

Modeling and Measuring Self-Regulated Learning in Teachable Agent Environments

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Abstract

Our learning by teaching environment has students take on the role and responsibilities of a teacher to a virtual student named Betty. The environment is structured so that successfully instructing their teachable agent requires the students to learn and understand science topics for themselves. This process is supported by adaptive scaffolding and feedback from the system. The feedback is instantiated through the interactions with the teachable agent and a mentor agent, named Mr. Davis. This paper provides an overview of two studies that were conducted with 5th grade science students and a description of the analysis techniques that we have developed for interpreting students' activities in this learning environment.

1 Introduction

Cognitive scientists have established that metacognition and self-regulation are important components for developing effective learning in the classroom and beyond (Zimmerman 2001). Researchers (*e.g.*, (Zimmerman, Bandura, and Martinez-Pons 1992; Pintrich 2000)) have demonstrated that students' SRL capabilities can play a significant role in high school academic achievement. (Brown and Palincsar 1989) have demonstrated that younger students can acquire and apply metacognitive skills, such as planning and monitoring through instruction. However, students in typical classrooms are rarely provided opportunities to learn and exercise these strategies (Paris and Paris 2001).

Our research team has been developing computer-based-learning environments that utilize the learning-by-teaching approach to instruction in order to foster students acquisition of knowledge and development of sophisticated metacognitive strategies. The system embodies the social constructive learning framework and provides students with opportunities for self-directed, open-ended learning in the domains of science and mathematics (Biswas et al. 2005). In the system, students engage in the iterative process of reading and building causal concept maps for science topics, such as ecology and thermoregulation. The environment is structured so that successfully instructing their teachable agent ("Betty") requires the students to learn and understand the

topic for themselves. Our previous work has shown that students' find the task of teaching and interacting with Betty to be motivating, and it also helps them enhance their own learning (Chase et al. 2009; Schwartz et al. 2009). The teachable agent's performance is a function of how well it has been taught by the student, which provides the student with a less threatening way of assessing their own understanding and areas of confusion (*e.g.*, "Ugh, Betty is so stupid, now I've got to figure out another way to help her learn this stuff"). Based upon the students level of progress and pattern of activities, the system triggers responses from Betty or Mr. Davis at appropriate times to provide the student with guidance on problem-solving and metacognitive strategies. As a result, the students are more likely to both increase their knowledge of the specific domain content and develop more sophisticated problem-solving and metacognitive strategies, which in turn helps their preparation for future learning (Bransford and Schwartz 1999).

This paper presents analyses from two studies that were conducted in middle school science classrooms, in which students taught their agent about complex science topics. One of our goals was to determine the degree to which the agents metacognitive and SRL prompts could help improve student learning. Within this framework, we have developed methods to identify and interpret students' learning strategies based on their activity traces on the system. In addition, we report the results of a second study to determine students' acceptance of the strategies discussed by the two agents, and how the feedback provided by the agents influenced their subsequent learning activities.

2 Measuring Self-Regulated Learning

To effectively design, test, and refine a system promoting SRL skills requires the ability to identify and measure metacognitive processes. The traditional approach to measuring students' self-regulated learning (SRL) has been through the use of self-report questionnaires (*e.g.*, (Pintrich et al. 1993; Weinstein, Schulte, and Palmer 1987)). The underlying assumption in these questionnaires is that self-regulation is an aptitude that students possess. For example, the questionnaire items might attempt to assess students' inclination to elaborate as they read a passage, or to determine their approach to managing available time resources (Perry and Winne 2006; Zimmerman 2008). This

approach has been useful, as the self-report questionnaires have been shown to be good predictors of students' standard achievement test scores and they correlate well with achievement levels. However, Hadwin and others (Azevedo and Witherspoon 2009; Hadwin et al. 2007) have argued that while the questionnaires provide valuable information about the learners' self-perceptions, they fail to capture the dynamic and adaptive nature of SRL as students are involved in learning, knowledge-building, and problem-solving tasks.

Increasingly, researchers have begun to utilize trace methodologies in order to examine the complex temporal patterns of self-regulated learning (Azevedo and Witherspoon 2009; Biswas et al. 2010; Hadwin et al. 2007; Zimmerman 2008). Perhaps the most common type of data collected, and the focus of this chapter, are computer logs, which can record every action that the student performs within a computer-based learning environment. More recently, trace data is being supplemented with other sources of data, such as concurrent verbal think-alouds (e.g., (Azevedo and Witherspoon 2009)). Combining trace and think-aloud protocols provides more insight into the students' thought processes that govern the use of strategies. Furthermore, they can be used to validate the results of the trace data analysis.

3 Betty's Brain and Self-Regulated Learning

The Betty's Brain system, illustrated in Figure 1, implements the learning-by-teaching paradigm to help middle school students develop cognitive and metacognitive skills in science and mathematics domains (Biswas et al. 2005). The system supports five primary types of activities: (1) *Read*: hypermedia resources that contain all of the science information needed for students to build their concept maps. (2) *Edit*: students explicitly teach Betty by creating a concept map with the nodes being the relevant science concepts, and the links represent causal relations between the nodes. (3) *Query*: check their teaching by asking Betty questions, which she answers using causal reasoning through chains of links. (4) *Explain*: probe Betty's reasoning, by asking her to explain her answer to a query; and (5) *Quiz*: students assess how well they have taught Betty by having her take a quiz, which is a set of questions chosen by the Mentor agent.

Figure 2 illustrates our conceptual cognitive/metacognitive model that we employ in the design of the Betty's Brain system. For knowledge construction in the Betty's Brain system (i.e., building causal concept maps), we identify two key types of self-regulation strategies: (i) *information seeking*, in which students study and search available resources in order to gain missing domain information or remediate existing knowledge, and (ii) *information structuring*, in which students structure the information by causal and taxonomic relationships to build and revise their concept maps. Information seeking involves strategies that focus on effective use of the resources in the system, whereas information structuring focuses on strategies for construction and revision of the concept map. The model also posits two types of monitoring strategies: (i) *checking*, where students use the query or the quiz features to test the correctness of their concept map, and

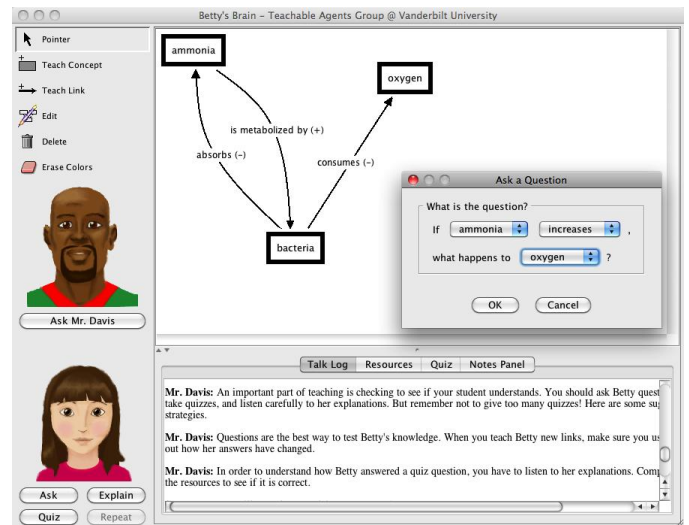


Figure 1: Betty's Brain system with query window

(ii) *probing*, a stronger monitoring strategy, where students systematically analyze their map in greater detail, by asking for explanations to follow the causal reasoning steps and locate potential errors in the maps. Effective guidance (i.e., relevant and timely feedback) based on this SRL model makes students aware and helps them develop good learning strategies. Betty's persona incorporates metacognitive awareness that she conveys to the students at appropriate times to help them develop and apply monitoring and self-regulation strategies (Wagster et al. 2007). Mr. Davis, the mentor, provides help in the form of suggested behavior patterns linked to effective SRL strategies (e.g., "if you are not sure, check the resources to see if Betty is answering her questions correctly."). In other words, the agent feedback is triggered by students' activity patterns and linked to strategies for knowledge construction and monitoring implied by our model.

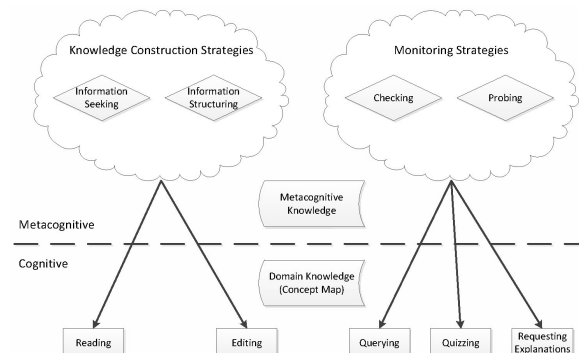


Figure 2: Our model of SRL strategies linked to activities in Betty's Brain

4 Experimental Studies

We have conducted several classroom studies with the teachable agent system in middle school science classrooms. At the beginning of each study, the science teacher introduces students to the topic during regular classroom instruction. The intervention phase starts with an overview of causal relations and causal mapping during a 45-minute class period. This is followed by a hands-on training session with the system the next day. Over the next 4 or 5 days, the students teach Betty by building up a causal concept map for the science topic, which represents what Betty knows. To assess students' acquisition of science domain knowledge and causal reasoning skills, we employ two measures. The first was pretest to posttest gain score. These tests contain a mix of content-related multiple choice and free response items (Biswas et al. 2010) that were administered before the students were introduced to causal reasoning and at the end of the intervention, respectively. The second measure examined students' final maps, in terms of completeness and accuracy

We analyze the results from two classroom studies. The first study compared the students use of self regulated learning (SRL) strategies as they used the system. We had two questions: (1) Would students who taught an agent use more SRL strategies in their learning and teaching tasks? and (2) Would students who received SRL feedback from the agents use more sophisticated SRL strategies than students who did not? The second study used verbal protocol analysis to study the effectiveness of different kinds of SRL strategies, and also compared if the feedback provided by one agent was more effective than the feedback provided by the other agent.

Study 1: Modeling student's SRL strategies

Our participants were 56 students in 5th grade science classrooms. Students were assigned to one of three conditions using stratified random assignment based on standardized test scores. All students created river ecosystem concept maps over five 45-minute sessions. Two of the conditions (i) the learning-by-teaching (LBT) group, and (ii) the self-regulated learning-by-teaching (SRL) group created their map to teach Betty so that she could pass a test on her own. The third group, the intelligent coaching system (ICS) group, provided the control condition and was told to create the map to learn for themselves. They could also query their map and ask for explanations, but in this case, it was Mr. Davis, and not Betty, who responded to them.

We adopt a state-based representation, i.e., a hidden Markov model (HMM) (Rabiner 1989), to analyze student learning behaviors. The states in a HMM are hidden, meaning that they cannot be directly observed in the environment/system. Instead, they produce output (e.g., student activities in the Betty's Brain system) that can be observed. By providing a concise representation of student learning strategies and behaviors, HMMs have the potential of providing a higher-level view of how students approach their learning tasks (e.g., what strategies they use and how they switch between strategies) (Jeong and Biswas 2008;

Biswas et al. 2010). We have developed an algorithm designed to generate HMMs from a set of student activity sequences (Li and Biswas 2002; Jeong and Biswas 2008). The first step in the analysis is to extract each students' activity sequences over the period of the study from the log files. Each element of the activity sequence is labeled as one of the five primary activity types: READ (read the resources), QUER (query Betty on a portion of the map), EXPL (ask Betty to explain her answer to a query), QUIZ (ask Betty to take a quiz), and EDIT (add, edit, or delete concepts and links in the concept map).

Although all students had access to the full set of actions, not all of them used them effectively. We addressed this issue by developing a *relevance score* that took into account how much the current action could be linked to other recent actions. Each student action was assigned a relevance score that depended on the number of relevant previous actions within a pre-specified window. This score provides a measure of *informedness* for knowledge construction activities and, similarly, a measure of *diagnosticity* for monitoring activities. Overall, the relevance score provides a rough measure of strategy consistency or coherence over a sequence of actions. The relevance score is employed in HMM generation by refining the labeling of student activities. Each of the actions in an activity sequence is assigned a label, H (high) or L (low), based on its relevance score, in order to maintain the context and relevance information of the actions in the sequence. For example, a QUER-H activity implies that the query the student asked is related to other activities recently performed, while a QUER-L implies that the query activity is unrelated to the students' recent activities.

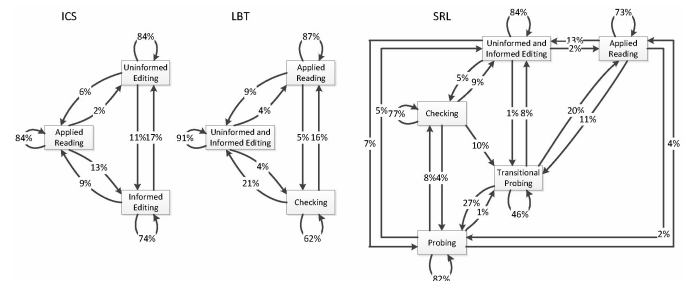


Figure 3: HMMs derived from student activity sequences

The HMM models derived for the ICS, LBT, and SRL groups are shown in Figure 3. The possible transitions between states are shown as arrows, and the transition probabilities are expressed as percentages. For example, the ICS behavior model indicates that there is an 84% likelihood that a student who just performed an applied reading action will next perform another applied reading action, but there is a 13% chance that the student will perform an informed editing action next. States in the models are named based on an interpretation of their outputs (activities), which are described in greater detail in (Biswas et al. 2010). The models for the ICS and LBT groups each have three states, but the activities associated with some of those states differ significantly. Further, the derived model for the SRL group has

five states instead of three and shows some interesting differences in the set of actions associated with those states.

We used the activities associated with a state to categorize the states of the three derived HMM models. This produced seven different states that are described below.

1. *Applied reading*: students are primarily engaged in reading the resources and applying the knowledge gained from reading by editing their maps. This state combines information-seeking and information structuring.
2. *Uninformed editing*: students are primarily making uninformed changes to their map, indicating the use of suboptimal trial-and-error or guessing strategies for information structuring.
3. *Informed editing*: students are primarily making informed changes to their map (information structuring) based on relevant queries or quiz questions.
4. *Uninformed and informed editing*: students are primarily making changes to their map, some of which are based on relevant queries or quizzes.
5. *Checking* - students are querying and quizzing Betty to check the correctness of their concept maps. However, the use of queries and quizzes is unfocused.
6. *Probing* - students combine querying and quizzing with the explanation feature, which illustrates the chain of links that were followed to generate an answer to a question. Further, the queries, explanations, and quizzes are focused on a particular area of the map, and the results inform map editing. This combination implies a deeper, focused monitoring strategy.
7. *Transitional probing* - students perform activities similar to the probing state, but generally with lower relevance scores, suggesting that they may be transitioning to probing a different area of the concept map.

As discussed above, each of the interpreted states can be mapped onto one or more knowledge construction and monitoring strategies outlined in our conceptual SRL model that was illustrated in Figure 2. The models provide evidence that the SRL condition uses more effective monitoring and knowledge construction strategies than the LBT and ICS conditions.

We probed further to determine the prevalence of individual states suggested by a generated HMM. To do this, we calculate the proportion of *expected state occurrences* by condition in Table 1. This measure employs state transition probabilities and average activity sequence lengths to calculate an expected value for the proportion of individual state occurrences. Although states corresponding to knowledge construction behaviors account for a significant percentage of behaviors in all groups, the HMMs for LBT and SRL groups also show use of monitoring strategies (10% for LBT and 49% for SRL). The SRL HMM also includes more states suggesting a greater number (and possibly greater complexity) in the types of strategies employed. Further, the activities involved in these additional states suggest use of the more advanced monitoring behavior of probing that is absent from the ICS and LBT HMMs.

Behaviors	ICS	LBT	SRL
	Prop. (%)	Prop. (%)	Prop. (%)
Applied Reading	33	30	17
Uninformed Editing	36	-	-
Uninformed & Informed Editing	-	60	34
Informed Editing	31	-	-
Checking	-	10	13
Transitional Probing	-	-	7
Probing	-	-	29

Table 1: Proportion of expected state occurrences by condition

The results of the HMM analysis identify differences in strategies employed by the different groups of students, but it does not directly indicate how this affected student learning. Table 2 shows the learning gains measured by tests and map scores for each condition in the study. Results show that the two groups that taught Betty (LBT and SRL) outperformed the ICS group on gains in both test and map scores with statistically-significant performance differences between the SRL and ICS groups. The gain score differences between conditions for the multiple choice test questions were not statistically significant. However, for the free response questions, the SRL group showed greater gains than the ICS group ($p < 0.1$ and a relatively large effect size of $\hat{d} = 0.72$). For the gain in correct map concepts, the SRL group outperformed the ICS group ($p < 0.05$, $\hat{d} = 0.81$), and the LBT group ($p < 0.01$, $\hat{d} = 1.05$). Similarly, for the gain in correct map links, the SRL group again outperformed the ICS and LBT groups ($p < 0.05$, $\hat{d} = 0.97$ and $p < 0.1$, $\hat{d} = 0.72$, respectively).

Gain Score	Conditions		
	ICS	LBT	SRL
Multiple Choice	0.4 (2.4)	1.1 (3.1)	0.4 (1.5)
Free Response	1.9 (3.0)	4.3 (3.2)	4.8 (4.7)
Map Concepts	8.1 (2.4)	7.3 (2.7)	10.4 (3.1)
Map Links	12.2 (3.8)	12.7 (5.3)	16.2 (4.4)

Table 2: Mean pre-to-post test and concept map score gains

It is clear that the students who taught Betty outperformed the other students both in learning gains and the use of more effective strategies. The fact that the SRL group had higher free response and map score gains than the LBT group further supports the results of the HMM analysis that the SRL feedback led to use of better learning strategies and better performance in learning tasks.

Study 2: Comparing the Mentor and Teachable Agent Feedback

In order to assess the effectiveness of different forms of feedback in our system, we conducted a study, which included a talk-aloud protocol to determine students' reactions to the agent feedback. The study was conducted in three 5th grade science classrooms in the same school as study 1¹. All stu-

¹Study 1 and study 2 were conducted in different years.

dents worked on a newer version of the SRL system from study 1, where the feedback from the two agents was better organized into categories. Students worked in pairs chosen by the teachers to ensure that the paired students were at similar academic levels and had compatible personalities.

Students worked on the topic of pollution in river ecosystems for three 45 minute periods. We recorded student conversations and interactions using webcams. After the study was concluded, two coders reviewed all of the video data and recorded students responses to the feedback. For every instance in which the TA or the mentor provided feedback, the coders noted whether the students' subsequent discussion *affirmed*, *dismissed*, or *deferred* the agent's feedback. Inter-rater reliability for the coding scheme was over 85%, and the results are summarized in Table 3.

Students explicitly referenced the feedback from Betty and Mr. Davis about a third of the time. In these discussions, they sometimes affirmed (e.g., "We should do that" or "We need to read more" responding to feedback suggesting the students read the resources), sometimes dismissed (e.g., "No, I don't want to read" or "Let's just keep giving her quizzes" responding to feedback suggesting students teach Betty more between giving her quizzes), and occasionally deferred (e.g., "Hold on, we will get to that in a second") agent feedback². Table 3 shows the differences between students in affirming or dismissed feedback from the two agents. Students were more likely to affirm feedback from Mr. Davis, and were more likely to dismiss feedback from Betty. This suggests that students paid less attention to the self-reflective feedback from Betty, who was treated like a peer or even someone who did not seem to know as much as the students, than they did to the more explicit, strategy-oriented feedback from Mr. Davis, who had the status of an authority figure.

Agent	N	Referenced	Affirmed	Dismissed	Deferred
Betty	649	34%	6%	16%	2%
Mr. Davis	275	30%	18%	10%	2%

Table 3: Student verbal response to agent feedback

To understand how students' verbal responses related to learning, we analyzed the study results for the two metacognitive categories of feedback from each agent: (1) knowledge construction strategies, and (2) monitoring strategies. Students who more frequently affirmed the knowledge construction strategy feedback from either the TA or the mentor had higher map scores. Students who dismissed either the knowledge construction or the monitoring feedback from either agent had lower map scores (negative correlations). However, when the students affirmed the monitoring feedback, the results were surprising. Affirming Mr. Davis's monitoring feedback showed a positive correlation with map score, but affirming Betty's monitoring feedback resulted in a negative correlation with map score. Overall the students seemed to affirm the knowledge construction feed-

²Some student discussions that referenced the feedback neither affirmed, dismissed, or deferred the feedback.

back more, and affirming this feedback implied higher map scores.

To determine whether the students verbal responses to feedback matched their expected actions in the system, we analyzed student actions immediately following each agent feedback statement. Table 4 reports for both Betty and Mr. Davis (1) the average number of feedback events by category per student, (2) the average proportion of subsequent activities that matched the actions advised by the feedback (using a window size of 3 actions³), and (3) the correlation between the percentage of matched actions and the students' final map scores.

Feedback Category → Agent ↓	Measures	Knowledge Construction	Monitoring
Betty	Feedback Events	5.77	13.08
	Action Match	28.2%	0.5%
	Map score Correlation	0.52 ^a	-0.41
Mr. Davis	Feedback Events	2.46	5.54
	Action Match	24.02%	33.0%
	Map score Correlation	0.11	0.26

Table 4: Action Response to Feedback and Corresponding Map Score Correlations (^a p < .1)

Overall, the correlation between percentage of matching actions and the students' final map scores was positive (0.34 for Betty and 0.36 for the Mentor). More detailed analysis by category of metacognitive feedback, showed a positive correlation between students' final map scores and their following Betty's and Mr. Davis's advice on knowledge construction feedback. The more the students subsequent actions matched the feedback the better was their map scores, as measured by the correlations: 0.52 for following Betty's and 0.11 for matching the Mentor's knowledge construction advice. These results differ from the verbal responses to feedback, where students affirmed Mr. Davis's knowledge construction feedback more than they did Betty's, and the corresponding correlations with map scores was also higher for the mentor (0.37 versus 0.2). On the other hand, for monitoring feedback Mr. Davis was more effective than Betty. Though the relative number of Betty monitoring feedback events was high compared to Mr. Davis's (13.1 to 5.5), student actions after Betty feedback showed a poor match to the feedback content (about 0.5%). For the mentor feedback the match was at 33%. Combining this information with the verbal response results indicates that the students were more dismissive of Betty's monitoring feedback, and at the same time they rarely followed up with activities that matched the feedback content. In addition, the correlation between the activity match percentage and students' map scores was negative, implying those who affirmed Betty's monitoring feedback or tried to apply it ended up with lower map scores. On the other hand, Mr. Davis's monitoring feedback had more affirmations and there were more attempts to follow his suggestion, and also resulted in higher map scores (though the

³We employed a variety of different window sizes, and all of them produced similar results.

correlations were not statistically significant.)

5 Discussion and Conclusions

The Betty's Brain system is designed to leverage the benefits of learning by teaching and causal reasoning to help students learn science. The teaching interactions and agent feedback support students' engagement and promote the development and use of educationally-productive cognitive and metacognitive processes. In study 1, students who utilized learning by teaching versions of our system (*i.e.*, the LBT and SRL groups) constructed better concept maps than students who used the non-teaching ICS version of the system. Moreover, students' performance was strongest when the system explicitly supported their use of self-regulated learning strategies by having Betty model and prompt for such behaviors, and having the mentor provide additional strategy-oriented advice.

Our approach to analyzing students activity sequences using hidden Markov models produced good results. We were able to characterize students activity patterns into a number of (good and bad) knowledge construction and monitoring strategies. The interpretation of student behaviors with the HMMs also matched the SRL feedback model we implemented in the Betty's Brain system. Although the HMM analysis illustrated the effectiveness of providing metacognitive feedback in the Betty's Brain system, it did not indicate which agent or types of feedback were most effective in promoting SRL behaviors. Our second study that included a talk-aloud protocol showed students' were more receptive to the explicit, strategy-oriented advice from the mentor agent, as opposed to the self-reflective, but less explicit, feedback from the teachable agent. Further, students were more likely to affirm the knowledge construction feedback from each agent than the monitoring feedback. This analysis also showed a positive correlation between affirming feedback and students' map scores, except in the case of Betty's monitoring feedback. Additional analysis of student responses to feedback, in terms of actions taken following feedback events, showed a similar differentiation between knowledge construction and monitoring feedback.

Since students appeared to be more receptive to the explicitly strategy-oriented feedback from the more authoritative agent, *i.e.*, the mentor, it may be especially fruitful to improve the mentor agent's feedback. We intend to continue analyzing the data from this and future studies in order to better understand how specific phrasing and different forms of metacognitive feedback affect student behavior. We have also been conducting studies to determine how to make the timing and content of strategy feedback more relevant to the student's current activities on the system.

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