Smart Open-Ended Learning Environments that support Learners Cognitive and Metacognitive Processes

Gautam Biswas, James R. Segedy, and John S. Kinnebrew

Dept. of EECS/ISIS, Vanderbilt University, Nashville, TN 37235. USA.

{gautam.biswas,james.segedy,john.s.kinnebrew}@vanderbilt.edu

Abstract. Metacognition and self-regulation are important for effective learning; but novices often lack these skills. Betty's Brain, a Smart Open-Ended Learning Environment, helps students develop metacognitive strategies through adaptive scaffolding as they work on challenging tasks related to building causal models of science processes. In this paper, we combine our previous work on sequence mining methods to discover students' frequently-used behavior patterns with context-driven assessments of the effectiveness of these patterns. Post Hoc analysis provides the framework for systematic analysis of students' behaviors online to provide the adaptive scaffolding they need to develop appropriate learning strategies and become independent learners.

Keywords: open-ended learning environments, metacognition, measuring metacognition, scaffolding, sequence mining.

1 Introduction

Open-Ended Learning Environments (OELEs) are learner-centered [1]. They employ supporting technology, resources, and scaffolding to help students actively construct and use knowledge for complex problem-solving tasks [2,3]. Our research group has developed an OELE called Betty's Brain, where students learn about science topics by constructing a visual causal map to teach a virtual agent, Betty. The goal for students using Betty's Brain is to ensure that their agent, Betty, can use the causal map to correctly answer quiz questions posed to her by a Mentor agent, Mr. Davis [4].

In Betty's Brain, learners are responsible for managing both their cognitive skills and metacognitive strategies for learning the domain material, structuring it as a causal map, and testing Betty's understanding in order to obtain feedback on the quality of their map. This places high cognitive demands on learners [2], especially those who lack well-organized domain knowledge structures and effective self-regulation strategies [5].

An important implication of this is that OELEs require methods for measuring students' understanding of these important skills and strategies, while providing scaffolds that help them practice and learn these skills. Moreover, these systems must focus on cognition and metacognition in an integrated fashion. Supporting learners in developing their metacognitive knowledge may not be sufficient for achieving success in learning and problem solving, especially when learners lack the cognitive skills and background knowledge necessary for interpreting, understanding, and organizing critical aspects of the problem under study [2]. Learners with poor self-judgment abilities often resort to suboptimal strategies in performing their tasks [6,7]. However, research studies have shown that proper scaffolding helps students improve their metacognitive awareness and develop effective metacognitive strategies [8].

In this paper, we present an extension of our previous work in analyzing students' behaviors on the system using sequential pattern mining methods [4]. Primarily, the extension involves interpreting and characterizing behavior patterns using metrics motivated by a cognitive/metacognitive model for managing one's own learning processes in OELEs. While the results in this paper represent a post hoc analysis of student behaviors, our goal is to use such results to assess students' cognitive and metacognitive processes in real-time as they work on their learning tasks[1].

2 Betty's Brain

Betty's Brain (Fig. 1) provides students with a learning context and a set of tools for pursuing authentic and complex learning tasks. These tasks are organized around three activities: (1) reading hypertext resources to learn the domain material, (2) building and refining a causal map, which represents the domain material, and (3) asking Betty to take a quiz. Students explicitly teach Betty by constructing a causal map that links concepts using causal relations, e.g., "absorbed heat energy increases

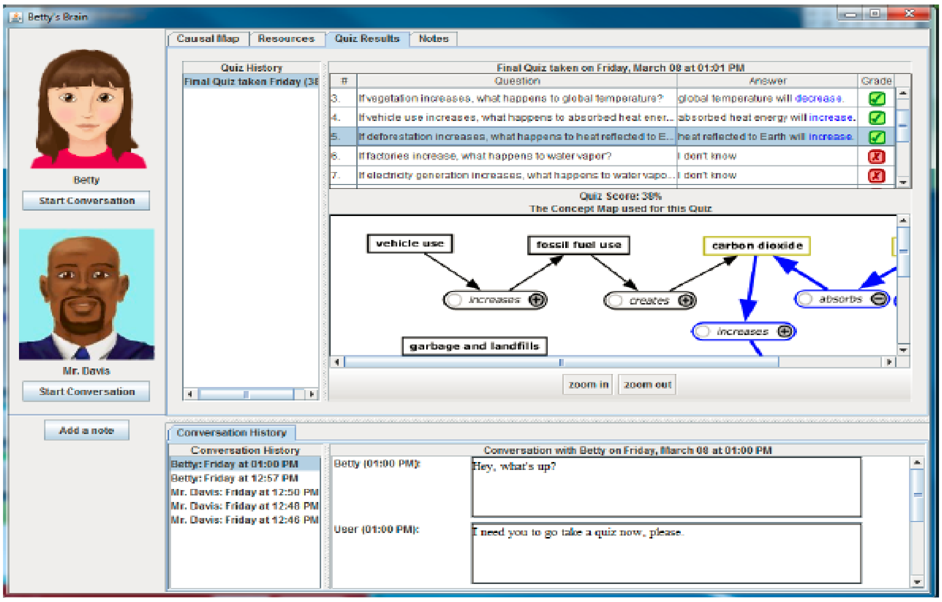

Fig. 1. Betty's Brain System showing Quiz Interface

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[1] To download Betty's Brain, and get more details about the system, visit www.teachableagents.org

global temperature." Students can check what Betty knows by asking her questions, e.g., "if garbage and landfills decrease, what effect does it have on polar sea ice?" To answer questions, Betty uses qualitative reasoning that operates through chains of links [4]. The learner can further probe Betty's understanding by asking her to explain her answer. Betty illustrates her reasoning by explaining her solution and animating her explanation by highlighting concepts and links on the map as she mentions them.

Learners can assess Betty's (and, therefore, their own) progress in two ways. After Betty answers a question, learners can ask Mr. Davis, to evaluate the answer. Learners can also have Betty take a quiz on one or all of the sub-topics in the resources. Quiz questions are selected dynamically such that the number of correct answers is proportional to the completeness of the map. The remaining questions produce incorrect answers, and they direct the student's attention to incorrect and missing links.

After Betty takes a quiz, her results, including the causal map she used to answer the questions, appear on the screen as shown in Fig. 1. The quiz questions, Betty's answer, and the Mentor's assigned grade (i.e., correct, correct but incomplete, or incorrect) appear on the top of the window. Clicking on a question will highlight the causal links that Betty used to answer that question. To help students keep track of correct and incorrect links, the system allows students to annotate them with a green check-mark (correct), a red X (incorrect), or a gray question mark (not sure).

2.1 Measuring Cognition and Metacognition

To interpret students' learning behaviors on the system, we have developed a model that exploits the synergy between the cognitive and metacognitive processes needed for effective learning. Overall, this model includes four primary processes that students are expected to engage in while using Betty's Brain: (1) Goal Setting & Planning, (2) Knowledge Construction (KC), (3) Monitoring (Mon), and (4) Help Seeking. In this work, we focus on the KC and Mon process models.

Knowledge construction includes metacognitive strategies for (1) *information seeking*, i.e., determining when and how to locate needed information in the resources, and (2) *information structuring*, i.e., organizing one's developing understanding of the domain knowledge into structural components, e.g., causal links. In executing these metacognitive processes, learners rely on their understanding of the relevant cognitive processes linked to information seeking (finding causal relations while reading the resources) and structuring (converting the causal information to links that are added to appropriate places in the map).

Monitoring processes include (1) *model assessment* of all or a part of the causal model and then interpreting the derived information, and (2) *progress recording* to mark which parts of the causal model are correct, and which may need further refinement. Successful execution of metacognitive monitoring processes relies on students' abilities to execute cognitive processes for assessing the causal model (via questions, explanations, quizzes, and question evaluations) and recording progress (via note taking and annotating links with correctness information).

We have developed a set of data mining methods [7] for analyzing students' learning activity sequences and assessing their cognitive and metacognitive processes as they work in Betty’s Brain. In addition, we have developed methods for measuring how student behaviors evolve during the course of the intervention depending on the type of feedback and support that they received from the Mentor agent. In particular, we are interested in studying whether students' suboptimal behaviors are replaced by better strategies during the intervention.

To assess student activities with respect to our cognitive/metacognitive model, we calculate four measures: *map edit effectiveness*, *map edit support*, *monitoring effectiveness*, and *monitoring support*. Map edit effectiveness is calculated as the percentage of causal link edits that improve the quality of Betty’s causal map. Map edit support is defined as the percentage of causal map edits that are supported by previous activities. An edit is considered to be supported if the student previously accessed pages in the resources or had Betty explain quiz answers that involve the concepts connected by the edited causal link. Monitoring effectiveness is calculated as the percentage of quizzes and explanations that generate specific correctness information about one or more causal links. Finally, monitoring support is defined as the percentage of causal link annotations that are supported by previous quizzes and explanations. Link annotations are supported (correct or incorrect) if the links being annotated were used in a previous quiz or explanation. For support metrics, a further constraint is added: an action can only support another action if both actions occur within the same time window; in this work, we employed a ten-minute window for support.

In order to calculate these measures and perform data mining of student behaviors, the system records many details of student learning activities and associated parameters in log files. For example, if a student accesses a page in the resources, this is logged as a Read action that includes relevant contextual information (e.g., the page accessed). In this work, we abstracted the log files into sequences of six categories of actions: (1) Read, (2) Link Edit, (3) Query, (4) Quiz, (5) Explanation, and (6) Link Annotation. Actions were further distinguished by context details, such as the correctness of a link edit.

3 Method

Our analysis used data from a recent classroom study with Betty's Brain in which students learned about the greenhouse effect and climate change. The study tested the effectiveness of two scaffolding modules designed to help students' understanding of cognitive and metacognitive processes important for success in Betty's Brain. The knowledge construction (KC) support module scaffolded students' understanding of how to identify causal relations in the resources, and the monitoring (Mon) support module scaffolded students understanding of how to use Betty’s quizzes to identify correct and incorrect causal links on the causal map. Participants were divided into three 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 KC module was activated when three out of a student's last five map edits were incorrect, at which point Mr. Davis would begin suggesting strategies for identifying causal links during reading. Should students continue to make incorrect map edits despite this feedback, the KC module activated the tutorial for identifying causal relations in short text passages. Students completed the tutorial session when they solved five consecutive problems correctly.

The monitoring group (Mon-G) used a version of Betty's Brain that was activated after the third time a student did not use evidence from quizzes and explanations to annotate links on the map. At this time, Mr. Davis began suggesting strategies for using quizzes and explanations to identify and keep track of which links were correct. Should students continue to use quizzes and explanations without annotating links correctly, the Mon module activated a tutorial that presented practice problems on link annotation. Students had to complete five problems correctly on the first try to complete the tutorial session. Finally, the control group (Con-G) used a version of Betty's Brain that included neither the tutorials nor the support modules.

Our experimental analysis used data collected from 52 students in four middle Tennessee science classrooms, taught by the same teacher. Learning was assessed using a pre-post test design. Each written test consisted of five questions that asked students to consider a given scenario and explain its causal impact on climate change. Scoring (max score = 16) was based on the causal relations that students used to explain their answers to the questions, which were then compared to the chain of causal relations used to derive the answer from the correct map.

Performance on the system was assessed by calculating a score for the causal map that students created to teach Betty. This score was computed as the number of correct links (the links in the student's map that appeared in the expert map) minus the number of incorrect links in the student's final map. We also used the log data collected from the system to derive students' behavior patterns, interpret them using our cognitive/metacognitive model, and study the temporal evolution of the observed KC and Mon strategies over the period of the intervention. Students spent four class periods using their respective versions of Betty's Brain with minimal intervention by the teacher and the researchers.

4 Results

Table 1 summarizes students' pre-post gains and final map scores by group. A repeated measures ANOVA performed on the data revealed a significant effect of time on test scores ($F = 28.66$, $p < 0.001$). Pairwise comparison of the three groups revealed that the Mon-G had marginally better learning gains than KC-G, which had better learning gains than the Con-G group. In particular, the Mon-G learning gains were significantly better than the Con-G gains at the 0.1 significance level ($p < .075$), indicating the intervention may have resulted in better understanding of the science content. The small sample size and the large variations in performance within groups made it difficult to achieve statistical significance in these results. However, one positive aspect of this finding is that while students in the Mon-G and KC-G spent an average of 10% and 17% of their time in the tutorials, respectively, they learned, on average, just as much, if not more, than the Con-G students.

Table 1. Pre-Post Test Gains and Map Scores

Measure	Con-G	KC-G	Mon-G
Pre-Post Test Gain	1.03 (1.99)	1.28 (2.33)	2.41 (1.92)
Map Score	8.87 (8.20)	9.55 (6.64)	9.53 (7.55)

To assess students' overall behaviors, we calculated the effectiveness and support measures in Table 2. The KC-G students had the highest scores on both map editing effectiveness and support, suggesting that the KC feedback helped students read more systematically while constructing their maps (however, only the map edit support showed a statistically-significant difference, KC-G > Con-G, $p = 0.02$, and the map edit effectiveness illustrated a trend, KC-G > Con- G, $p = 0.08$). However, the monitoring support did not seem to have the same effect on the Mon-G group. The Mon-G students did have the highest monitoring effectiveness, but it was not statistically significant. Further, the Con-G students had the highest monitoring support average ($p < 0.10$). It is not clear why the Mon or KC support and tutorials resulted in students performing less-supported monitoring activities.

Table 2. Effectiveness & Support Measures by Group

Measure	Con-G	KC-G	Mon-G
Map edit effectiveness	0.46 (0.13)	0.52 (0.07)	0.5 (0.12)
Map edit support	0..46 (0.26)	0.66 (0.18)	0.58 (0.22)
Monitoring effectiveness	0.3 (0.22)	0.32 (0.21)	0.4 (0.20)
Monitoring support	0.61 (0.30)	0.32 (0.4)	0.33 (0.32)

In order to investigate student learning behavior in more detail, we employed sequence mining analyses to identify the 143 different patterns of actions that were observed in the majority of students. Table 3 lists the 10 most frequent patterns that employed at least two actions and could be interpreted as a metacognitive strategy in our cognitive/metacognitive model. Each pattern is defined by two or more primary actions, and each action is qualified by one or more attributes. For example, [Add correct link] describes a student's addition of a causal link that was correct. The → symbol implies that the action to the left of the arrow preceded the action to the right of the arrow.

The average frequency is calculated as the average number of times per student a particular behavior pattern was used in each group. The last column represents our interpretation of the type of strategy a particular behavior represents. In this study, the type of strategy corresponding to a behavior was determined by the category of the cognitive process (KC or Mon) implied by the individual actions that made up the behavior. Therefore, some behaviors (e.g., pattern #3: [Quiz] → [Remove incorrect link]) span KC and Mon (KC+Mon) strategies.

The frequency numbers indicate that for almost all of the top 10 behaviors the CON-G showed a higher frequency of use than the two experimental groups. This may be partly attributed to the time the KC-G and Mon-G groups spent in tutorials, therefore, away from the primary map building task. However, an equally plausible reason is that the CON-G students used more trial-and-error approaches, spending less time systematically editing and checking the correctness of their maps. This is further supported by looking at the highest average frequency behaviors for each of the groups. Four of the top five behavior strategies for the Mon-G students are primarily Mon or KC+Mon related (patterns 1, 3, 5, and 7), involving quizzes, map editing, and explanations. KC-G students, on the other hand, more often employed KC strategies related to adding and removing links along with a couple of strategies that combine KC and Mon activities. The Con-G students seem to have employed KC and Mon strategies in about equal numbers.

Table 3. Comparison of Pattern Frequencies across Conditions

Pattern	Avg. Frequency			Model Category
	CON	KC	MON	
[Add incorrect link] → [Quiz]	11.20	7.35	8.24	KC+Mon
[Add incorrect link] → [Remove incorrect link]	6.00	12.65	3.71	KC
[Quiz] → [Remove incorrect link]	7.87	6.10	6.29	KC+Mon
[Add concept] → [Add correct link]	7.53	6.75	4.94	KC
[Quiz] → [Explanation]	8.40	3.80	5.35	Mon
[Remove incorrect link] → [Add incorrect link]	4.53	9.20	3.41	KC
[Add correct link] → [Quiz]	5.87	4.05	5.06	KC+Mon
[Remove incorrect link] → [Quiz]	5.93	4.45	4.12	KC+Mon
[Explanation] → [Explanation]	5.67	2.95	4.88	Mon
[Add incorrect link] → [Quiz] → [Remove same incorrect link]	5.27	3.75	3.82	KC+Mon

A particularly interesting example of a strategy is the pattern: [Add incorrect link (AIL)] → [Quiz (Q)] → [Remove same incorrect link (RIL)]. This could represent a strategy where a student first adds a link (which happens to be incorrect) and then takes a quiz to determine if the quiz score changes. Depending on the outcome (in this case, the score likely decreased), the student determines that the link added was incorrect, and, therefore, removes it. This may represent a trial-and-error strategy. To study this pattern further we developed two measures: (1) a measure of *cohesiveness* of the pattern, i.e., in what percentage of the AIL → Q → RIL patterns was the delete action supported by the quiz result; and (2) a *support* measure, i.e., in what percentage of the AIL → Q → RIL patterns was the addition of the link supported by recent actions. The MON group had higher cohesiveness (41.9 to 38.0 and 37.3 for the CON and KC groups) and support (27.7 to 20.3 and 187.7 for the CON and KC groups) measures, implying that they used this pattern in a more systematic way than the other two groups.

5 Discussion and Conclusions

The results presented in the previous section provide evidence that a combination of systematically-derived measures of cohesiveness and support can be used with data mining methods to better interpret students' learning behaviors and strategies. In our work on investigating cognitive and metacognitive processes in Betty's Brain, we had to carefully instrument the system to collect rich data on the students' activities and the context associated with those activities. Post hoc mining and analysis show that it is possible to interpret students' behaviors and that related context information allows us to better characterize and interpret these strategies. Our analyses in this study focused on students' knowledge construction and monitoring strategies. This study showed that the interventions produced changes in student behavior that were consistent with the scaffolding they were provided, implying that these metacognitive strategies can be effectively taught in computer-based learning environments.

Future work will involve refining the methods presented in this paper to discover and define strategies in a more systematic way. Further, we will extend our measurement framework to more tightly integrate theory-driven measures with data-driven mining for analyzing student cognition and metacognition during learning. Ultimately, we hope to find better ways of inferring students' intent (i.e., goals) from their observed behaviors and strategies while using the system..

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References

1. Bransford, J., Brown, A., & Cocking, R. (eds) (2000) *How people learn*. National Academy Press Washington, DC, Washington.
2. Land, S., Hannafin, M.J., & Oliver, K. (2012) Student-Centered Learning Environments: Foundations, Assumptions and Design. In Jonassen, D. H., & Land, S. (Eds.) *Theoretical foundations of learning environments* (2nd ed.) New York, NY: Routledge, pp. 3-26.
3. Quintana, C., Shin, N., Norris, C., & Soloway, E. (2006). Learner-centered design: Reflections on the past and directions for the future. *The Cambridge handbook of the learning sciences*, pp. 119-134.
4. Leelawong, K. & Biswas, G. (2008) Designing learning by teaching agents: The Betty's Brain system. International *Journal of Artificial Intelligence in Education*, 18(3):181-208.
5. Zimmerman B (2001) Theories of self-regulated learning and academic achievement: An overview and analysis. In: Zimmerman B, Schunk D (eds) *Self-regulated learning and academic achievement: Theoretical perspectives*, Erlbaum, Mahwah, NJ, pp 1-37.
6. Azevedo, R., et al. (2012). The Effectiveness of Pedagogical Agents' Prompting and Feedback in Facilitating Co-adapted Learning with MetaTutor. In *Intelligent Tutoring Systems* (pp. 212-221). Springer Berlin/Heidelberg.
7. Kinnebrew, J.S.& Biswas, G. (2012) Identifying learning behaviors by contextualizing differential sequence mining with action features and performance evolution. In: *Proceedings of the 5th International Conference on Educational Data Mining*, Chania, Greece.
8. Kramarski, B. & Mevarech, Z. (2003) Enhancing mathematical reasoning in the classroom: effects of cooperative learning and metacognitive training. *AERA Journal* 40(1):281-310.