Using a Cognitive/Metacognitive Task Model to Analyze Students Learning Behaviors

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Abstract. Adapting to learners' needs and providing useful, individualized feedback to help them succeed has been a hallmark of most intelligent tutoring systems. More recently, to promote deep learning and critical thinking skills in STEM disciplines, researchers have begun developing open-ended learning environments that present learners with complex problems and a set of tools for learning and problem solving. To be successful in such environments, learners must employ a variety of cognitive skills and metacognitive strategies. This paper discusses a framework that combines a theory-driven, top-down approach with a bottom-up, pattern-discovery approach for analyzing learning activity data in these environments. Combining these approaches allows for more complex qualitative and quantitative interpretation of a student's cognitive and metacognitive abilities. The results of this analysis provide a foundation for developing performance- and behavior-based learner models in conjunction with adaptive scaffolding mechanisms to promote effective, personalized learning experiences.

Keywords: metacognition, theory-driven top-down analysis, pattern-driven bottom-up analysis, effectiveness measures, pattern mining, adaptivity, tutoring.

1 Introduction

Adapting to learners' needs and providing useful, individualized feedback to help them succeed has been a hallmark of most intelligent tutoring systems [12]. To promote deep learning, critical thinking, and problem-solving skills in STEM disciplines, researchers have begun developing open-ended learning environments (OELEs) that provide a learning context and a set of tools for learning and solving complex problems [8]. To be successful in these environments, learners have to employ metacognitive processes to manage, coordinate, and reflect on relevant cognitive processes as they search for, interpret, and apply information to construct and test potential problem solutions. This can present significant challenges to novice learners. They may lack both the proficiency to use the system's tools and the experience and understanding necessary to explicitly regulate their learning and problem solving. Traditionally, learning behavior in intelligent tutors and OELEs are assessed with theory-driven metrics and context-driven hypotheses about the students' learning tasks. In recent

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years, data mining techniques that analyze students' logged activity data have also been utilized to discover important aspects of how students learn [13].

This paper discusses a framework for analyzing learning activity data in OELEs that combines top-down metrics and bottom-up pattern discovery. This integrated framework can be employed to build detailed models of students' learning behaviors and strategies, which can subsequently identify opportunities for providing adaptive scaffolds to students as they use the system. We instantiate this task-driven analytics framework in the context of Betty's Brain [9], an OELE in which students learn science by constructing causal models. A case study illustrates the benefits of incorporating top-down and bottom-up techniques in concert to characterize the learning behavior of students in an OELE.

2 Background and Related Research

Flavell [3] defined metacognition as "*thinking about one's own thinking*." From an information-processing perspective, Winne [18] described cognition as dealing with knowledge of objects and operations on objects (the object level), while characterizing metacognition as the corresponding meta level that contains information about when to use particular cognitive processes and how to combine them to accomplish larger tasks. Metacognitive monitoring brings the two levels together, as it describes the process of observing and evaluating one's own execution of cognitive processes in order to exercise control for improving cognition.

In general, control or regulation of cognition [2] and application of strategies to regulate one's learning are fundamental components of metacognition. Winne and Hadwin [19, 20] have proposed a model of self-regulated learning called COPES. Learning according to this model occurs in four weakly sequenced and recursive stages: (1) task definition, where the students develop their own understanding of the learning task, (2) goal setting and planning, which follow the task definition phase and represent the students' approach to working on the learning task, (3) enactment of tactics, which represents that phase where the students' carry out their plans for learning, and (4) adaptations to metacognition, which are linked to both in-the-moment adjustments of one's tactics and post-hoc evaluation of one's approach based on successes and failures achieved during enactment.

Like COPES, we adopt a task modeling approach to interpret students' learning behaviors in the Betty's Brain environment. Patterns derived from students' activity sequences can be interpreted as stemming from students' cognitive and metacognitive processes associated with the learning tasks. To represent these aspects, we have created a model (reported in [5, 15]) that describes tasks important for success in Betty's Brain. A key aspect of this model is the set of dependency relations that map higher-level metacognitive tasks (e.g., deciding which component of the science model to focus on) to lower-level cognitive tasks (e.g., recognizing a causal relationship while reading a text passage). This approach emerges from the link between cognitive task proficiency and metacognitive planning [8, 17]. Metacognitive knowledge by itself may not be sufficient to achieve success, especially when learners lack the cognitive skills and background knowledge necessary for understanding and organizing the problem under study [1].

Several OELEs have been designed to provide adaptive scaffolds. For example, Ecolab [11] intervenes whenever the student specifies an incorrect relationship (e.g., caterpillars eat thistles). It notifies students that the relationship is incorrect, and provides corrective hints. Should students continue to struggle, the system will tell students exactly how to complete the task (e.g., you need to model the relationship "caterpillars eat grass"). Learners using Ecolab are free to choose the order in which they perform their learning activities, and the system uses information about the number of student errors to select activities that are within the student's zone of proximal development [10]. If students choose a learning activity that the system has deemed too easy or too difficult, the system prompts them to reconsider their choice. In Crystal Island [16] learners take on the role of a microbiologist to find the identity and source of an infectious disease plaguing the island research station. As learners explore the island and complete tasks, the system keeps track of the number of laboratory experiments that learners have conducted, and after every five experiments, it intervenes and requires students to correctly answer questions about microbiology. The agent also tracks information that learners encounter while conversing with computer-controlled characters, and it quizzes students on that information later.

These two analysis techniques do not take into account how students coordinate their use of system tools to complete their learning tasks. Our approach combines a cognitive and metacognitive model of the learning task with theory-driven measures to analyze students' activities and use of tools. Specifically, we track information related to students' ability to apply information they have previously encountered within the learning environment as they complete their learning and problem-solving tasks. However, an analysis based on these theory-driven measures and patterns of actions derived from the task model is not sufficient to cover the wide variety of different behaviors and strategies students employ during learning and problem-solving. Therefore, our analysis framework includes data-driven sequence mining techniques [6, 7] to identify the patterns of activity that students actually employ in the learning environment. In this paper, we map the identified patterns of student actions back into the context of students' sequences of activities, employing the theory-driven measures to differentiate behaviors that result in the same activity pattern, and then link them to skills or strategies in the cognitive/metacognitive task model.

3 Betty's Brain: An OELE for Learning Science

The Betty's Brain learning environment [9] presents students with the task of teaching scientific models to a virtual agent named Betty. These models take the form of causal concept maps that represent the relevant science phenomena as a set of entities connected by directed links that represent causal relations. Once taught, Betty can use the map to reason about the domain by answering causal questions and explaining those answers. The goal for students using Betty's Brain is to teach Betty a causal map that matches a hidden, expert model of the domain.

The students' learning and teaching tasks are organized around three activities: (1) reading hypertext resources, (2) building the map, and (3) assessing the correctness of the map. The hypertext resources describe the science topic under study (e.g., climate change) by breaking it down into a set of sub-topics. Each sub-topic describes a system or a process (e.g., the greenhouse effect) in terms of entities (e.g., absorbed heat energy) and causal relations among those entities (absorbed heat energy increases the average global temperature). As students read, they need to identify causal relations and then explicitly teach those relations to Betty by adding them to the current causal map.

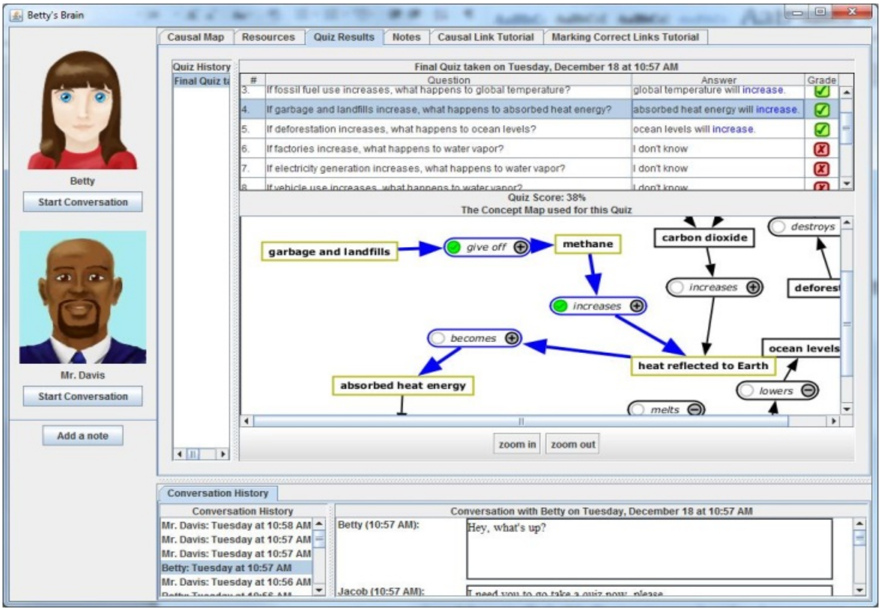

Fig. 1. The Betty's Brain system showing the quiz interface

Learners can assess the quality of their current map by having Betty take a quiz on one or all of the sub-topics in the resources. Figure 1 illustrates the Betty's Brain quizzing interface. Quizzes are designed to reflect the current state of the student's map: a set of questions is chosen (in proportion to the completeness of the map) for which Betty will generate correct answers. The rest of the quiz questions produce either incorrect or incomplete answers. These answers can be used to infer which causal links are correct and which causal links may need to be revised or removed from the map. Should learners be unsure of how to proceed in their learning task, they can ask Mr. Davis for help. Mr. Davis responds by asking the learner about what they are trying to do, and he provides information and examples based on learners' questions.

4 Framework Integrating Theory- and Data-Driven Analysis

Our framework for analyzing OELE learning activity data integrates top-down information acquisition/application measures and bottom-up sequential pattern discovery. The analysis involves: (1) sequential pattern mining to identify common action patterns; (2) mapping identified patterns back into action sequences to analyze them with theory-driven measures; and (3) linking the identified behaviors back to skills and strategies in the cognitive/metacognitive task model.

4.1 Theory-Driven, Top-Down Analysis

The theory-driven portion of our integrated framework, illustrated in figure 2, incorporates a cognitive and metacognitive model of the tasks that students are expected to complete as they progress through an open-ended learning task. In order to analyze data in Betty's Brain, we have developed a task model that represents student activities as a set of cognitive and metacognitive activities related to: (1) knowledge construction, which consists of both information seeking and solution construction; and (2) solution evaluation [5, 15]. The directed links in the model represent dependency relations. The model indicates that each of these high-level characterizations involves a set of metacognitive tasks, and each specific task could be accomplished by applying any of a number of metacognitive strategies. Information seeking tasks depend on one's ability to read, understand, interpret, and translate information from the resources. Solution construction tasks depend on one's ability to apply information gained during information seeking and solution evaluation to constructing and refining the causal map. Finally, solution evaluation tasks depend on the learner's ability to interpret the results of solution assessments (quizzes) as actionable information that can be used to refine the solution in progress.

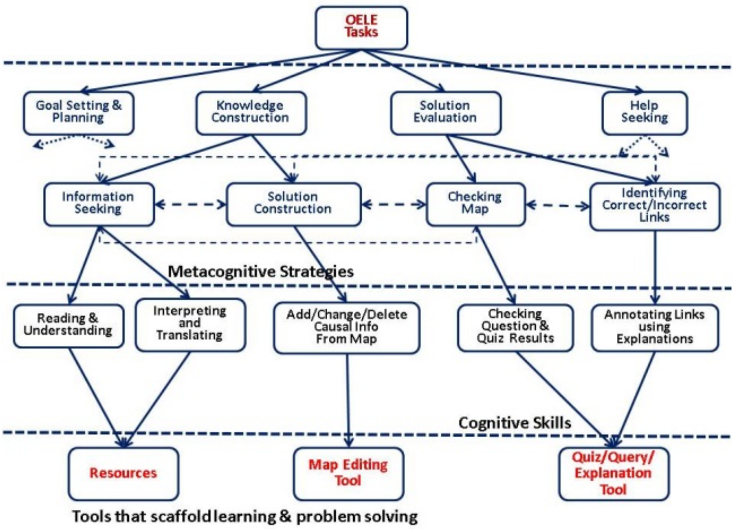

Fig. 2. Cognitive/Metacognitive Task Model in Betty's Brain

The structure of the cognitive and metacognitive model provides two key pieces of theory-driven information that can be used to judge the quality of student behaviors in Betty's Brain. First, the dependency relations between metacognitive and cognitive tasks indicate that analyzing a student's behaviors in an OELE must utilize information about the student's cognitive ability levels. Second, the dependency of solution construction on information seeking and solution evaluation tasks indicates that students must coordinate their use of system tools in order to filter information and apply what they learn to the construction of a correct solution. Such coordination requires some amount of metacognitive regulation as students decide how to apply the information they have learned. Thus, analyzing student learning behaviors must also assess students' metacognitive regulation through their ability to logically coordinate their use of multiple tools within the system.

To assess a student's cognitive ability levels, our approach judges each action students take on the system in terms of its effectiveness [14]. Actions in an OELE are considered effective if they move the learner closer to their task goal, and students with higher proportions of effective actions are considered to have a higher mastery of the cognitive processes listed in the model. In this paper, we focus on solution construction effectiveness. Solution construction actions are considered effective when they improve the overall quality of the solution in progress.

To assess one aspect of student metacognitive regulation, our approach evaluates student behaviors using a measure of coherence called action support. Support for a particular action represents the extent to which it is informed by information that could have been acquired through previous actions. For example, information seeking actions (e.g., reading about a causal relationship) can provide support for future solution construction actions (e.g., adding the corresponding causal link to the map). Students with higher proportions of supported actions are considered to have a higher mastery of strategies for coordinating their use of tools within the environment.

4.2 Data-Driven, Bottom-Up Analysis

To identify student behaviors in the learning environment, our framework applies a sequential pattern mining algorithm to logged records of student actions. To effectively perform sequential data mining on learning interaction traces, raw logs must first be transformed into an appropriate sequence of actions. In this step, researcher-identified categories of actions, corresponding to the relevant system tools and interfaces in the cognitive/metacognitive task model, define the set of actions that may appear in the activity sequences. This filters out irrelevant information (e.g., cursor position) and combines qualitatively similar actions (e.g., performing the same action through different interface features). The resulting activity sequences form the input to a sequential pattern mining algorithm that identifies common patterns of action.

In the analysis presented, we employ an algorithm (from Pex-SPAM [4] to identify patterns that meet a given sequence mining support threshold, i.e., the identified patterns occur in at least a given percentage of the sequences. To identify patterns that are common to the majority of the students, we apply a sequence mining support threshold of 50% on the sequential pattern mining algorithm.

4.3 Integrating Theory-Driven Measures with Data-Driven Analysis

Common behavior patterns identified by the sequence mining algorithm have to be interpreted and analyzed by researchers to identify a relevant subset of important patterns that provide a basis for generating actionable insights (e.g., how to scaffold user interactions with the learning environment to encourage specific, productive behaviors). Our framework maps the patterns back into student sequences to identify the individual occurrences of each pattern and then analyzes these instances of the patterns in context to more effectively interpret and differentiate different behaviors that result in the same action pattern. To do this, we employ the information acquisition and application measures along with a measure of pattern coherence, which describes whether or not pairs of actions form a coherent pattern such that: (i) an earlier action provides support for a later action, or (ii) both actions are supported by a common previous action (which may have occurred before the pattern instance).

By analyzing the action support and effectiveness of the discovered frequent pattern instances, our framework can distinguish a variety of behaviors and strategies that are defined by the same sequence of actions. The support and effectiveness measures apply to individual actions, and may be used to refine the definition of canonical actions by applying thresholds to the action support and effectiveness values. For example, this may result in further classifying a *read* statement as an *ineffective-read* versus an *effective-read*. Whereas this information may be very useful in contextualizing the meaning and use of derived patterns that contain these actions, they may also have the effect of reducing the frequency of the observed pattern. For example, the qualification of actions by their action support and effectiveness measures may reduce the occurrence of patterns that contain these actions to below 50%, making those patterns ineligible for further analysis. To overcome this problem, our integrated framework incorporates these measures for further interpretation only after discovering common patterns using the sequence mining approach.

5 OELE Study and Results

Our analysis is based on data collected from a recent middle school classroom study with Betty's Brain. The study tested the effectiveness of two support modules designed to scaffold students' understanding of cognitive skills and metacognitive strategies important for success in building the correct causal map. The *Knowledge Construction* (KC) support module scaffolded students' understanding of how to construct knowledge by identifying causal relations in the resources, and the *Solution Evaluation* (SE) support module scaffolded students understanding of how to monitor Betty's progress using the quiz results to identify correct and incorrect causal links on Betty's map. Participants were divided into four treatment groups. The *Knowledge Construction group* (KC-G) used a version of Betty's Brain that included the KC support module and a causal link tutorial that they could access at any time during learning. The *Solution Evaluation group* (SE-G) used a version of Betty's Brain that included the SE support Module and a marking links correct tutorial that they could access at any time during learning. In addition to the KC and SE groups, the experiment included a *Control group* (Con-G) and a *Full Support group* (Full-G). The control group used a version of Betty's Brain that included neither the tutorials nor the support modules, and the full support group used a version of Betty's Brain that included both tutorials and support modules.

Students used the Betty's Brain system to learn about climate change. The expert map includes 22 concepts and 25 links representing the greenhouse effect, human activities linked to the greenhouse effect, and potential impact of the greenhouse effect on climate. The hypermedia resources on climate change contain 31 hypertext pages with a Flesch-Kincaid reading grade level of 8.4. Learning was assessed using a pre-post test design. Each written test was made up of five questions that asked students to consider a given scenario (e.g., a significant increase in the use of road vehicles) and explain its causal impact on climate change. The maximum combined score for the five questions was 16.

The experimental analysis reported in this paper used data from 20 KC-G students, 17 SE-G students, 15 Con-G students, and 16 Full-G students. The study was conducted for 9 school days, with students participating for a 60-minute class period each day. The first four class periods included a pre-test and training with Betty's Brain and causal modeling. Students then spent four class periods (days 5-8) working with their respective versions of the Betty's Brain system with minimal intervention by the teachers and the researchers. On the ninth day, students completed the post-test that was identical to the pre-test.

To extract the activity sequences for mining, log events captured by the learning environment were mapped to sequences of canonical actions in five primary categories [6, 7]: (1) Reading: students access a page in the resources; (2) Causal Map Editing: students edit the causal map, with actions further divided by whether they operate on a causal link or a concept and whether the action was an addition, removal, or modification; (3) Querying Betty: students use a template to ask Betty a question, and she uses causal reasoning with the current map; (4) Explanation: students ask Betty to explain her answer to a query or quiz question; and (5) Quizzing: students have Betty take a quiz.

Table 1 presents student pre-to-post learning gains and students' best causal map scores[1] for each treatment in the intervention. A repeated measures ANOVA performed on the pre- and post-test data revealed a significant effect of time on pre-to-post-test scores ($F = 59.31$, $p < .001$, $\eta 2p = 0.481$), but it failed to reveal a significant effect of treatment ($F = 0.988$, $p > .05$, $\eta 2p = 0.044$). Similarly, an ANOVA revealed no significant effect of the treatment on map scores. Clearly all students learned as the result of the intervention and several students produced a significant portion of the correct causal map.

However, the small sample sizes and the large variations in performance within groups (much more so than across groups) make detailed analysis of the experimental treatments difficult. Therefore, in our application of the analysis framework to data

[1] The best map score is the highest map score a student achieved at any time during the intervention, calculated as the number of correct casual links minus the number of incorrect causal links.

from this study, we focus on analyzing the different learning behaviors corresponding to a given action pattern and comparing the occurrence of these behaviors between students who had high map scores and those who had low map scores, without regard to treatment. The median map score was 7.5, so we consider the students with a map score of 7 or lower as the "*LowMap*" group and the ones with a map score of 8 or higher as the "*HiMap*" group. Below we apply our analysis framework to this data.

Table 1. Performance [mean (s.d.)] by Treatment

Group	*Pre-Test*	*Post-Test*	*Gain*	*Best Map*
Con	5.07 (2.03)	6.10 (2.64)	1.03 (1.99)	8.87 (8.20)
KC	3.85 (2.54)	5.13 (3.37)	1.28 (2.33)	9.55 (6.64)
SE	4.41 (1.97)	6.82 (2.33)	2.41 (1.92)	9.53 (7.55)
Full	3.88 (1.77)	6.78 (2.76)	2.91 (1.76)	7.25 (6.36)

The results of the sequence mining on students' action sequences showed that [Remove Link (RL)]→[Read (R)]→[Add Link (AL)] was one of a set of frequent patterns. This pattern suggests the possibility of the student correcting their map by removing a link and reading relevant resources to replace it with a corrected link. The pattern coherence and effectiveness measures allowed us to break this pattern down into a number of distinct behaviors. First, coherent versions of the pattern (i.e., in which the two link edits are coherent and the read followed by link addition are coherent) appear to indicate an informed map correction behavior. However, when the two link edits are not coherent, rather than a correction, the link removal appears to be part of a different behavior from the link addition. Therefore, we also consider the sub-pattern R→AL separately as an informed map editing behavior if the sub-pattern is coherent and an uninformed map editing behavior if it is not. Additionally, any of these different behaviors can be effective (improve the map score) or ineffective (reduce the map score or leave it unchanged).

Table 2 lists these different behaviors and their frequency in the analyzed study. Overall, the majority of informed map correction attempts were ineffective (a 38% effectiveness rate), despite the majority of all informed map additions being effective (a 58% effectiveness rate). This suggests that further support and scaffolding may be important for helping students integrate their solution evaluation and knowledge construction activities in order to not only identify problems, but also to correct them. Interestingly, the *HiMap* group tended to employ the informed map correction behavior about as effectively as the *LowMap* group (39% versus 37%, respectively), despite having a higher overall effectiveness for link edits in general (58% versus 50%). However, the *HiMap* group was over three times more likely to engage in informed map correction (149 instances versus 46 instances, respectively). Further, as figure 3 illustrates, the *HiMap* group tended to perform the majority of their informed map correction activities later in the intervention than the *LowMap* group. This suggests that the *HiMap* group persisted with this important monitoring activity longer than the *LowMap* group, which may have been a factor in the *HiMap* group's greater success.

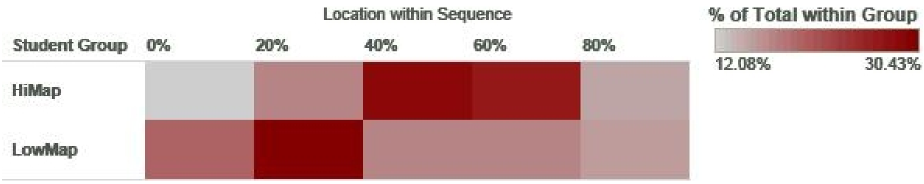

Fig. 3. Heat map of informed map correction occurrences by group

Analysis of the R→AL sub-pattern further illustrates the importance of considering pattern coherence and effectiveness in analyzing student behavior. While 64% of the instances of this pattern were coherent (i.e., corresponding to informed map editing as opposed to uninformed map editing), this ratio varied between the HiMap group, where 69% of the instances corresponded to informed map editing, and the LoMap group, where only 59% of the additions were informed. This less systematic behavior in employing reading to directly inform map additions may have contributed to the lower performance in the LoMap group.

Further, effectiveness differed drastically between coherent and incoherent instances of the R→AL pattern in both groups. Although the HiMap group performed more effectively than the LoMap group in both cases (60% to 51% effectiveness when the pattern was coherent, and 34% to 21% when it was not), this still suggests that further scaffolding of systematic knowledge construction strategies could provide tangible benefits both to the high- and low-performing students.

Table 2. RL→R→AL Behaviors

Pattern	**Coherent**	**Effective**	**Behavior Interpretation**	**Occurrence**
RL→R→AL	Yes	Yes	Informed Map Correction (Effective)	75
RL→R→AL	Yes	No	Informed Map Correction (Ineffective)	120
R→AL	Yes	Yes	Informed Map Addition (Effective)	509
R→AL	Yes	No	Informed Map Addition (Ineffective)	366
R→AL	No	Yes	Uninformed Map Addition (Effective)	140
R→AL	No	No	Uninformed Map Addition (Ineffective)	344

6 Conclusion

In this paper, we have presented a framework for analyzing learning activity data in open-ended learning environments that integrates top-down, theory-driven measures and bottom-up, data-driven pattern discovery. For top-down analysis of learning behaviors, our framework focuses on (i) the learner's acquisition and application of information encountered while they perform their task-related activities in the learning environment and (ii) the impact of these activities with respect to the learning task. For bottom-up, data-driven discovery of learning behaviors, our framework employs data mining techniques for identifying frequent patterns of action in logs of students' learning and problem-solving activities. This integrated analysis framework can be used to build and extend learner models to employ evidence of learning behaviors and strategies from a combination of the theory-driven measures and the patterns of student actions.

We presented results from a case study of activity patterns identified in data from the Betty's Brain learning environment. This analysis illustrates the importance of differentiating discovered patterns of action with action support, pattern coherence, and effectiveness measures in the context of the students' other activities. Further, the analysis showed potentially important differences between high and low-performing students in terms of their learning behaviors, which were not apparent from analysis with either the theory-driven measures or the action pattern mining in isolation. These results illustrate the benefits of incorporating top-down and bottom-up techniques in concert to precisely characterize the learning behavior of students in an open-ended environment and have direct implications for extending the learner model employed in Betty's Brain. In future work, we intend to incorporate pattern detectors, based on the identified patterns and the information acquisition/application measures, into the Betty's Brain learner model in order to directly test the results of this analysis in improving learner scaffolding.

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