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Modeling Learners' Metacognitive Skills in Open Ended Learning Environments

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Abstract: In this paper, we discuss improving thinking skills using Open Ended Learning Environment (OELE). In order to guide the students in OELE, their thinking skills should be inferred from their actions with the OELE. Learner modeling to infer students' thinking skills in OELE and our approach is discussed.

Keywords: OELE, Thinking Skill, Self-regulated learning, Metacognitive, Cognitive skills.

1. Introduction

Thinking Skills are the mental process needed to solve problems – they involve collecting information, identifying various approaches to solve the problem, choosing the best approach, and monitoring one's progress toward finding the right solution. Thinking skills are classified by (Beyer 1987), into three level based on its complexity. Broader thinking skills such as problem-solving, decision making, and conceptualizing are complex skills and labeled as level 1. Problem-solving skill involves recognizing the problem, devising/choosing a solution plan, executing it and evaluating the solutions. Decision-making skills involve choosing the best solution plan. Conceptualizing is also an important component in developing problem-solving skills. Critical thinking skills (level 2) such as determining the credibility of the source, identifying logical fallacies, and determining the strength of an argument or claims are a set of discrete mental operations that analyze the accuracy of data and information collected. These operations include both analysis and evaluation and are used repeatedly in various stages of applying level 1 thinking skills (Beyer 1988). Information processing skills such as Recall, translate, interpret, application, analysis, evaluation, and reasoning (inferencing) are considered as the most basic thinking skills and less complex, that is level 3. These skills are relatively simpler and are used repeatedly in various combinations to execute level 1 and level 2 thinking skills.

Teaching thinking skills to K-12 student is an important but non-trivial task because it requires students to structure the solution process, search for information, interpret it, explore alternate solution paths and apply it, to construct and test potential solutions (Brophy 2013; Winne 2010). Recently researchers have started using open-ended learning environment (OELE) to teach thinking skills to students in K-12 classes (Land 2000; Segedy, et al., 2015; Biswas et al. 2016; Basu et al. 2016). In general, OELE systems provide students with a complex problem to solve, tool and resources that support the problem-solving task (Jonassen et al. 2002). In OELE, the students will use problem-solving skills such as planning, metacognitive monitoring, analyzing and regulating, (Kinnebrew et al. 2016), in order to achieve their learning goal. Examples of such OELE used for education are MetaTutor (Azevedo et al., 2012), Betty's Brain (Leelawong and Biswas, 2008), and Crystal Island (Jonathan et al., 2011).

Students' performance in OELEs can be measured using traditional constructs, such as pre- to post-test gains, transfer learning, and quizzes. However, measuring student metacognitive skills that is, students' awareness of thinking skills and when they should apply, also how students apply their thinking skills to solve problems is still an open-ended research question. In this paper, we discuss the existing methods for learner modeling and propose a data-mining based approach for learner modeling in OELEs. In next section, we briefly describe an OELE that has been used extensively in our group, and also discuss some of the metacognitive processes that students employ to solve problems in this domain. In section 3 we review existing literature in learner modeling. We discuss our proposed approach in section 4 and conclude this paper in section 5.

2. Background

In this section, we describe Betty's Brain OELE and metacognition.

2.1 Betty's Brain OELE

The Betty's Brain learning environment (Leelawong and Biswas, 2008), provides students (learners) the task, of teaching a science topic to a teachable agent named Betty. In order to teach their agents, students construct a visual causal map that consists of a set of entities connected by directed links that represent the causal relation between entities. Betty uses the map to answer causal questions and explain those answers. The students' goal is to teach Betty's by drawing the causal map that matches a hidden, expert model of the domain. Students' learning and teaching are organized into three categories of activities: (1) reading hypertext resources, (2) building the map, and (3) assessing the correctness of the map (Davis, et al., 2003). Students iterate among these activities till they have taught Betty a correct model. Information extraction process that is reading hypertext resources, describes the science topic under study (e.g., climate change) by breaking it down into a set of subtopics. 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 the topic, they extract the causal relations between entities and construct the causal map to teach to Betty. Figure 1 illustrates the Betty's Brain system interface.

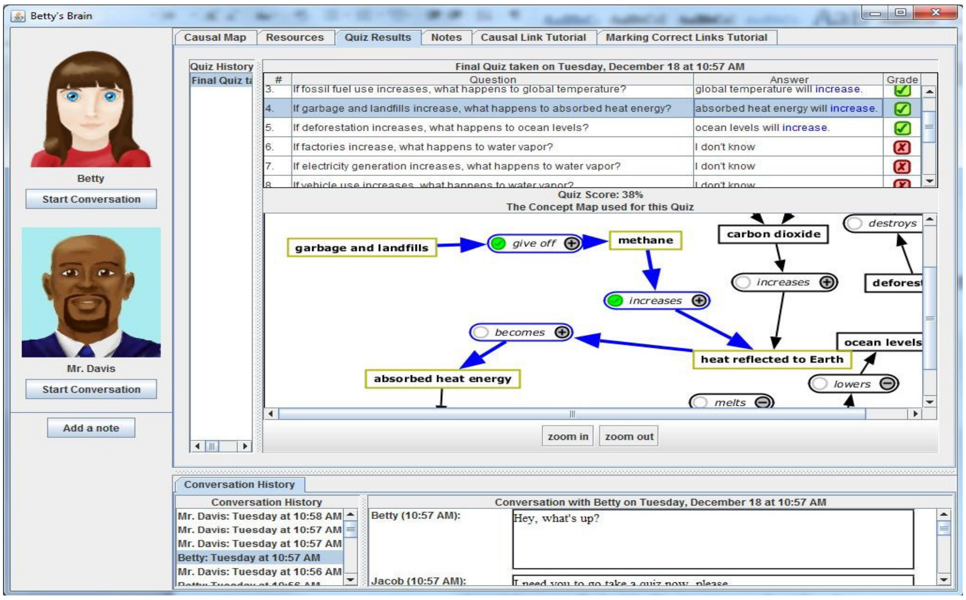


Figure1. Betty's Brain interface. Agent Betty and tutor Mr. Davis are shown. The menu tab in top shows resources to read, tutorial to create the causal map and to take the quiz. The quiz interface is shown in this figure.

To assess their own understanding and success in teaching Betty, students can use two ways, 1) Ask Betty to answer cause and effect questions using a template. To verify Betty's answer, student can ask another pedagogical agent named Mr. Davis, to check the answers. Mr. Davis acts as a tutor. Mr. Davis compares the portion of map developed by a student with the expert model; if both match then Betty's answer is correct. 2) Students can ask Betty to take the quiz on one or all sub-topics in the resources. Quiz questions are selected dynamically by comparing Betty's current causal map to the expert map. Since the quiz is 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. If the student created the causal map for one sub-topic then the rest of the quiz questions show either incomplete or incorrect answers. By analyzing the answer, students can understand that which causal links are correct and which links need to correct. It will help students to collect information again and build the model to teach Betty. If the students are not able to proceed in their learning task, they can interact with the tutor, Mr. Davis and ask for help via menu-based conversation. Then conversation allows the student to choose from a set of pre-specifies options.

2.2 Metacognition

Metacognition (Flavell, 1976) describes the ability to reason about and explicitly manage one's own cognitive processes. In the context of learning, metacognition can be considered a subset of self-regulated learning (SRL). SRL is a theory of active learning that describes how learners are able to set goals, create plans for achieving those goals, continually monitor their progress, and revise their plans to make better progress in achieving these goals (Zimmerman & Schunk, 2011). In terms of SRL, metacognition deals directly with cognition without explicitly considering its interactions with emotional or motivational constructs (Whitebread & Cárdenas, 2012). Our focus on metacognition is centered on students' understanding and use of strategies, which have been defined as consciously-controllable processes for completing tasks (Pressley et al., 1989). Strategies comprise a large portion of metacognitive knowledge; they consist of declarative, procedural, and conditional knowledge that describe the strategy, its purpose, and how and when to employ it (Schraw et al., 2006). The important goal in developing adaptive support for students' working in OELEs is to explicitly teach students the strategies for regulating their learning as they solve complex, open-ended problems. In next section, we discuss related research works to model learners' metacognitive processes.

3. Learner Modeling in Intelligent Tutoring Environment

Learning modeling approaches used in intelligent learning environments (ILE), (Desmarais and Baker 2012) & (Chrysafiadi and Virvou 2013), are briefly discussed in this section. Most commonly used learner modeling approach is the overlay model, it assumes that the learner model is a subset of a domain model that is learner has partial but correct knowledge of some components of the domain. Perturbation model is an extension of overlay modeling; it includes learner's misconceptions that are derived as deviations from the domain model. Stereotype approach is another widely used approach for learner modeling in ILEs (Chrysafiadi and Virvou 2013). Stereotype approach clusters learners based on certain characteristics, which are shared among learners in the cluster. Machine Learning (ML) techniques analyze learner's interaction with the system to classify their behavior. ML techniques canbe used to classify the learners into predefined groups as in Stereotypes (supervised) or new clusters are created based on learner's behavior (unsupervised). Constraint-Based Model (CBM), are developed based on the theory that learners learn from mistakes. In CBM, domain knowledge is represented by a set of constraints and learner knowledge is represented by a set of constraints violated by the learner. To implement constraint knowledge, learning content should contain all possible constraints required to learn that topic. Transfer modeling translates the actions of learners in the systems to skills and knowledge. Learners' skills are represented as ontologies for reuse and to extend the modeling approach to different application contexts.

In OELE, learners are not expected to follow a fixed learning path to achieve their goal hence modeling learners in OELE is a difficult task. From existing research, in OELE, a) stereotype approach using ML techniques are used to cluster the learners based on their behavior (Conati and Kardan. 2013), b) transfer models to model learners' skills or c) combination of a and b were used.

3.1 Learner modeling in OELE

Modeling students' behavior in OELE is a challenging task as it involves modeling students' both students' cognitive abilities as well as their self-regulatory learning behavior. Student model in OELE should capture students', cognitive, metacognitive, and the contextual influence on their performance.

In existing research, researchers have analyzed log data from students' interaction with system, derived analytic measures for characterizing different aspects of student learning behaviors, and and then clustered the students into groups based on the set of analytic measures. One such approach is by Conati and Kardan. (2013). In their system, student behavior in Interactive simulation (IS) environments derived from log data of their interactions with the system is used for classifying students into groups using an k-means clustering algorithm followed by associated rule mining, to create stereotypical models of user behavior. To improve the performance of student modeling (Kardan and Conati 2013), combined the eye gaze data collected using eye-tracker. The results show that combined data improved the performance of student modeling.

In Segedy et al. (2015), students' learning and success in teaching Betty in Betty's Brain are predicted using Coherence Analysis approach on tasks performed by the students. Task modeling is used to interpret student actions on the system in terms of higher level tasks. In task model, student's interaction with the system such as accessing resource page, taking a quiz, building the maps are transferred into a particular thinking skill, for example utilizing the access the resource page is transferred to higher order thinking skill of information seeking and acquisition. CA approach analyzes student's behavior by combining student's actions on the system to produce action coherence. For example, accessing resource page that provides information about two concepts provides support for editing causal link that connects those concepts in the causal map. CA approach analysis reports that CA provides insight into students' open-ended problem-solving strategies and predicts the students' task performance and learning gain.

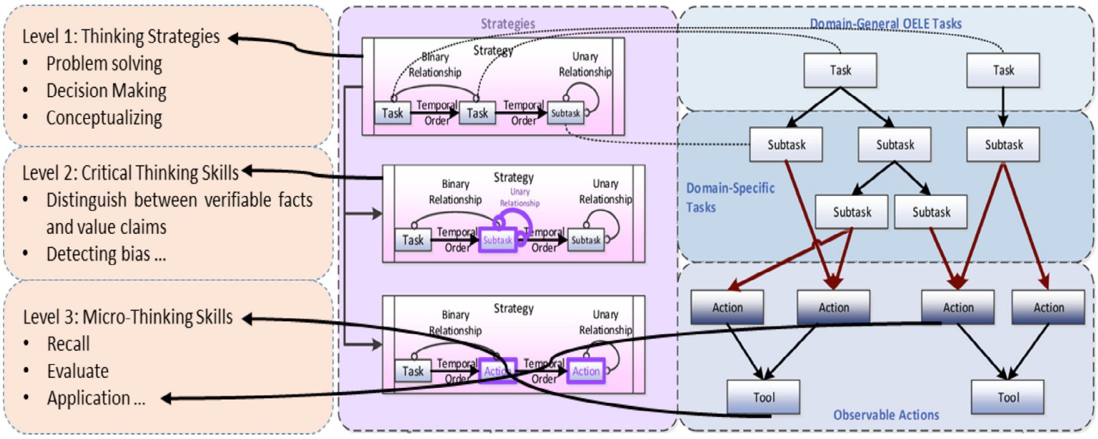
In (Kinnebrew et al. 2014), temporal sequences of students' action in Betty's Brain are analyzed using sequence mining methods. The most frequently occurring sequences of students' action are then interpreted as strategies of the students to succeed in the learning task. The students' cognitive skills and learning behaviors identified using data mining techniques are then used to interpret learning behaviors by mapping to metacognitive strategies based on a cognitive/metacognitive task model. In a recent study, Kinnebrew et al. (2016), analysis of students' activity sequences that access the coherence among students' actions and data-driven pattern discovery methods, which are explained in above two related research work, to interpret students' open-ended learning and problem-solving behaviors. The results show the data mining approach provided important inferences which are not considered in task-based model. For example, the difference in the learning strategies of high and low performing students. In this paper, we extend the sequence mining approach used in (Kinnebrew et al. 2016). Our approach in discussed in next section.

4. Learner Modeling in OELE using Data Mining Techniques

We propose to extend the learner modeling approach by Kinnebrew et al. (2016) in this paper. In this section, we discuss how task and strategy model is created from the students' interaction with Betty's Brain, and our proposed model is explained.

Figure 2b shows the generic task and strategy model proposed in (Kinnebrew et al. 2016). The task model is represented as a directed (acyclic) graph, along with its subtasks in OELE. At the lowest level are the observable actions performed by the student with OELE. Links from a task/subtask to actions indicate the actions to be executed to complete the task/subtask. The strategy model describes how actions, or higher-level tasks and subtasks, can be combined to provide different approaches or strategies for accomplishing learning and problem-solving goals. Figure 2 illustrates that strategy can be created by unary relation of task, binary relation between two task and by temporal ordering of tasks. Sequence mining methods are used to derive frequently occurring sequences of students' actions. They are then interpreted using a task and strategy model.

In the existing approach, sequence mining is performed on sequences of actions. The time spent on each task and the results of the student's action in that task is not considered during the sequence mining. Considering time spent on reading resources might identify new learner behaviors, which may define new strategies after analysis. In our approach, during sequence mining, log data will be represented as triple (task, performance, time) for each instance. We plan to implement our proposed approach in log data we collected from our experiments and analyze the new patterns.



a. Thinking skills by Beyer b. Task and Strategy Model for OELE (Kinnebrew et al. 2016).

Figure 2. Links between Task and Strategy Model and Levels of Thinking Skills

In next section, we describe the Figure 2, that is discuss how task and strategy modeling is connected to the thinking skills.

5. Connecting Task and Strategy Model to Thinking Skills

Although OELEs are used to teach thinking skills, the learner modeling in OELEs are linked to hierarchical task and strategy models. Typically, they may be considered to be different, but we show that there are links between the task and strategy models used in OELEs and level of thinking skills we discussed in the introduction. The task and strategy model illustrates that a) higher level tasks may comprise multiple lower-level tasks and b) the combination of multiple tasks/subtasks as a strategy represents the coordination of multiple learning and problem-solving activities, with supporting skills and cognitive processes. These two properties and hierarchical representation of strategy model map on to a number of the thinking skills discussed earlier.

Figure 2, shows the link between OELE task model (Kinnebrew, et al., 2016) and thinking skills (Beyer, 1988). Inference from the users' interactions with the system, will inform us about micro-thinking skills such as recall, and application. The strategy model developed from tasks and subtasks is similar to the level 1 and level 2 thinking skills. Both OELE's task and strategy model and thinking skills are further used to infer the learners' metacognition skills (planning, assessing and monitoring).

6. Conclusion

Thinking skills are important for students in middle schools. The significance of OELEs in helping students develop thinking skills has been demonstrated (Basu et al. 2016). To understand students learning in OELE and to guide them, student's metacognitive skills are tracked and modeled in the OELE. In this paper, a) we have discussed how we may use the learner modeling in OELEs to infer the thinking skills and b) proposed a learner modeling approach using data mining techniques to model learner's strategies. The link between OELE task model and thinking skills, established in this research article is preliminary, and we will extend it in future work by extending the task modeling framework to decision making systems, such as UrbanSim (Wansbury et. al., 2010), and establish the link between OELE and thinking skills.

We plan to test our proposed learner modeling approach using data collected from Betty's Brain and CTSiM tutors. In order to test our approach, we preprocess the raw data to include time spent on each task/sub-task and the performance of that task. Using sequence mining techniques, we will discover patterns of tasks and sub-tasks form the log data. These emerging patterns will be further analyzed and used to identify the strategies used by the learner. The learner model comprising domain level skills learned, cognition and metacognition will be developed. The proposed sequence mining approach can be applied to other OELEs and representation of data can be varied based on the OELE used.

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