Leveraging Affect for Narrative-Centered Guided Discovery Learning Environments

Scott W. McQUIGGAN and James C. LESTER
Department of Computer Science, North Carolina State University, Raleigh, NC 27695
{swmcquig, lester}@ncsu.edu

Abstract. Affective reasoning holds significant potential for intelligent tutoring systems. Incorporating affective reasoning into pedagogical decision-making capabilities could enable learning environments to create customized experiences that are dynamically tailored to individual students’ ever changing levels of engagement, interest, motivation, and self-efficacy. Because physiological responses are directly triggered by changes in affect, biofeedback data such as heart rate and galvanic skin response can be used to infer affective changes in conjunction with the situational context. However, biofeedback hardware is intrusive and cumbersome in deployed applications. This paper explores the importance of self-efficacy in ITSs, motivation in discovery learning approaches, and describes CRYSTAL ISLAND, a prototype narrative-centered guided discovery learning environment. CRYSTAL ISLAND served as a testbed for several studies that suggest it is possible to build models of affective constructs from observations of situational context and student physiological response.

Introduction

Affect has begun to play an increasingly important role in intelligent tutoring systems. Recent years have seen the emergence of work on affective student modeling [10], detecting student emotions [9, 12, 23, 37], modeling agents’ emotional states [2, 16, 22], devising affectively informed models of social interaction [18, 34, 37], and detecting student motivation [14]. All of this work seeks to increase the fidelity with which affective and motivational processes are modeled in intelligent tutoring systems in an effort to increase the effectiveness of tutorial interactions and, ultimately, learning.

Self-efficacy is an affective construct that has been found to be a highly accurate predictor of students’ motivational state and their learning effectiveness [42]. Defined as “the belief in one’s capabilities to organize and execute the courses of action required to manage prospective situations” [4], self-efficacy has been repeatedly demonstrated to directly influence students’ affective, cognitive, and motivational processes [3]. Self-efficacy holds much promise for intelligent tutoring systems (ITSs). Foundational work has begun on using models of self-efficacy for tutorial action selection [6] and investigating the impact of pedagogical agents on students’ self-efficacy [19]. Self-efficacy is useful for predicting what problems and sub-problems a student will select to solve, how long a student will persist on a problem, how much overall effort they will expend, as well as motivational traits such as level of engagement [39, 42]. Thus, if an ITS could increase a student’s self-efficacy, then it could perhaps enable the student to be more actively involved in learning, expend more effort, and be more persistent; it could also enable them to successfully cope in situations where they experience learning impasses [3].

Because self-efficacious students are effective learners, it is important to incorporate mechanisms for diagnosing student affect (self-efficacy [3], emotional state [36], and motivation [26]) to effectively inform pedagogical decision-making. Self-efficacy influences students’ reasoning, their level of effort, their persistence, and how they likely feel; it shapes how they make choices, how much resilience they exhibit when confronted with failure, and the level of success they will likely achieve [3, 39, 42].

Emotional state is often an indication of how a student feels she is performing on a given task. For example, students often take pleasure in successfully completing tasks, while negative emotions, such as frustration, often accompany learning impasses. Motivation is an internal state that influences the activities students’ engage in and their persistence in such activities. It can also increase activity levels in students and guide students in the
direction of particular goals [24]. Adapting tutorial strategies that foster positive affective states affords a broad range of potential learning benefits, such as effectiveness, efficiency and transfer, since students tend to persist longer and put forth more effort in problem-solving activities when they enjoy what they are learning and believe in their abilities to succeed [42]. For these reasons, it is essential to coordinate affective reasoning with pedagogical and tutorial strategies.

We are currently investigating a variety of information channels for reasoning about affect, and particular self-efficacy. For example, monitoring physical changes (such as physiological response) in the student, observing her behaviors and relevant events occurring in the virtual world, tracking both narrative and tutorial planning actions, and considering internal models of believable characters in the virtual world are a few of the potential sources of information available. However, recognizing student affective states is a challenging task and many approaches to date have required the use of invasive or distracting technologies. For practical purposes, deployable systems will call for affective reasoning techniques that limit or eliminate learning disruption. The ability to reason about student affect could provide potentially useful information about how the student feels about her learning experience. This would allow narrative and tutorial planning to consider refinements that may increase student interest, engagement, motivation, and self-efficacy by selecting specific tasks and providing directed guidance given the student’s situation.

This paper is structured as follows. Section 2 discusses the challenges of guided discovery learning. Sections 3 and 4 then discuss how motivation and self-efficacy can be leveraged in narrative-centered guided discovery learning environments, respectively. Section 5 introduces the CRYSTAL ISLAND learning environment and illustrates its behavior in a learning scenario. Section 6 summarizes the results of affect recognition studies conducted with CRYSTAL ISLAND.

1. Affect in Narrative Inquiry-Based Learning Environments

1.1 Guided Discovery Learning

It has long been recognized that discovery is a key element of the scientific enterprise, and recent years have seen a growing focus on discovery in education. For more than a decade, science education reform efforts by organizations such as the US National Research Council and the National Academy of Sciences have set forth standards promoting a greater emphasis on discovery learning [1, 32]. In discovery learning (or inquiry-based learning), students approach a new topic via learning-by-doing. Instead of being presented problems and solutions in an expository fashion, students are given problems to solve, a rich environment in which to explore the problems, and a set of tools and techniques for constructing solutions. While early accounts of discovery learning focused on concept discovery [8], contemporary work views discovery learning as scientific investigation. Thus, the process of discovery learning is analogous to the scientific method: students design and perform experiments, collect data, and evaluate hypotheses [13]. First and foremost, discovery learning is active learning. As noted in the National Science Education Standards [32], discovery learning is “something that students do, not something that is done to them.”

Discovery learning offers several advantages over more didactic approaches. It tends to increase students’ ability to remember what they have learned, to apply their new knowledge, and to transfer it to new tasks more effectively than with more passive approaches that might emphasize activities such as reading textbooks [7, 13]. In addition to the cognitive benefits of discovery learning, it also offers potential motivational benefits. It enables students to become more active science learners (rather than passive consumers of information), it increases students’ beliefs that scientific theories change as new evidence becomes available (rather than being seen as unchangeable entities), and perhaps most importantly, it makes science more concretely meaningful (rather than seeming too abstract) [41].

Despite the potential benefits of discovery learning, in the absence of appropriate scaffolding, discovery learning can be ineffective. Early findings suggested that discovery learning augmented with guidance can be more effective than pure discovery learning in enabling students to apply their knowledge to new problems [40]. Furthermore, students may sometimes learn incorrect concepts through discovery learning, and discovery learning may be inefficient [17]. A recent analysis of thirty years of studies of discovery learning suggests that discovery learning accompanied by guidance in the form of feedback and coaching is more effective than unguided discovery learning [27]. Thus, guided discovery appears to be a promising alternative to either didactic instruction or pure discovery learning. In our laboratory we are investigating guided discovery learning in narrative environments for science learning.
1.2 Motivation in Narrative Learning Environments

Narrative-centered guided discovery environments for learning may offer motivational benefits. Motivation is critical in learning environments, for it is clear that from a practical perspective, educational software that fails to engage students will go unused. Game playing experiences and educational experiences that are intrinsically motivating can be distinguished from those that are intrinsically motivating [25]. In contrast to extrinsic motivation, intrinsic motivation stems from the desire to undertake activities sheerly for the prospective reward. Narrative-centered discovery learning could provide the four key intrinsic motivators identified in the classic work on motivation in computer games and educational software [26]: challenge, curiosity, control, and fantasy.

Narrative-centered discovery learning can feature challenging tasks of intermediate levels of difficulty, i.e., tasks that are not too easy and not too difficult, targeting desirable levels of student intrinsic motivation. Dynamically created narratives can feature problem-solving episodes whose level of difficulty is customized for individual students. In discovery approaches, learning is inherently presented as a challenge, a series of problem-solving goals, that once achieved provide a deeper understanding of the domain. Devising narratives and providing tutorial feedback that both maintain a delicate level of uncertainty about the possibility of attaining each goal and sufficient reporting of student performance and progress is critical to sustaining effective levels of challenge.

Curiosity requires students to be inquisitive, an essential attribute for successful learning in narrative-centered discovery learning environments. Since discovery learning compels students to obtain knowledge throughout learning episodes on their own (materials are not provided explicitly prior to interaction) students are likely to question the completeness of their acquired knowledge as they progress, searching for new answers, stimulating their curiosity.

Narrative-centered discovery learning environments can empower students to take control of their learning experiences; students can choose their own paths, both figuratively (through the solution space) and literally (through the storyworld), while being afforded significant guidance crafted specifically for them. The narrative structure of guided discovery learning can provide unobtrusive direction by indirectly highlighting a subset of possible goals (i.e., blinking lights in a particular room in the environment, or a character audibly coughing in the student’s right audio channel) for the student’s next action consideration, maintaining the student’s perception of control.

Narrative-centered discovery learning is innately fantasy-based. Fantasy refers to a student’s identification with characters in the interactive narrative and the imaginative situations created internally and off-screen by the student. All narrative elements ranging from plot and characters to suspense and pacing can contribute to vivid imaginative experiences. The openness of discovery learning provides scaffolding to support all levels of student imagination, increasing motivation and engagement. Effective narrative tutorials will engage characters in the storyworld that either the individual students perceive as possessing some cognitive, emotional, or physical similarities with themselves, or that the individual student admires, expresses feelings of compassion towards, or for which the student conveys empathetic feelings.

In short, narrative can provide the guidance essential for effective discovery learning and the “affective scaffolding” for achieving high levels of motivation and engagement.

1.3 Self-Efficacy in Intelligent Tutoring Systems

To supplement the natural motivational effects of narrative learning environments we have begun to investigate techniques for modeling student affect. In particular, we have become interested in diagnosing student efficacy. Self-efficacy influences students’ reasoning, their level of effort, their persistence, and how they feel; it shapes how they make choices, how much resilience they exhibit when confronted with failure, and what level of success they are likely to achieve [4, 39, 42]. While it has not been conclusively demonstrated, many conjecture that given two students of equal abilities, the one with higher self-efficacy is more likely to perform better than the other over time. Highly efficacious students exhibit more control over their future through their actions, thinking, and feelings than inefficacious students [5]. Self-efficacy is intimately related to motivation, which controls the effort and persistence with which a student approaches a task [21]. Effort and persistence are themselves influenced by the belief the student has that she will be able to achieve a desired outcome [3]. Students with low self-efficacy perceive tasks to be more challenging than they actually are, often leading to feelings of anxiety, frustration and stress [5]. In contrast, students with high self-efficacy view challenge as a motivator [5, 26]. Self-efficacy has been studied in many domains with significant work having been done in computer literacy [11] and mathematics education [35]. It is widely believed that self-efficacy is domain-specific; whether it crosses domains remains an open question. For
instance, students with high self-efficacy in mathematics may be inefficacious in science, or a highly efficacious student in geometry may experience low efficacy in algebra.

A student’s self-efficacy is influenced by four types of experiences [3, 42]. First, in enactive experiences, she performs actions and experiences outcomes directly. These are typically considered the most influential category. Second, in vicarious experiences, she models her beliefs based on comparisons with others. These can include peers, tutors, and teachers. Third, in verbal persuasion experiences, she experiences an outcome via a persuader’s description. For example, she may be encouraged by the persuader, who may praise the student for performing well or comment on the difficulty of a problem. Her interpretation will be affected by the credibility she ascribes to the persuader. Fourth, with physiological and emotional reactions, she responds affectively to situations. These experiences, which often induce stress and anxiety and are physically manifested in physiological responses such as increased heart rate and sweaty palms, call for emotional support and motivational feedback.

Self-efficacy holds great promise for ITSs. Self-efficacy beliefs have a stronger correlation with desired behavioral outcomes than many other motivational constructs [15], and it has been recognized in educational settings, that self-efficacy can predict both motivation and learning effectiveness [42]. Thus, if it were possible to enable ITSs to accurately model self-efficacy, they may be able to leverage it to increase students’ academic performance. Two recent efforts have explored the role of self-efficacy in ITSs. One introduced techniques for incorporating knowledge of self-efficacy in pedagogical decision making [6]. Using a pre-test instrument and knowledge of problem-solving success and failure, instruction is adapted based on changes in motivational and cognitive factors. The second explored the effects of pedagogical agent design on students’ traits, which included self-efficacy [19].

2. Crystal Island

In our laboratory we are developing a narrative-centered guided discovery learning environment, CRYSTAL ISLAND [31] (Figure 1). Valve Software’s Source™ engine, the 3D game platform developed for Half-Life2, was used to implement the world, interface, and semi-autonomous characters in CRYSTAL ISLAND, which serves as a testbed for investigating affective issues in inquiry-based learning in the domains of microbiology and genetics for middle school students. CRYSTAL ISLAND’s narrative takes place at a research outpost situated on a previously unexplored volcanic island. The learner is cast as a visitor to the island and the child of the lead scientist. The narrative unfolds as members of the research team begin to fall ill, leaving the learner to solve a developing science mystery, thereby saving the expedition. The learner progresses by analyzing the genetic makeup of chickens responsible for transmitting an unidentified infectious disease.
through their eggs. In doing so, she is free to explore and interact with the world, its objects, and other characters. Throughout this process, the structure of the developing narrative is characterized by the inquiry-based learning activities of question development, hypothesis generation, data collection, and hypothesis testing. To solve the mystery the learner must navigate the island, which includes the lead scientist’s house, the laboratory, the infirmary, the dining hall, and the men and women’s living quarters; manipulate objects, such as eggs, food, books, and mechanical devices; and interact with other research team members to gather relevant information. Ultimately, the learner must deduce the breed of the chicken that is responsible for the epidemic, and solve the mystery.

Consider a “typical” interaction with the CRYSTAL ISLAND environment: a learner navigates the world for a period of time, interacting with characters, gradually gathering information about infectious diseases and related topics. As members of the research team fall ill, the accumulated information allows the student to conclude that an infectious disease is the culprit: an illness transmittable between organisms. After learning this concept, an interaction with the nurse suggests that the island’s eggs may be responsible for the spreading illness. If the learner can deduce which chickens are responsible for the infected eggs, the mystery may be solved. The learner interacts with several of the remaining healthy research team members to learn the relationships between the eggs and chickens and develop the necessary genetics background. The learner also utilizes an apparatus in the laboratory to perform tests on potentially contaminated eggs. Eventually, the learner concludes that white-feathered chickens are responsible for the bad eggs due to a codominant trait. The learner solves the mystery and reports the finding to the nurse.

3. Experimental Results

Effectively modeling student affect requires a representation of situational contexts. Because affect is fundamentally a cognitive process in which the user appraises the relationship between herself and her environment [16, 20], affect recognition models should take into account environmental information used in student appraisals as well as information encoding student responses to their appraisals, such as monitoring physiological changes. To this end we have investigated a rich representation of situational contexts to model empathetic behavior [28] and a comparable representation of environmental information extended to include physiological response data [29].

A key challenge posed by affective reasoning, particularly for directing synthetic agent behavior, is devising empirically informed models of empathy that accurately respond in social situations. In our laboratory we developed CARE1, a data-driven affective architecture and methodology for learning models of empathy by observing human-human social interactions [30]. First, in CARE training sessions, one trainer, the student, directs her synthetic agent to perform a sequence of tasks while another trainer manipulates companion agents’ affective states to produce empathetic behaviors (spoken language, gesture, and posture). CARE tracks situational data including locational, intentional, and temporal information to induce a model of empathy. At runtime, CARE uses the model of empathy to drive situation-appropriate empathetic behaviors for companion agents. To date we have completed two complementary studies investigating the predictive accuracy and perceived accuracy of CARE-induced models of empathy.

The first experiment was a wizard-of-Oz study in which one participant acted as an empathizer observing student interactions and making empathetic decisions regarding when and how a companion agent collaborating with the student in the learning environment should behave. For instance, empathizers would often associate student feelings of frustration with long delays between goal achievements. Thus they often directed their empathizing character to parallel the perceived student affect, by having their character explicitly state the desired empathetic emotion, exclaiming, “This situation appears to becoming quite frustrating.” The announcement of frustration is automatically accompanied with a pre-defined behavior sequence. During interactions the empathizer was blind to the student participant. The only information available to the empathizer regarding the student was their own observations of the student’s character in the interactive environment. These observations likely correspond to some of the same situational data used by the student in appraisal processes. Collected data consisted of student actions in the environment and empathizer decisions. Two sets of models were then induced to effectively model the empathizers’ decisions. The first model determines when to exhibit an empathetic behavior. The other model selects which affective state should be expressed by the companion agent. The best performing CARE-induced models have predicted training decisions of “when” and “how” to be empathetic with 89% and 80% accuracy, respectively. These results suggest that the CARE paradigm can provide the basis for effective empathetic behavior control in embodied companion agents.

1 CARE: Companion-Assisted Reactive Empathizer.
The second study investigated the perceived accuracy of CARE generated empathetic behaviors. Perceived accuracy tells us whether the behaviors generated by a model are actually perceived to be socially appropriate in practice. Perceived accuracy is an important aspect of empathetic accuracy because, ultimately, we seek to create models of empathy that will generate behaviors that are deemed to be appropriate for a given social context by human observers. The results of this experiment suggest that study participants perceived the empathetic behaviors controlled by CARE-induced empathy models as being as appropriate and as accurate as human empathizers were in similar situations [28].

Also in our laboratory we have begun to investigate inductive approaches to modeling student efficacy in intelligent tutoring systems [29] in the domain of microbiology and genetics. Because self-efficacious students are effective learners, endowing intelligent tutoring systems with the ability to diagnose self-efficacy could lead to improved pedagogy. We have explored two families of self-efficacy models: a static self-efficacy model, learned solely from pre-test (non-intrusively collected) data with tutoring environment information, and a dynamic self-efficacy model, learned from both static data as well as runtime physiological data collected with a biofeedback apparatus. In this experiment participants interacted with a problem-solving system answering questions from the genetics tutorial system. As students worked on each problem they also manipulated a self-efficacy slider, indicating their belief in their ability to successfully solve the problem at hand. Induced models utilized observed student behaviors in the problem-solving system and collected efficacy levels to be used as class labels.

To date we have utilized naïve Bayes and decision tree modeling techniques for their preliminary predictive power and robustness to large multidimensional data. The highest performing static model is able to predict students’ real-time levels of self-efficacy with 85.2% accuracy, while the best physiologically informed dynamic model performed at 86.9% accuracy. Dynamic model performance was statistically significant from that of the baseline model, which performed at 80.6% accuracy. The experiment revealed two important implications for the design of runtime self-efficacy modeling. First, even without access to physiological data, induced decision-tree models can make reasonably accurate predictions about students’ self-efficacy. Sometimes physiological data is unavailable or it would be too intrusive to obtain the data. In these situations, decision-tree models that learn from demographic data and data gathered with a validated self-efficacy instrument administered prior to problem solving and learning episodes, can accurately model self-efficacy. Second, if runtime physiological data is available, it can significantly enhance self-efficacy modeling. Given access to HR and GSR, self-efficacy can be predicted more accurately.

4. Conclusion and Future Work

A promising approach to constructing models of affect is inducing them rather than manually constructing them. Machine learning techniques can be leveraged to induce models of affect for ITSs. To date, we have seen the appearance of induced models of self-efficacy and empathy models. Incorporated into runtime ITSs, these models offer the potential for increasing motivation and learning effectiveness.

Several directions for future work are suggested by the results obtained to date. First, it will be important to investigate how to design pedagogical planning components that are informed by models of student affect, such as self-efficacy. Of particular interest here is the problem of dynamically creating pedagogical goals that take into account affective considerations. Second, it will be important to explore how models of self-efficacy can increase the utility of affect recognition models. Combining predictions of student efficacy with detection of student frustration could inform intervention decisions. For example, in potentially frustrating (but pedagogically useful) situations, efficacy may help predict how long a student may be capable of persisting without an intervention.

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