Utilizing Dynamic Bayes Nets to Improve Early Prediction Models of Self-Regulated Learning

Jennifer Sabourin, Bradford Mott, James Lester

North Carolina State University, Raleigh, North Carolina
{jlrobiso, bwmott, lester}@ncsu.edu

Abstract. Student engagement and motivation during learning activities is tied to better learning behaviors and outcomes and has prompted the development of learner-guided environments. These systems attempt to personalize learning by allowing students to select their own tasks and activities. However, recent evidence suggests that not all students are equally capable of guiding their own learning. Some students are highly self-regulated learners and are able to select learning goals, identify appropriate tasks and activities to achieve these goals and monitor their progress resulting in improved learning and motivational benefits over traditional learning tasks. Students who lack these skills are markedly less successful in self-guided learning environments and require additional scaffolding to be able to navigate them successfully. Prior work has examined these phenomena within the learner-guided environment, CRYSTAL ISLAND, and identified the need for early prediction of students' self-regulated learning abilities. This work builds upon these findings and presents a dynamic Bayesian approach that significantly improves the classification accuracy of student self-regulated learning skills.

Keywords : Student modeling, intelligent tutoring systems, self-regulated learning

1 Introduction

The focus on encouraging student engagement and motivation has been growing rapidly in recent decades in both classroom-based and computer-based instruction. This attention is guided by the empirical findings that students' feelings of interest and motivation towards an activity, domain, or learning in general has a powerful influence on how long they will persist with a task and how willing they are to initiate an activity [1–4].

A common approach to encouraging engagement involves increasing student autonomy and allowing each individual student to guide his or her own learning [5–7]. The insight behind this approach is that students will be able to focus on tasks and topics that fit within their own learning goals and interests [8]. However, while this approach has gained popularity, there is increasing evidence that not all students are successful at guiding their own learning [5, 9, 10]. To be successful, students must be

adfa, p. 1, 2011.

capable of setting meaningful learning objectives. They must then identify activities, behaviors, and strategies that may achieve these goals, monitor and evaluate their progress and alter their behavior and strategies accordingly. Unfortunately there is evidence that not all students are capable of guiding their own learning in this way [11] and may consequently experience limited success with systems that require these skills [5, 6, 12].

The ability to set learning goals, identify successful strategies and evaluate personal success is the hallmark of a self-regulated learner. Students who exhibit self-regulated learning (SRL) skills are able to drive their own learning and are often more successful in learning tasks and academic settings [13]. While SRL skills can be taught and often improve with practice [14], students who have not yet developed appropriate SRL strategies are more likely to flounder in self-guided learning systems. However, there is evidence that with appropriate scaffolding, these environments can be beneficial in improving learning and interest as well as aid in development of SRL skills [15, 16].

The issue of how to appropriately level and support SRL strategies in learning environments remains an important open question with a variety of conflicting evidence [17–21]. However, there is consensus that appropriate scaffolding involves a delicate balance of allowing autonomy but providing support when necessary [22]. To do this successfully, teachers and tutoring systems must be able to accurately identify a student's skill level and utilize this knowledge to deliver an appropriately leveled amount of support.

This paper describes an investigation of these issues within the self-guided game-based learning environment, CRYSTAL ISLAND. Prior work examining SRL behaviors in CRYSTAL ISLAND has indicated that students who are able to regulate their behaviors experience greater learning gains and report more interest and motivation, while students without these skills are significantly less successful [23]. These results have highlighted the need for targeted scaffolding based on early recognition of students' self-regulatory skills. This work uses Bayesian modeling techniques incorporating both empirical and theoretical knowledge to classify self-regulated learners early into their interaction with CRYSTAL ISLAND. Models learned from a corpus including data from 260 middle school students show significant promise in early prediction of self-regulated learning skills. The methodology, findings, and implications of this work are discussed.

2 Related Work

Identifying and scaffolding metacognitive behaviors such as self-regulated learning (SRL) has been a focus of much work in the intelligent tutoring systems community due to the strong influence of these behaviors on learning [5, 13, 24]. For example, in MetaTutor, a hypermedia environment for learning biology, think-aloud protocols have been used to examine which regulatory strategies students use, while analysis of students' navigation through the hypermedia environment helps to identify profiles of self-regulated learners [24, 25]. Similarly, researchers have identified patterns of behavior in the Betty's Brain system that are indicative of low and high levels of self-regulation [26] and utilized sequence mining techniques to further explore these patterns [27]. Aleven *et al*. [28] have hand-crafted a model of help-seeking behavior based on pedagogical theories of when students ought to seek help and the variety of help-seeking behaviors that are thought to be detrimental to learning.

While previous work has focused primarily on examining SRL in highly structured problem-solving and learning environments, there has also been work on identifying SRL behaviors in open-ended exploratory environments. For example, work by Shores *et al.* has examined early prediction of students' cognitive tool use in order to inform possible interventions and scaffolding [29]. Understanding and scaffolding students' SRL behaviors is especially important in open-ended learning environments where goals may be less clear and students do not necessarily have a clear indicator of their progress [30]. In order to be successful in this type of learning environment, students must actively identify and select their own goals and evaluate their progress accordingly. While the nature of the learning task may have implicit overarching goals such as 'completing the task' or 'learning a lot,' it is important for students to set more specific, concrete and measurable goals [31]. However, not all students are equally successful in regulating their learning in this way [5, 6, 9, 11].

This work represents an initial step in scaffolding such metacognitive behaviors by first predicting a student's skill level early into interaction with an open-ended self-guided learning environment so that future scaffolding can be targeted to a student's individual abilities. Prior work to predict self-regulated learning has demonstrated promise in being able to identify self-regulated learners early into their interaction with an open ended environment [23], though predictive accuracies were not believed to be sufficiently high for a functional runtime system. This work builds upon these findings by using Bayesian modeling techniques and incorporating theoretical and empirical knowledge to improve early prediction capabilities.

3 Method

The investigation of SRL behaviors was conducted with students from a local middle school interacting with CRYSTAL ISLAND, a self-guided game-based learning environment being developed for the domain of microbiology that follows the standard course of study for eighth grade science in North Carolina [32].

3.1 Crystal Island

CRYSTAL ISLAND (Figure 1) features a science mystery set on a recently discovered volcanic island. Students play the role of the protagonist, Alex, who is attempting to discover the identity and source of an unknown disease plaguing a newly established research station. The story opens by introducing the student to the island and the members of the research team for which her father serves as the lead scientist. As members of the research team fall ill, it is her task to discover the cause and the specific source of the outbreak. Typical game play involves navigating the island,

Fig. 1. CRYSTAL ISLAND learning environment

Fig. 2. Self-report device

manipulating objects, taking notes, viewing posters, operating lab equipment, and talking with non-player characters to gather clues about the disease's source. To progress through the mystery, a student must explore the world and interact with other characters while forming questions, generating hypotheses, collecting data, and testing hypotheses.

3.2 Study Procedure

A study with 296 eighth grade students was conducted. After removing instances with incomplete data or logging errors, there were 260 students remaining. Among the remaining students, there were 129 male and 131 female participants varying in age and race. Participants interacted with CRYSTAL ISLAND in their school classroom, although the study was not directly integrated into their regular classroom activities. Pre-study materials were completed during the week prior to interacting with CRYSTAL ISLAND. The pre-study materials included a demographic survey, researcher-generated CRYSTAL ISLAND curriculum test, and several personality questionnaires. Personality was measured using the Big 5 Personality Questionnaire, which indexes student personality across five dimensions: openness, conscientiousness, extraversion, agreeableness and neuroticism [33]. Goal orientation was measured using a 2-dimensional taxonomy considering students' mastery or performance orientations along with their approach or avoidance tendencies [34]. Students' affect regulation tendencies were measured using the Cognitive Emotion Regulation Questionnaire which consists of nine subscales, each representing a different cognitive regulation strategy [35].

Immediately after solving the mystery, or after 55 minutes of interaction, students moved to a different room in order to complete several post-study questionnaires including the curriculum post-test. Students also completed two questionnaires aimed to measure students' interest and involvement with CRYSTAL ISLAND including the Intrinsic Motivation Inventory [36] and the Presence Questionnaire [37].

During the interaction students were prompted every seven minutes to self-report their current mood and status through an in-game smartphone device (Figure 2). Students selected one emotion from a set of seven options, which included the following: anxious, bored, confused, curious, excited, focused, and frustrated. After selecting an emotion, students were instructed to briefly type a few words about their current status in the game, similarly to how they might update their status in an online social network.

3.3 SRL Classification

The typed status reports were later tagged for SRL evidence using the following four ranked classifications: (1) specific reflection, (2) general reflection, (3) non-reflective statement, or (4) unrelated. (See [23] for more details). This ranking is motivated by the observation that setting and reflecting upon goals is strongly associated with self-regulatory behavior and that specific goals are more beneficial than those that are more general [9]. Students were then given an overall SRL score based on the average score of their statements. An even ternary split was then used to assign the students to a High, Medium, and Low SRL category.

From the 260 students, a total of 1836 statements were collected, resulting in an average of 7.2 statements per student. All statements were tagged by one member of the research team with a second member of the research team tagging a randomly selected subset (10%) of the statements to assess the validity of the protocol. Inter-rater reliability was measured at $\kappa = 0.77$, which is an acceptable level of agreement. General reflective statements were the most common (37.2%), followed by unrelated (35.6%), specific reflections (18.3%) and finally non-reflective statements (9.0%).

The ternary split of students into High, Medium, and Low SRL classes has yielded interesting findings in prior work [23]. One important finding is that High and Medium SRL students have both higher prior knowledge and higher learning gains than Low SRL students. This shows that Low SRL students start with some disadvantage and that the overall gap in knowledge is increased after interactions with CRYSTAL ISLAND. Though all groups have significant learning gains, Low SRL students are not receiving the same advantages of interaction with CRYSTAL ISLAND. Further analyses indicated that High SRL students reported experiencing significantly more interest, enjoyment, and attributed greater value and importance to the task than either Medium or Low SRL students.

Together these findings motivate the need for detection and scaffolding of SRL skill levels. Low-SRL students require more guided instruction and scaffolding to learn as effectively as their peers. Evidence suggests that Medium-SRL students may need slightly more scaffolding to have an optimal experience but overall are effectively learning on their own. Meanwhile, High-SRL students are experiencing the positive benefits expected from a self-guided learning experience and should not receive any intervention. The first step toward delivering targeted scaffolding based on SRL skill level is to first classify a student as a High, Medium, or Low SRL student early into their interaction with CRYSTAL ISLAND.

4 Early Prediction of SRL Behaviors

Initial classification of student SRL behaviors was conducted manually after the completed interaction with CRYSTAL ISLAND. In order to provide adaptive scaffolding, these classes must be recognized early into the interaction so that students do not spend too much time floundering with too little guidance. To this end, empirical models were learned from the corpus of student data and trained to classify SRL skill level early into the interaction.

4.1 Corpus

The comprehensive corpus for modeling SRL behavior originally included a total of 49 features. Of these, 26 features represented personal data collected prior to the student's interaction with CRYSTAL ISLAND. This included demographic information, pre-test score, and scores on the personality, goal orientation, and emotion regulation questionnaires. The remaining 23 features represented a summary of students' interactions in the environment. This included information on how students used each of the curricular resources, how many in-game goals they had completed, as well as evidence of off-task behavior (details on off-task behavior can be found in [38]). Additionally, data from the students' self-reports were included, such as the most recent emotion report and the character count of their "status."

In order to examine early prediction of the students' SRL-use categories, these features were calculated at four different points in time resulting in four distinct datasets. The first of these (**Initial**) represented information available at the beginning of the student's interaction and consequently only contained the 26 personal attributes. Each of the remaining three datasets (**Report$_{1\text{-}3}$**) contained data representing the student's progress at each of the first three emotion self-report instances. These datasets contained the same 26 personal attributes, but the values of the remaining 23 in-game attributes differentially reflected the student's progress up until that point. The first self-report occurred approximately 4 minutes into game play with the second and third reports occurring at 11 minutes and 18 minutes, respectively. The third report occurs after approximately one-third of the total time allotted for interaction has been completed, so it is still fairly early into the interaction time.

4.2 Prior Work – Naïve Modeling Approaches

Prior work [23] has shown promise in being able to predict SRL class early into the interaction. This work compared the ability of naïve Bayes, neural network, logistic regression, support vector machine, and decision tree models to predict SRL class at different time intervals. Overall it was found that logistic regression and decision trees offered the best performance, correctly predicting 43% of students' classes before interaction begins and up to 57% of students' classes after one-third of their interaction with CRYSTAL ISLAND. Compared with a most-frequent-class baseline of 34%, this offers a significant improvement in the ability to recognize SRL skill. However, while both logistic regression and decision tree models significantly outperformed baseline measures, the predictive accuracy did not seem to be sufficient for guiding adaptive scaffolding though they represented a positive indication that a more targeted approach to modeling had the potential to be successful.

4.3 Current Approach – Informed Bayesian Modeling

The promising results of the initial modeling approaches raised two questions: *1) What features are most beneficial for predicting students' SRL classifications?* and *2) How can knowledge of the learning environment and the processes associated with SRL be used to guide the development of models?* These two questions guided the development of a predictive model that is informed from empirical corpus data as well as a theoretical understanding of self-regulated processes. The objective of this line of investigation was to further improve predictive accuracy so that a runtime system could be used to reliably detect and scaffold SRL behaviors.

Feature Selection. The first step in developing an informed predictive model was to identify the features that were most beneficial in predicting students' SRL classifications. Stepwise logistic regression was selected as the approach to addressing this problem. Stepwise logistic regression involves iteratively adding and removing features to a predictive logistic regression model based on whether the inclusion of the feature significantly improves the model's predictive capabilities.

The stepwise logistic regression was run using the SAS® 9.3 statistical modeling package. A significance level of $\alpha < 0.05$ was required for a feature to remain in the selected model. In total, 15 features were identified as significant to the predictive process. These features included 9 static personal traits as well as the total pretest score. The 6 in-game features related to the students' statuses, use of the in-game tools and students' off-task behaviors.

Bayesian Modeling. The next step in model development was to select a modeling approach which could take advantage of both empirical and theoretical knowledge of SRL in CRYSTAL ISLAND. A Bayesian approach was selected for a variety of reasons. First, Bayesian methodologies have been used to represent a wide variety of phenomena in intelligent tutoring systems including models of learning [39, 40], affect [41, 42], and hinting [43]. More importantly for this application, Bayesian networks can accommodate both empirical and theoretical knowledge [41, 42]. Bayesian networks operate by representing the relationship between variables in terms of a probability distribution. Bayesian networks involve two main components, (1) a network structure, which describes which variables are related to others, and (2) a set of conditional dependencies which provide the exact specifications for these relationships. Both the structure and the conditional dependencies can be learned using a variety of possible algorithms [44] or specified by hand.

The proposed model includes a structure which has been hand-crafted to include the features indicated as beneficial for predicting SRL class. The relationship between these variables is determined by a theoretical grounding of SRL processes including the key behaviors of planning and monitoring [31]. The exact values of the conditional dependencies are then learned using an Expectation-Maximization (EM) algorithm [44]. In this way the model takes advantage of theoretical knowledge related of SRL processes as well as empirical evidence of how these phenomena occur in the CRYSTAL ISLAND environment.

5 Results

A Bayesian network structure was constructed using the 9 personal a 6 in-game attributes identified in the feature selection step. Three hidden states were also created based on understanding of the CRYSTAL ISLAND environment and SRL processes. These included:

- **Resource Use:** This variable aggregates information of a variety of in-game behaviors all related to the effective use of the in-game resources. This includes off-task behavior, diagnosis worksheet use and testing behaviors.
- **Planning:** This variable seeks to represent students' tendencies to engage in planning behaviors before beginning a task, a hallmark of SRL. Features that indicate planning include openness and agreeableness which reflect how students approach novel situations, as well as the planning subscale of cognitive-emotion regulation questionnaire.

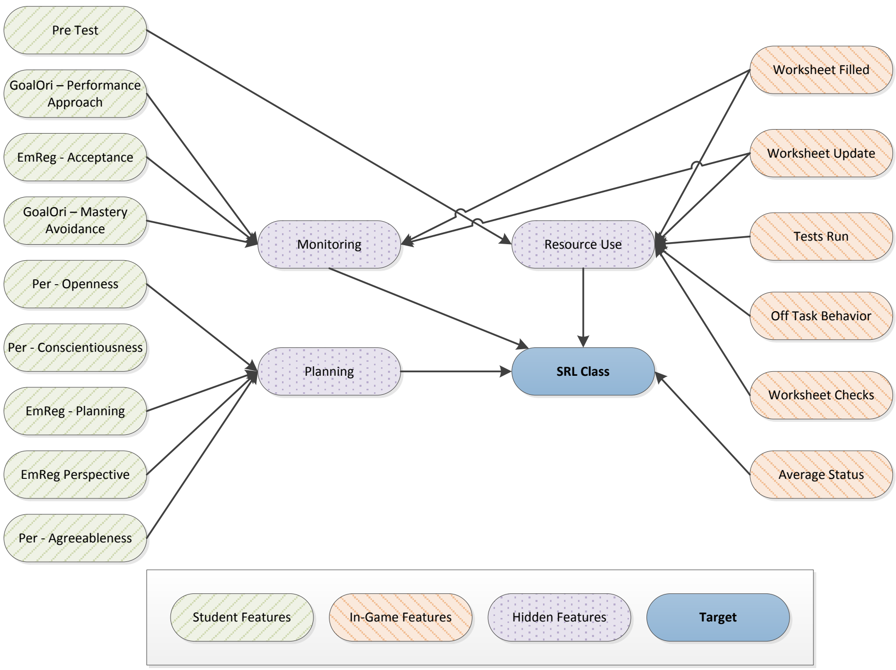

Fig. 3. Structure of Bayesian network for predicting SRL class

- **Monitoring:** This variable seeks to represent student behaviors and personal tendencies that lead to monitoring of learning activities, another hallmark of SRL. These include diagnose worksheet use, conscientiousness, and learning goals.

The structure was hand-crafted using the GeNIe modeling environment developed by the Decision Systems Laboratory of the University of Pittsburgh (http://dsl.sis.pitt.edu). This structure can be seen in Figure 3. Parameters were then learned using the EM algorithm provided by GeNIe using data from each of the four time-slices described in Section 4.1. However, since there is no in-game data available for the **Initial** dataset, this model included only the 9 personal attributes and 2 hidden attributes that do not involve in-game activities. Models were evaluated using 10-fold cross-validation.

Results indicated that the Bayesian network significantly outperformed both baseline measures and the naïve classifiers. At the **Initial** time slice, the handcrafted Bayesian network correctly predicted 64.8% of students' classifications and reached an accuracy of 68.5% by **Report$_3$**. This indicates that the model is twice as effective as the baseline measures. Examination of recall metrics indicate that the Bayesian model does not perform significantly better at recognizing any particular class.

While successful, the Bayesian model represents a static picture of SRL processes at a particular time. One of the key components of SRL is that a student's planning and monitoring activities impact future behaviors based on the success of adopted strategies. In order to account for the dynamic nature of SRL behaviors the static Bayesian network was extended into a dynamic Bayesian network. Dynamic Bayesian Networks (DBNs) are able to account for temporal relationships between variables,

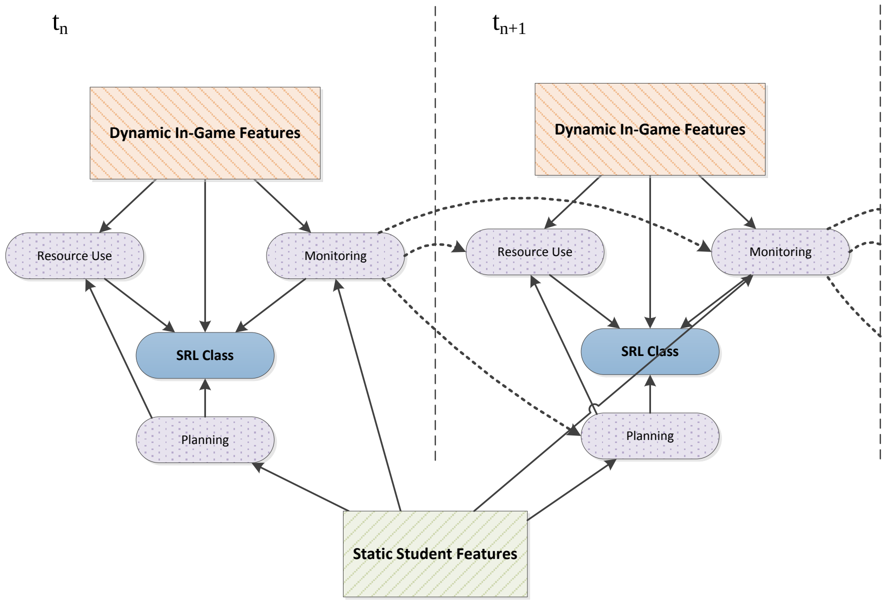

Fig. 4. Structure of dynamic Bayesian network for predicting SRL class

Table 1. Predictive accuracy for learned models

	Predictive Accuracy			
Model	Initial	Report_1	Report_2	Report_3
Top Prior Model	42.7	46.2	48.1	57.2
Bayesian Network	64.8	67.0	67.5	68.5
Dynamic Bayes Net	64.5	80.5	81.3	83.1

Table 2. Recall metrics for Bayesian models

	Bayesian Network				*Dynamic Bayesian Network*			
Class	Initial	Report_1	Report_2	Report_3	Initial	Report_1	Report_2	Report_3
Low	0.67	0.67	0.70	0.58	0.73	0.71	0.73	0.75
Medium	0.61	0.57	0.59	0.68	0.49	0.78	0.80	0.84
High	0.66	0.77	0.73	0.79	0.71	0.92	0.91	0.91

allowing observations at time t_n to inform observations at time t_{n+1}. Utilizing this framework, we extended the static Bayesian network to include temporal relationships between planning and monitoring across time. This extended dynamic Bayesian network is depicted in Figure 4. Again, the model was trained using GeNIe's EM algorithm and evaluated with 10-fold cross-validation.

Results indicated that for the **Initial** time slice the DBN achieved a predictive accuracy (64.5%) equivalent to that of the static Bayesian network. This finding is unsurprising as the model has no prior information to improve predictive accuracy. However, for each of the three time slices occurring during gameplay, the DBN is able to significantly outperform the static Bayesian network, reaching a predictive accuracy of 83.1% by $\textbf{Report}_\mathbf{3}$. Further examination of recall metrics indicates that the model correctly recognizes approximately the same percentage of Low-SRL students regardless of how much time has passed. The increase in predictive accuracy over time appears to come from an increased ability to distinguish Medium and High-SRL students further into the interaction. Overall, the DBN matched or outperformed the static Bayesian model and achieved predictive accuracies that are believed to be sufficient for guiding future scaffolding approaches.

6 Conclusion

Learner-guided systems offer significant promise in fostering engagement and motivation by providing autonomy and allowing students to direct their own learning. However, evidence suggests that some students lack the self-regulatory skills to receive the maximum benefit these systems may offer. This was found to be the case with detailed analyses of the CRYSTAL ISLAND environment. Students with more developed SRL skills learn more and report higher levels of engagement and interest when interacting with CRYSTAL ISLAND than students lacking these skills, suggesting the need to provide adaptive scaffolding based on students SRL abilities.

Machine-learned models capable of early prediction of SRL classification show promise in being able to identify which students would benefit most from adaptive scaffolding. Specifically, Bayesian techniques using both empirical data and theoretical grounding were able to classify students into groups of High, Medium and Low SRL skills early into their interaction with CRYSTAL ISLAND. Dynamic Bayesian networks, which reflect the temporal dynamics of planning and monitoring behaviors offered significant improvements over static models which did not incorporate these features.

This work represents the first step in providing adaptive, appropriately leveled scaffolding of SRL behaviors in CRYSTAL ISLAND. Many areas remain for future work. First, it will be important to identify which specific behaviors should be supported or guided by the adaptive system. Recent work has shown that High, Medium, and Low-SRL students utilize the features of the CRYSTAL ISLAND environment differently. Further work should be undertaken to attempt to gain a more detailed understanding of these differences with modeling techniques such as pattern mining or Markovian approaches. Next, leveled scaffolding will be developed and evaluated to identify how much scaffolding is appropriate for each SRL skill level. This scaffolding will encourage goal setting and monitoring behaviors and guide students towards strategies identified by the analysis of real student behaviors. It will be important to measure outcomes in terms of both learning and engagement as it is expected that too much guidance or support may reduce interest and enjoyment. Furthermore, it will be important to investigate the relative cost of misclassification and incorrect delivery of scaffolding. An objective cost metric balancing engagement and learning can guide learned models towards policies that optimize a scaffolding strategy. Finally, the findings from each of these investigations will be incorporated into a comprehensive version of CRYSTAL ISLAND, capable of early detection and adaptive, leveled scaffolding of self-regulate learning.

Self-regulated learning is an important skill impacting the success of students on a variety of learning tasks. Students without these skills are unable to make the most of learner-guided environments that provide autonomy and self-guided learning in the hopes of increasing engagement and interest as well as learning outcomes. Scaffolding tailored specifically to the skill-level of the student is necessary to balance the engagement benefits of autonomy and the learning benefits of guided learning activities. The empirical models discussed in this work represent the first step in developing a system capable of early identification of SRL skills so that adaptation can be tailored directly based on students' specific needs.

Acknowledgements. The authors wish to thank members of the IntelliMedia Group for their assistance, Omer Sturlovich and Pavel Turzo for use of their 3D model libraries, and Valve Software for access to the SourceTM engine and SDK. This research was supported by the National Science Foundation under Grants REC-0632450, DRL-0822200, IIS-0812291, DRL-1114655, and CNS-0739216. This material is based upon work supported under a National Science Foundation Graduate Research Fellowship.

References

1. Baker, R. S., D'Mello, S., Rodrigo, S. K. & Graesser, A. C. Better to Be Frustrated than Bored: The Incidence, Persistence, and Impact of Learners' Cognitive-Affective States during Interactions with Three Different Computer-Based Learning Environments. International Journal of Human-Computer Studies 68, 223–241 (2010).
2. Kanfer, R. & Ackerman, P. L. Motivation and Cognitive Abilities: An Integrative/Aptitude-Treatment Interaction Approach to Skill Acquisition. Journal of Applied Psychology 74, 657–690 (1989).
3. Pekrun, R., Goetz, T., Titz, W. & Perry, R. Academic Emotions in Students' Self-Regulated Learning and Achievement: A Program of Qualitative and Quantitative Research. Educational Psychologist 37, 91–105 (2002).
4. Picard, R. W. et al. Affective Learning — A Manifesto. BT Technology Journal 22, 253–269 (2004).
5. Young, J. D. The Effect of Self-Regulated Learning Strategies on Performance in Learner Controlled Computer-Based Instruction. Educational Technology Research and Development1 44, 17–27 (1996).
6. Easterday, M. W., Aleven, V., Scheines, R. & Carver, S. M. Using Tutors to Improve Educational Games. Proceedings of the 15th International Conference on Artificial Intelligence in Education 63–71 (2011).
7. Pintrich, P. R. & Groot, E. D. Motivational and self-regulated learning components of classroom academic performance. Journal of Educational Psychology 82, 33–40 (1990).
8. Pintrich, P. R. A Conceptual Framework for Assessing Motivation and Self-Regulated Learning in College Students. Educational Psychology Review 16, 385–407 (2004).
9. Kirschner, P. A., Sweller, J. & Clark, R. E. Why Minimal Guidance during instruction does not work: An analysis of the Failure of Constructivist, Discovery, Problem-Based, Experiential, and Inquiry-Based Teaching. Educational Psychologist 41, 75–86 (2006).
10. Alfieri, L., Brooks, P., Aldrich, N. & Tenenbaum, H. Does Discovery-Based Instruction Enhance Learning. Journal of Education Psychology 103, 1–18 (2011).
11. Ellis, D. & Zimmerman, B. J. Enhancing self-monitoring during self-regulated learning of speech. 205–228 (2001).
12. Azevedo, R., Moos, D. C., Greene, J. A., Winters, F. I. & Cromley, J. G. Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia? Educational Technology Research and Development 56, 45–72 (2008).
13. Zimmerman, B. J. Self-regulated learning and academic achievement: An overview. Educational Psychologist 25, 3–17 (1990).
14. Kostons, D., van Gog, T. & Paas, F. Training Self-Assessment and Task-Selection Skills: A Cognitive Approach to Improving Self-Regulated Learning. Learning and Instruction 22, 121–132 (2012).
15. Azevedo, R., Cromley, J. G., Winters, F. I., Moos, D. C. & Greene, J. A. Adaptive human scaffolding facilitates adolescents' self-regulated learning with hypermedia. Instructional Science 33, 381–412 (2005).
16. Aleven, V., McLaren, B. M., Roll, I. & Koedinger, K. R. Toward Meta-cognitive Tutoring: A Model of Help-Seeking with a Cognitive Tutor. International Journal of Artificial Intelligence in Education 16, 101–128 (2006).
17. Fiorella, L. & Mayer, R. E. Paper-based aids for learning with a computer-based game. Journal of Educational Psychology 104, 1074–1082 (2012).
18. Ifenthaler, D. Determining the Effectiveness of Prompts for Self-Regulated Learning in Problem-Solving Scenarios. Educational Technology & Society 15, 38–52 (2012).

19. Kauffman, D. Self-Regulated Learning in Web-Based Environments: Instructional Tools Designed to Facilitate Cognitive Strategy Use, Metacognitive Processing, and Motivational Beliefs. Journal of Educational Computing Research 30, 139–161 (2004).
20. White, B. & Frederiksen, J. Inquiry, Modeling, and Metacognition: Making Science Accessible to All Students. Cognition & Instruction 16, 3–118 (1998).
21. Davis, E. Prompting Middle School Science Students for Productive Reflection: Generic and Directed Prompts. Journal of the Learning Sciences 12, 91–142 (2003).
22. Koedinger, K. R. & Aleven, V. Exploring the Assistance Dilemma in Experiments with Cognitive Tutors. Educational Psychology Review 19, 239–364 (2007).
23. Sabourin, J., Shores, L., Mott, B., Lester, J. & Carolina, N. Predicting Student Self-Regulation Strategies in Game-Based Learning Environments. Proceedings of the 11th International Conference on Intelligent Tutoring Systems 470–475 (2012).
24. Azevedo, R. et al. The Effectiveness of Pedagogical Agents' Prompting and Feedback in Facilitating Co-Adapted Learning with MetaTutor. Proceedings of the 11th International Conference on Intelligent Tutoring Systems 212–221 (2012).
25. Azevedo, R., Johnson, A., Chauncey, A. & Burkett, C. Self-Regulated Learning with MetaTutor: Advancing the Science of Learning with MetaCognitive Tools. New Science of Learning: Cognition, Computers and Collaboration in Education 225–248 (2010).
26. Biswas, G., Jeong, H., Roscoe, R. & Sulcer, B. Promoting Motivation and Self-Regulated Learning Skills through Social Interactions in Agent-Based Learning Environments. 2009 AAAI Fall Symposium on Cognitive and Metacognitive Educational Systems (2009).
27. Kinnebrew, J. S. & Biswas, G. Identifying Learning Behaviors by Contextualizing Differential Sequence Mining with Action Features and Performance Evolution. Proceedings of the 5th International Conference on Educational Data Mining (2012).
28. Aleven, V., Roll, I., McLaren, B. M. & Koedinger, K. R. Automated, Unobtrusive, Action-by-Action Assessment of Self-Regulation During Learning with an Intelligent Tutoring System. Educational Psychologist 45, 224–233 (2010).
29. Shores, L. R., Rowe, J. P., & Lester, J. C. Early Prediction of Cognitive Tool Use in Narrative-Centered Learning Environments. Proceedings of the Fifteenth International Conference on Artificial Intelligence in Education. (2011).
30. Land, S. Cognitive requirements for learning with open-ended learning environments. Educational Technology Research and Development 48, 61–78 (2000).
31. Zimmerman, B. Goal Setting: A Key Proactive Source of Academic Self-Regulation. Motivation and Self-Regulated Learning: Theory, Research, and Applications 267–286 (2008).
32. Rowe, J P, Shores, L. R., Mott, B. W., & Lester, J. C. Integrating Learning, Problem Solving, and Engagement in Narrative-Centered Learning Environments. International Journal of Artificial Intelligence in Education. 166–177 (2011).
33. McCrae, R. & Costa, P. Personality in Adulthood: A Five-Factor Theory Perspective. (Guilford Press: New York, 1993).
34. Elliot, A. J. & McGregor, H. A. A 2 x 2 achievement goal framework. Journal of Personality and Social Psychology 80, 501–519 (2001).
35. Gernefski, N. & Kraati, V. Cognitive Emotion Regulation Questionnaire: Development of a Short 18-Item Version. Personality and Individual Differences 41, 1045–1053 (2006).
36. McAuley, E., Duncan, T. & Tammen, V. Psychometric properties of the Intrinsic Motivation Inventory in a competitive sport setting: A confirmatory factory analysis. Research Quarterly for Exercise and Sport 60, 48–58 (1989).
37. Witmer, B. G., & Singer, M. J. Measuring Presence in Virtual Environments: A Presence Questionnaire. Presence: Teleoperators and Virtual Environments 7, 225–240 (1998).

38. Sabourin, J., Rowe, J., Mott, B. & Lester, J. When Off-Task is On-Task: The Affective Role of Off-Task Behavior in Narrative-Centered Learning Environments. Proceedings of the 15th International Conference on Artificial Intelligence and Education 534-536 (2011).
39. Baker, R. S., Corbett, A. T. & Aleven, V. More Accurate Student Modeling Through Contextual Estimation of Slip and Guess Probabilities in Bayesian Knowledge Tracing. Proceedings of the Ninth International Conference on Intelligent Tutoring Systems 406–415 (2008).
40. Corbett, A. T. & Anderson, J. R. Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge. User Modeling and User-Adapted Interaction 4, 253–278 (1994).
41. Conati, C. & Maclaren, H. Empirically building and evaluating a probabilistic model of user affect. User Modeling and User-Adapted Interaction 19, 267–303 (2009).
42. Sabourin, J. L., Mott, B. W. & Lester, J. C. Modeling Learner Affect with Theoretically Grounded Dynamic Bayesian Networks. Proceedings of the 4th International Conference on Affective Computing and Intelligent Interaction 286–295 (2011).
43. Gertner, A., Conati, C. & VanLehn, K. Procedural help in Andes: Generating hints using a Bayesian network student model. Proceedings of the 15th National Conference on Artificial Intelligence (1998).
44. Alpaydin, E. Introduction to Machine Learning. (MIT Press: 2004).