A Temporal Model of Learner Behaviors in OELEs using Process Mining

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Abstract: Open-ended learning environments (OELEs) present learners with complex problems and a set of tools for solving these problems. Developing logging mechanisms that capture learners' interactions with the system provide a wealth of trace data that can be employed for studying relations between their behaviors and performance. Such analyses provide a framework for making the OELE intelligent in that it can adapt its feedback to meet the needs of individual learners. In our previous research, we have developed learner modeling schemes that are based on sequential pattern mining (SPM) and Hidden Markov models (HMMs) to represent and track the temporal sequence of learners' interactions with the OELE. We briefly discuss the pros and cons of these models, and then propose a process modeling approach to capture the temporal nature of learners' behaviors. We apply the process modeling method to data collected from students working with the Betty' Brain OELE, where students learn about scientific processes by building causal models.

Keywords: Process Mining, Temporal Behavior Analysis, Learner Behavior, and Betty's Brain

1. Introduction

Open-ended Learning Environments (OELEs) present users with complex problems to solve along with a set of tools and resources that scaffold the problem-solving task (Biswas, Segedy, & Bunchongchit, 2016). Users can explore multiple solution approaches and assess their evolving solutions to determine their progress toward their learning and problem solving goals. OELEs typically include logging mechanisms that track users' activities on the system as temporal sequences. Analytics and mining schemes can be applied to these activity sequences to assess, model, and interpret student learning behaviors and problem solving strategies (Basu, Biswas, & Kinnebrew, 2017; Kinnebrew, Segedy, & Biswas, 2017; Segedy, Kinnebrew, & Biswas, 2015).

In our previous research, we have developed learner modeling schemes that are based on sequential pattern mining (SPM) (Kinnebrew & Biswas, 2012; Kinnebrew, et al., 2017) and Hidden Markov models (HMMs) (Biswas, et al., 2010) representations to track the temporal sequence of learners' interactions with the OELE. We have also developed a Differential Sequence Mining (DSM) (Kinnebrew, Loretz & Biswas, 2013) to model less common but differentiating behavior patterns between two groups of students (e.g., high versus low performers or two groups subjected to different interventions). SPMs and DSMs provide a finer-grained but localized analysis of learning behaviors exhibited by students. Therefore, additional analyses are required for identifying overall learning behaviors that students exhibit when using an OELE.

In contrast, HMM learning behavior models represent an aggregated probabilistic model of students' overall learning behaviors captured in the form of a probabilistic automaton (Biswas, et al., 2010). However, these aggregated are hard to interpret because (a) the hidden states have to be identified and labeled to characterize behaviors, and (b) transitions have associated probabilities, making the models nondeterministic, and, therefore, presenting likely behaviors as opposed to the actual behaviors students exhibit at any given time (Rabiner, 1989). While they do provide a useful representation for aggregating and comparing the learning behaviors between groups of students, they are difficult to apply for interpreting students' current learning behaviors.

In this paper, we explore a a new methodology called *process mining* (Van der Aalst, 2011), to derive a holistic view of students' learning behaviors from their action temporal sequences derived from their work in OELEs., in this paper, we explore We demonstrate the effectiveness of this model by applying a process mining algorithm to analyze data from a recent study with Betty's Brain (Biswas, et al., 2005; Leelawong & Biswas, 2008), an OELE where students learn about scientific phenomena by building causal models. The results of this analysis provide a holistic temporal model of students' overall problem solving behaviors.

2. Background and Literature Review

Process mining (PM) represents a method for deriving process models from temporal data, where the temporal data may represent a sequence of events, where each event may represent an action taken by the student when working in one or more learning episodes in an OELE (Reimann, Frerejean, Thompson, 2009; Winne, Nesbit, 2009). PM adopts an automata- or Petri net-like visual representation to represent the temporal model or process. When applying PM techniques to logged problem solving actions, researchers (e.g., Günther & Van Der Aalst, 2007, Schoor & Bannert, 2012) assume that the present trace data— comprised of temporally ordered action sequences— can be mapped to one or more mental processes and the sequence of such processes can be interpreted as the students' temporal problem solving model.

In previous work, Bannert, Reimann, and Sonnenberg (2014) have applied process mining on qualitative data obtained through a think-aloud protocol to investigate learners' self-regulated learning activities (such as analyzing and monitoring behaviors during problem solving) by taking into account their temporal ordering with respect to learning outcomes. Sedrakyan, De Weerdt, & Snoeck (2016) employed process mining algorithms to study patterns of novices modeling activities that were indicative of learning outcomes. The authors argued that identification of modeling patterns when teaching conceptual modeling demonstrated the applicability of process mining techniques in interpreting students' cognitive learning processes, and this provided insights for generating process-oriented feedback instead of traditional outcome feedback. In a recent study, Juhaňák, Zounek, & Rohlíková (2017) used process mining to identify and differentiate between various types of non-standard student behaviors related to quiz-taking activities in a learning management system (LMS).

A number of algorithms have been developed for generating process models. Some examples are Alpha miner (Van Der Aalst, Weijters, & Marusterref, 2004), Heuristic miner (Weijters, Van Der Aalst, & De Medeiros, 2006), and Fuzzy miner (Günther, Van Der Aalst, 2007). In this paper, we use the Fuzzy miner algorithm implemented in ProM (Günther & Van Der Aalst, 2007), an open-source process mining tool (www.promtools.org), to visualize and explore the temporal differences in learning behavior sequences of high versus low performing students working on causal modeling tasks in the Betty's Brain environment.While applying process mining models on real time data, that involves more events and transition between the events, often provides more complex models showing all details but without suitable abstraction for the analysis. In ProM, Fuzzy mining algorithm is used to develop a simplified process model on real time data. Here, we briefly describe the algorithm and the metrics used to develop the process model. A detailed description of the Fuzzy mining algorithm appears in Günther & Van Der Aalst (2007). The Fuzzy mining algorithm analyzes temporal sequence data to develop a process models that contain a set of nodes (events or actions) and edges (transition between actions/nodes). In order to develop a simplified and abstract process model, the algorithm uses two key metrics, significance, and correlation. Significance is measured for both nodes and edges, by the *relative importance* of their occurrence compared to the total occurrence. For example, the nodes or edges that occur more frequently are considered as more significant. Correlation is measured only for nodes, by analyzing how two events are closely related. For example, the two nodes that co-occur more frequently compared to other events is considered to be more correlated. Based on the values of the two metrics, significance and correlation, the process model is simplified (Günther and van der Aalst 2007) by applying three rules.
1. highly significant nodes are preserved as is;
2. less significant nodes that are highly correlated are aggregated and grouped into clusters; and

3. less significant nodes with low correlations to other nodes are dropped thus creating more abstract forms of the model.

The abstraction level of the process model can be modified by changing three parameters: (1) *node cutoff*, (2) *edge cutoff*, and (3) *utility ratio*.

Node cutoff is applied to remove the nodes whose significance is below the node cutoff threshold and the edge cutoff is applied to filter edges whose utility value is below the edge cutoff threshold. The utility value of an edge, which is calculated as the weighed sum of significance and correlation of an edge based on the parameter utility ratio(ur), which is measured as:

$$Utility\ value\ of\ an\ edge\ =\ ur\ *\ significance\ of\ edge\ +\ (1-ur)\ *\ correlation\ value\ of\ edge$$

In addition to these parameters, in our work, to evaluate the derived models, we developed a metric called *map correctness*, which represents the number of log sequences that can be replayed accurately using the process model. It is measured as:

$$Map\ correctness = Percentage\ of\ nodes\ used\ in\ the\ model\ *\ Log\ conformance$$
$$(amount\ of\ events\ in\ the\ log\ could\ be\ replayed\ successfully)$$

Our aim in this research is to maintain the threshold of 75% for the *map correctness* by manipulating the three parameters. In order to achieve our goal of *Map correctness* $> 75\%$, the node threshold $= 0$ is fixed (to retain all the actions in the process model), and *utility ratio* (ur) $= 0.5$ (to provide balanced weight to both significance and correlation). Then, the edge cutoff value is varied to achieve our desired Map correctness value ($> 75\%$).

3. Learning Environment: Betty's Brain

The Betty's Brain learning environment (Leelawong, & Biswas, 2008; Davis. et al., 2003) assigns learners the task of teaching a science topic (e.g., Climate change) to a teachable agent named Betty by constructing a visual causal map consisting of a set of entities connected by directed causal links. As students build their map, they can ask Betty questions, and Betty can answer them and explain her answers by tracing the causal links on the map. The students' goal is to teach Betty a causal map that matches a hidden expert model of the topic.

Students' activities are categorized into three primary action types: (1) reading hypertext resources on the science topic (READ), (2) building the causal map (BUILD), and (3) assessing the correctness of the map (ASSESS). Students iterate among these action types until they have taught Betty a correct model or they run out of time. Figure 1 illustrates the Betty's Brain BUILD (Causal Map) interface. As students read the hypertext resources, they extract causal relations between entities and construct the causal map to teach Betty. Students can assess their own understanding and success in teaching Betty by:

- Querying Betty using a template for asking cause-effect questions. A "mentor" agent, Mr. Davis, helps grade Betty's answers by comparing them against a hidden expert model.
- Asking Betty to take a quiz, which helps them evaluate the current state of the map.

In addition to READ, BUILD and ASSESS actions, students can also carry out additional actions:
- Add to or view notes (NOTE; a 'note' is a text box in which students can collect or summarize information from the hypertext resources they deem relevant)
- Ask causal questions (QUER) to Betty, and after she answers it, they can ask her to explain her answer (QUER_EXPL)
- After taking the quiz (QUIZTAKEN) or after looking at quizzes that were administered earlier (QUIZVIEW), students can also ask Betty to explain (EXPL) her answer to a specific quiz question. She does this by highlighting the sequence of links used to answer the question as well as a step by step solution of how the answer was derived.

Students' actions along with the context in which each action was performed are recorded in log files.
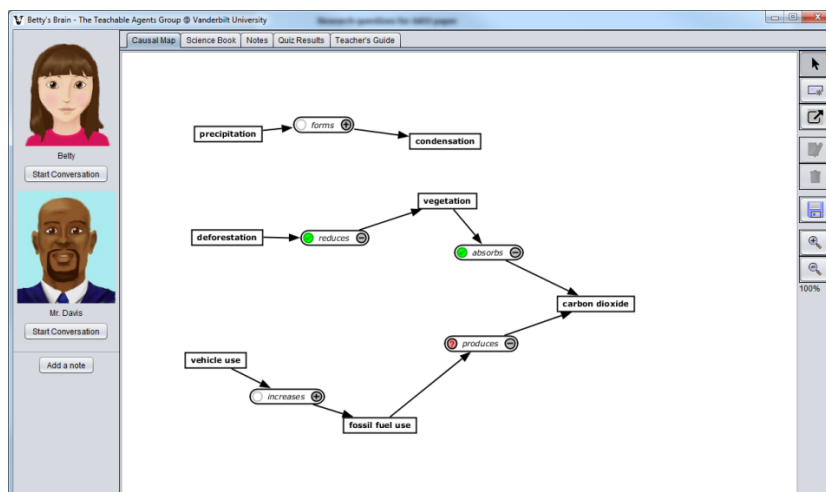
Figure 1. Betty's Brain system showing Causal Map Interface

Student performance in the Betty's Brain environment is measured by their current "map score", which is computed as the difference between the number of correct and incorrect links present in the student's map at any point of time. Students' learning behaviors in Betty's Brain are derived from a cognitive/metacognitive task model (Kinnebrew, Segedy, & Biswas, 2017). Their interactions with the system are mapped to particular skills (for example, reading hypertext resources is mapped to the information acquisition skill), which are then interpreted in terms of the overall learning objectives. A sequential combination of primitive skills, performed in a context, is interpreted as a problem solving strategy. Researchers have employed a combination of analytics methods (Kinnebrew, Segedy, & Biswas, 2017) and exploratory sequence mining techniques for detecting and characterizing students' metacognitive processes in Betty's Brain environment. Betty's Brain has been shown to significantly improve student learning, as measured by gains observed from pre- to post-tests. (Kinnebrew, et al., 2017, Segedy, et al., 2015).

For analyzing learners' behaviors, their logged actions are further classified based on time taken to perform each action and/or its impact on the current map score. For example, READ actions are characterized as READ-SHRT (3 seconds or less spent on reading a page) and READ-LONG (more than 3 seconds spent on a page). A linkedit (adding, modifying or deleting a causal link in the Causal Map Interface) action that increases the map score is logged with the suffix –EFF (for 'effective'), and a linkedit action that decreases the map score is logged with the suffix –INEFF (for 'ineffective'). A second qualifier for link edit actions is the suffix –SUP/UNSUP, which indicates that editing action performed is supported by information acquired from a previous READ or QUIZ action that occurred within the last 5 minutes (Segedy, et al., 2015). The descriptions of the actions used to develop the process model described in this paper are summarized in Table 1.

4. Method

4.1 Study Design

The data analyzed in this paper was obtained from a recent classroom study with 87 sixth-grade students from four classrooms in an urban public school in southeastern United States. The study lasted for 7 days. On day 1, students completed a paper-administered pre-test. On day 2, they were introduced to reasoning with causal maps and given sufficient hands-on training to familiarize themselves with the Betty's Brain system. Over the next four days (days 3-6), the students worked on building a causal model of climate change in the Betty's Brain environment. On the last day, they completed a post-test that was identical to the pre-test. The pre- and post-tests tested the students' knowledge on the science domain concepts and understanding of causal relations using a combination of multiple choice ($maximum\ score = 7$) and short-answer ($maximum\ score = 9$) questions.

Table 1

List of Betty's Brain Actions with descriptions used for deriving the Process Model

Primary Action Category	Actions	Description
READ	*READ-SHRT*	Reading resources in science page for < 3 seconds
	READ-LONG	Reading resources in science page for > 3 seconds
BUILD	*LINKEDIT-EFF-SUP*	Add or edit a causal link that is correct and supported by previous READ or QUIZ actions
	LINKEDIT-INEFF-SUP	Add or edit a causal link that is incorrect and supported by previous READ or QUIZ actions
	LINKEDIT-EFF-UNSUP	Add or edit a causal link that is correct but not supported by previous READ or QUIZ actions
	LINKEDIT-INEFF-UNSUP	Add or edit a causal link that is incorrect and not supported by previous READ or QUIZ actions
ASSESS	*QUIZTAKEN*	Betty takes a quiz when asked to do so,
	QUIZVIEW	Viewing results of quizzes (either the current one or those that were taken earlier)
	EXPL	Asking Betty to explain her answer to a quiz question, and viewing the highlighted map that she generates
	NOTE	Adding or viewing notes in the note taking interface

4.2 Data Preprocessing and Process Mining Analysis

For the purpose of our analyses, we grouped all the students ($n = 87$) into high performers (HI) and low performers (LO) based on the median value (11) of the overall map scores (which is a measure of their in-system performance in Betty's Brain). Students with a map score greater than 13 ($median\ value + 2$) were labeled "HI" ($n = 41$). The average map score for this group was 20.58 ($sd = 4.15$). and those with a map score less than 9 ($median\ value - 2$) were labeled "LO" ($n = 39$). The average map score for this group was 4.03 ($sd = 2.2$). Data for students ($n = 7$) in the median range $(9,13)$ was discarded to maintain sufficient distinction between the two groups. The maximum map score students can obtain in the climate change unit is 25.

Students' activity traces logged in the Betty's Brain system was preprocessed to extract the time-stamped sequence of student actions. To reduce the complexity of our process models, we randomly sampled 10 HI (average $map\ score\ was$ 19.3 ($sd = 4.8$)) and 10 LO (average $map\ score\ was$ 4.45 ($sd = 2.02$)) students. The action sequences of our chosen HI and LO students served as inputs to create a process mining model of actions using the ProM tool.

5. Results

The action frequencies for the high and low students are listed in Table 2. Frequencies are presented as percentages computed in relation to the total number of actions performed by a group. Overall, students in the HI group performed more actions (4276) compared to the students in the LO group (2324). The HI group students performed more EXPL actions (26% of the total) related to checking their map, as compared to students in the LO group (8.1%). On the other hand, the LO students has a higher frequency of READ-SHRT actions (23.6%) as compared to HI group (14.7%). Similarly, the LO group performed more READ-SHRT actions (23.6%) as compared to READ-LONG actions (16.7%), and also more ineffective (incorrect) causal link edits (LINKEDIT-INEFF-UNSUP - 9.3% + LINKEDIT-INEFF-SUP - 2.8%) compared to effective (correct) causal link edits (LINKEDIT-EFF-UNSUP - 5.6% + LINKEDIT-EFF-SUP - 4.1%). The students in the HI group performed more READ-LONG actions compared to READ-SHRT actions, and more effective link edits compared to ineffective link edits. An overall comparison of the values in Table 2, shows that the students in the HI group not only performed more actions compared to the students in LO group,

but they also performed more meaningful and effective actions such as READ-LONG, EXPL (assessing their performance) and effective causal link edits.

Table 2

Number of Occurences and Relative frequency of Betty's Brain Actions of 10 High (HI) and 10 Low (LO) performing Students

| Actions | HI | | LO | |
	Number of Occurrence	Relative Frequency (%)	Number of Occurrence	Relative Frequency (%)
All actions	4276		2324	
EXPL	1112	26.01%	187	8.05%
READ-SHRT	627	14.66%	548	23.58%
QUIZVIEW	545	12.75%	418	17.99%
READ-LONG	520	12.16%	387	16.65%
QUIZTAKEN	460	10.76%	169	7.27%
LINKEDIT-EFF-SUP	367	8.58%	94	4.04%
LINKEDIT-INEFF-UNSUP	220	5.14%	217	9.34%
LINKEDIT-EFF-UNSUP	206	4.82%	130	5.59%
LINKEDIT-INEFF-SUP	158	3.70%	66	2.84%
NOTE	61	1.43%	108	4.65%
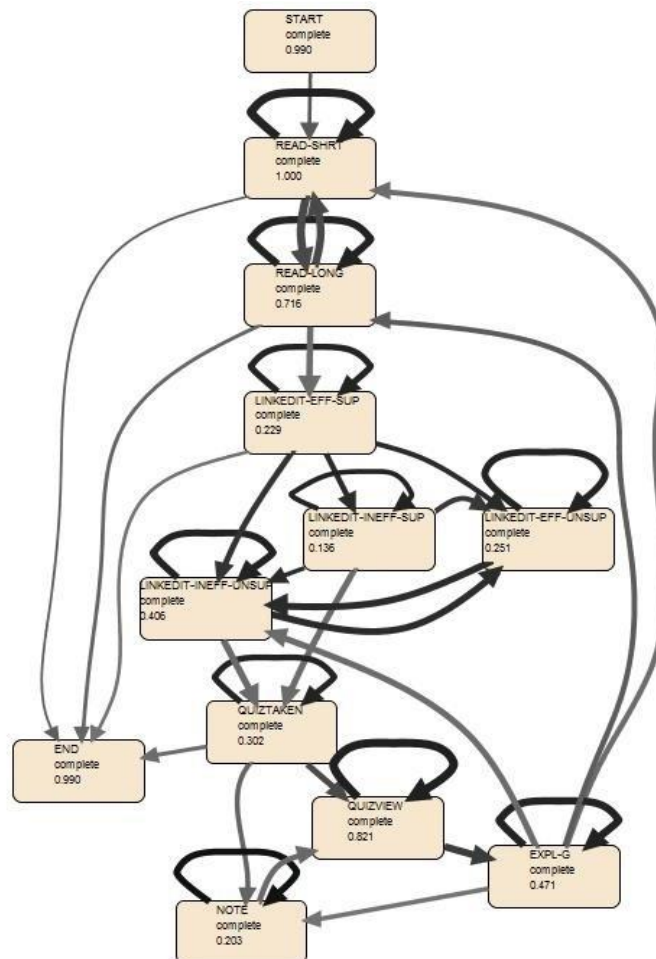
a.   Process Model of Learners in Low (LO) group
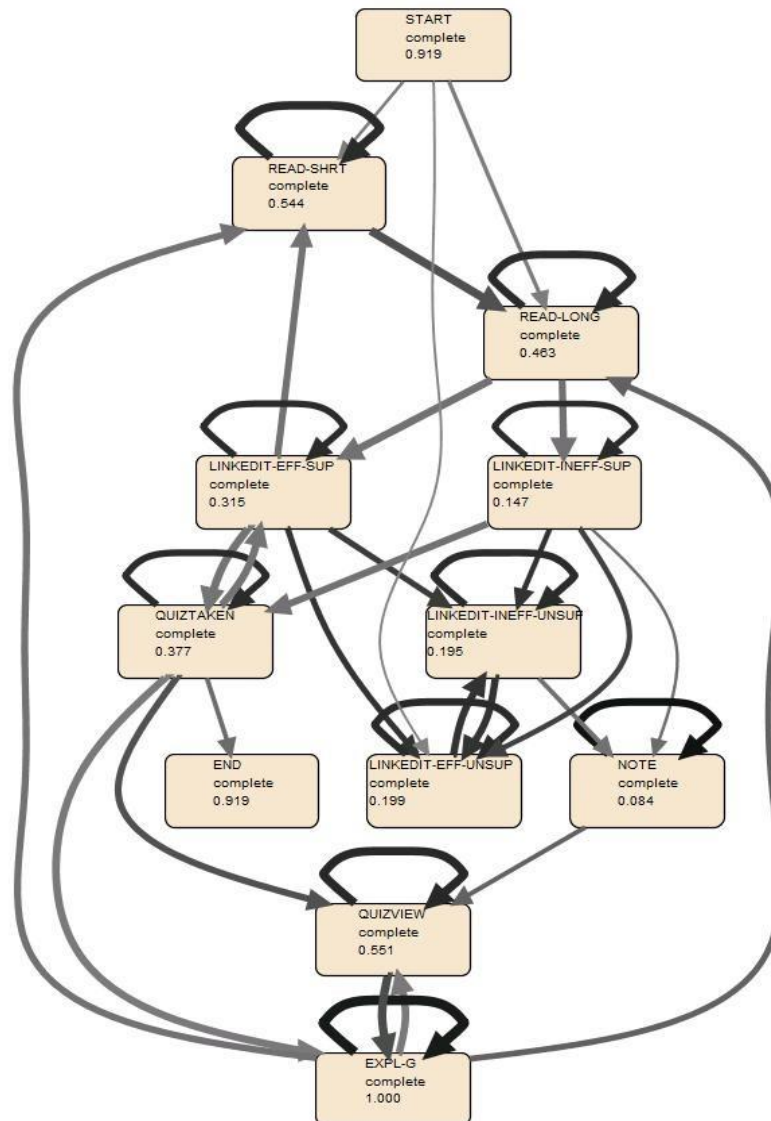
b.   Process Model of Learners in High (HI) group

Figure 2: Process Model of Learners' Behavior

The process models of learning behaviors generated by the Fuzzy mining algorithm for the low (LO) and high (HI) performing students are shown in Figures 2(a) and 2(b), respectively. In order to retain 75% accuracy in matching the sequences from the log file, we converged on the following parameter values: $node\ cutoff\ =\ 0$ (keep all action nodes) and $utility\ ratio\ =\ 0.5$ (only retain links whose $utility\ ratio > 0.5$). In the PM in Figure 2, the rectangular nodes represent actions. The significance metric is represented by the numerical value (between 0 and 1) within each action node. The thickness and darkness of the edges indicate the significance and correlation values associated with the edges, respectively.

The process models derived include the 10 types of actions discussed previously in Tables 1 and 2. Comparing the two models in Figures 2(a) and 2(b) shows some interesting commonalities as well as differences in the learning behaviors of the LO and HI groups. First, we observe a significant number of common processes in both models. For example, both groups show a strong loop between unsupported effective and ineffective causal link edit actions. READ-LONG actions are followed by supported link edit actions. There exists strong connection from the QUIZTAKEN and QUIZVIEW actions to the EXPL action in both models.

However, the difference in the two models (LO versus HI) provides more interesting comparisons between the respective learning behaviors of the two groups. . This helps us understand why LO group students were not as successful as the HI group in their model building tasks. First, for the LO group (Figure 2a); there is a strong cyclical loop between READ-SHRT and READ-LONG actions. In contrast, no such loop occurs in the HI group model (Figure 2b). The HI

group students, while showing a strong connection from READ-SHRT to READ-LONG($significance = 0.4, correlation = 0.65$), do not display a connection in the reverse direction (READ-LONG to READ-SHRT). Instead, the only strong outward connection from READ-LONG for HI group is to the LINKEDIT-EFF-SUP node. This suggests that the HI students seemed to be more effective in translating what they read into finding and adding correct links to their causal map models. In contrast, the LO group was unable to find useful information to support their map building actions. Instead they cycled through long and short reading instances. The short read instances may correspond to looking through the topic of contents or just glancing at page headers when searching for relevant science content. The fact that there were many instances of such READ-SHRT action clearly indicates that the LO group was often unsuccessful in translating these search instances into successful map editing actions.

When we look more closely at the BUILD actions performed by the HI and LO groups, Figure 2a, shows that the LINKEDIT-EFF-SUP action has strong connections to other BUILD actions (such as LINKEDIT-EFF-UNSUP, LINKEDIT-INEFF-SUP, and LINKEDIT-INEFF-UNSUP), but no connection to any ASSESS or READ type of action. This may imply that the LO group tried to add multiple links to their map in sequence, but made a lot of errors in the process. For the HI group (Figure 2b), we observe that the LINKEDIT-EFF-SUP action is connected to QUIZTAKEN and READ-SHRT actions. This suggests that the HI students, after adding a correct causal link to their map, tried to validate the correctness of the updated causal map using the quiz as an assessment tool, or by going back to the resource pages and doing a quick read to confirm the correctness of their additions.

Next, checking the solution assessment (ASSESS) actions for the two groups again shows contrasting behaviors. Figure 2a shows that LO students, after looking at the explanations for quiz answers, transition to a number of different actions, such as LINKEDIT-INEFF-UNSUP (unable to interpret the quiz results), READ-LONG, READ-SHRT, and NOTE taking. On the other hand, HI students (in Figure 2b), after looking at the explanations to quiz answers (EXPL-G), consistently transition to READ-LONG, which is followed by a correct link edit (LINKEDIT-EFF-SUP). This clearly indicates a situation, where LO students may be able to especially benefit from in-time scaffolding. The ability to interpret and use quiz results is an essential debugging task that students need to employ to become efficient learners.

The differences in learners' behaviors inferred from process model give us a lot of useful information that can be utilized to provide personalized scaffolds for productive learning of low (LO) and high (HI) performing groups of students. For example, scaffolding students in the HI group when they perform ineffective link edits may help them to get past their "unsupported effective to ineffective linkedit" loops. Similarly, for students in LO group, providing feedback after effective supported link edits may help them to assess their map using the QUIZ action or go back to do additional READs to ensure that they find the correct information for building their maps. Also, suggesting the students in LO group perform a READ-LONG action after EXPL action might help them to convert their knowledge gained by reading to effective link edits.

6. Discussion and Conclusion

In this work, we presented a process modeling approach for analyzing learning behaviors from students' interaction with an OELE. We used the Fuzzy miner algorithm in process model to contrast the processes of high and low performers. Results from a recent classroom study with Betty's Brain show that this modeling approach is effective in characterizing learners who show different levels of performance.

From the process model, we discovered that high performing students not only execute more actions, but their actions are also supported (i.e., linked to information generated from previous actions) and effective (they help the students accomplish the goal of building a correct map). Their pre- to post-test scores (not reported in this paper) also show that students who perform more effective actions in the system learn their science content better. In order to contrast the results obtained from PM approach to the results of SPM algorithm, we applied the SPM algorithm to the actions sequences obtained from students in both HI and LO groups. The SPM results provide the list of most frequent actions, self-loop between actions (for example EXPL → EXPL → EXPL), and most frequent patterns (for example READ-LONG → READ-SHRT) for both groups. Overall, the

SPM algorithm and its variation Differential sequence mining (DSM), provides the localized behavior of students such as frequent processes (patterns), the significance of each action and differential behavior patterns in HI vs LO groups. However, the process model provides both the information on frequent patterns and also the holistic view of students' action sequences to represent their learning behavior. In other words, the PM model shows how students combine different behavior patterns over time, which is not readily available from the SPM results.

In future work, we propose to extend the current research along three dimensions. First, we propose to reconstruct the process model using more fine-grained action sequences (for example NOTETAKEN and NOTEVIEW instead of just the NOTE action) to analyze the learner's behavior in finer detail. Second, we propose to develop feedback algorithms based on the process model developed in this paper, to scaffold LO and HI performing learners and measure its impact on their learning. Third, we intend to integrate SPM and PM to study the learning transition between most frequent patterns for scaffolding. We propose to achieve this by developing process model on most frequent patterns exhibited by students.

Acknowledgments

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