on the client-site of the system for different participants. In fact, there have already been some researchers working on the so-called open user modeling – the approach that permits participants to observe and reflect on the authoring/teaching/learning process. For example, in (Bull, Wasson, Johnson, Petters and Hansen, 2012), the authors proposed the Next-TELL open learner model to enable teachers to make evidence-based decisions on how to facilitate group interactions. In (Hsiao, Bakalov, Brusilovsky and König-Ries, 2011), the authors proposed a social open student modeling that provided the visualization of not only the student's own learning behavior, but also the parallel views with their peers.

Additionally, the generated learning behavior patterns also suggested the likeness and perceived ease of use of the provided features and tools for supporting further improvement of the Topolor system: 1) **Social interaction** actions were performed most frequently, so this is the most popular feature. Therefore it is necessary to enhance existing social interaction tools or provide more tools to support. 2) Not all the students performed **assessment** actions, which suggest that we need to improve quizzing tools to be more attractive and easier to use, considering the importance of assessment in e-learning. 3) The observation that **auxiliary** actions were not performed by all the students makes us consider the usability and necessity of *to-do* and *note* tools. Further research is needed to investigate whether it is necessary to improve these tools. 4) Since **social interaction** actions and **navigation** actions were switched often, it may be necessary to integrate them better.

There were some limitations in this pilot: only 21 students were involved in the experimental study. While we extracted valid data from 16 of them; we only took into consideration the chronological order of actions in the action sequences; we grouped the repetitive actions in the *directed acyclic graph*, meaning we considered the non-repetitive actions. In the future, we will conduct further study with more students and use more data mining methods to analyze learning behavior data. During the 2 hours session, it was the first time for the students to use Topolor, so their curiosity may have resulted in their exploration of the system rather than a purely learning process, although this seems unlikely as the core functions were often quickly examined and the students rapidly fell into observable patterns other than that of exploration. Additionally, one of the most important drawbacks of using log data to analyze learning behavior patterns is that it does not provide insight into the cause of phenomena observed. For example, as shown in Figure 6, after performing several **social interactions**, there was a 0.4375 probability that the students started to perform **auxiliary** actions rather than the **navigation** actions we expected, but we could not extract the reason for this. Hence we require a formative, qualitative analysis e.g. using questionnaires and structured interviews to further investigate this.

CONCLUSION AND FUTURE WORK

To conclude, we have analyzed and reported on learning behavior patterns in Topolor, a social adaptive personalized e-learning system. We conducted an experimental study with the help of 21 4th year MSc level students from the Department of Computer Science, at the University of Warwick, tracked and logged the students' usage data into a database during the 2 hours experimental session, and then extracted the learning behavior data from this database. We analyzed these learning behavior data by the proposed utilization of data mining methods and visualization tools to explore the learning behavior patterns, focusing on the analysis on *action frequency* and *action sequence*. From the analysis, we have found some interesting individual learning behavior patterns as well as some common learning behavior patterns. Our empirical investigative study suggested how to utilize the combination of data mining methods and visualization tools to analyze learning behavior patterns in adaptive educational hypermedia systems; our promising discoveries suggested the possible directions to improve implicit user modeling for such systems. As Topolor has been recently opened to the public with the expectation of collecting a larger set of user-system interaction data, our future work plan includes extracting more learning behavior data and an in-depth analysis of learning behavior patterns, taking into consideration the repetition of the actions as well as the time spent on performing each action.

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