Affect Recognition and Expression in Narrative-Centered Learning Environments

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Affect has begun to play an increasingly important role in intelligent tutoring systems. The intelligent tutoring system community has seen the emergence of work on affective student modeling (Conati & Mclaren, 2005), detecting frustration and stress (Burleson, 2006; McQuiggan, Lee, & Lester, 2007), modeling agents' emotional states (André & Mueller, 2003; Graesser, Person, & Magliano, 1995), devising affect-informed models of social interaction (Johnson & Rizzo, 2004; Paiva et al., 2005), detecting student motivation (de Vicente & Pain, 2002), and diagnosing and adapting to student self-efficacy (Beal & Lee, 2005). All of this work seeks to increase the fidelity with which affective and motivational processes are understood and utilized in intelligent tutoring systems in an effort to increase the effectiveness of tutorial interactions and, ultimately, learning.

This level of emphasis on affect is not surprising given the impact it has been shown to have on learning outcomes. Student affective states influence problem-solving strategies, the level of engagement exhibited by the student, and the degree to which he or she is motivated to continue with the learning process (Kort, Reilly, & Picard, 2001; Picard et al., 2004). All of these factors have the potential to influence both how students learn in a single session and their learning behaviors in the future. Consequently, developing techniques for keeping students in an affective state that is conducive to learning has been the focus of much recent work (Arroyo, Woolf, Royer, & Tai, 2009; Chaffar & Frasson, 2004; D'Mello et al., 2008; Forbes-Riley, Rotaru, & Litman, 2008).

Unfortunately, there is not yet a clear understanding of how emotions occur during learning and this problem is compounded by evidence that individual learning environments can strongly impact students' emotional experiences (Rodrigo & Baker, 2011). It is also unclear which emotional states are optimal for individual

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students. This is likely to vary based on student needs and experience. Affective experiences may also have immediate and long-term effects on how students perceive learning and their levels of confidence and motivation moving forward. Finally, current research on how best to respond to student affect has yielded varying and often conflicting conclusions (Beal & Lee, 2005; Shute, 2008). For these reasons, it is challenging to design affective support systems for learning environments.

The goal of this research is to examine these issues within narrative-centered learning environments. These environments embed the educational process within a story with the objective of leveraging narrative's motivating features such as compelling plots, engaging characters, and fantastical settings (Malone & Lepper, 1987). These environments also offer the potential for creating affective experiences that complement those provided by more typical interactive learning environments (McQuiggan, Robison, & Lester, 2010). The ability to understand and control the emotional experiences of students in narrative-centered learning environments could lead to significant gains for student learning and motivation.

Related Work

There is a strong connection between affect and learning. Teachers and tutors alike motivate students to learn and craft educational experiences to increase student efficacy to support learning (Meyer & Turner, 2007). Affect influences the cognitive, motivational, and behavioral processes of students (Linnenbrink & Pintrich, 2001), and it appears that affect impacts learning and cognition in at least four ways: memory, strategy use, attention, and motivation (Pekrun, 1992). Therefore, a critical requirement of pedagogically successful intelligent tutoring systems is providing them with the ability to recognize, understand, and respond to student affect.

Work on affect recognition (Picard, 1997) has explored a variety of physical cues, which are produced in response to affective changes in the individual. These include visually observable cues such as body and head posture, facial expressions, and posture, and changes in physiological signals such as heart rate, skin conductivity, temperature, and respiration (Ekman & Friesen, 1978; Frijda, 1986). Psychologists have used electroencephalograms (EEG) to monitor users' brain activity for detection of task engagement (Pope, Bogart, & Bartolome, 1995) and user attention (Mekeig & Inlow, 1993). Heart rate measurements have been used to adapt challenge levels in computer games (Gilleade & Allanson, 2003), detect frustration and stress (Prendinger, Mayer, Mori, & Ishizuka, 2003), and monitor anxiety and stress (Healey, 2000). Galvanic skin response (GSR) has been used to sense user affective states, such as stress (Healey), student frustration for learning companion adaptation (Burleson, 2006), frustration for lifelike character adaptation in a mathematical game (Prendinger et al., 2003), and multiple user emotions in an educational game (Conati, 2002).

Recent work seeking to characterize the affective experience of learners interacting with intelligent learning environments has considered student affective trajectories occurring during learning. D'Mello, Taylor, and Graesser (2007) studied the likelihood of affective transitions among six affective states (boredom, flow, confusion, frustration, delight, and surprise) that were found to be relevant to complex learning (Craig, Graesser, Sullins, & Gholson, 2004). In general, learners are likely to persist in the same affective state (e.g., transitioning from a state of boredom to boredom is likely, and in some cases, significantly more likely than transitioning to another affective state). This analysis was conducted in the AutoTutor learning environment (Craig et al.; D'Mello et al., 2007). Baker, Rodrigo, and Xolocotzin (2007) were able to replicate many of the findings of D'Mello et al. (2007) when they calculated the likelihood of affective transitions in the Incredible Machine: Even More Contraptions, a simulation-based learning environment (2007). Baker et al. (2007) extended their analyses to investigate how usage choices affect emotion transitions. This work found that bored and confused learners are particularly likely to game the system. Further, it was found that students who game the system are unlikely to transition into a confused state (Baker et al.). An understanding of learners' affective experiences will inform the next generation of affect response modules that seek to optimize learning experiences.

Empathetic approaches to user affect have been shown to alter the affective state of the user as well as other qualities such as motivation (D'Mello et al., 2008; McQuiggan et al., 2010). Recent work has yielded models of when an empathetic response is appropriate (McQuiggan & Lester, 2007), how it ought to be delivered and when parallel or reactive empathy is preferable (McQuiggan, Robison, et al., 2008). These behaviors have also been shown to have an impact on the affective experiences of students (McQuiggan et al., 2010). Other work with empathetic synthetic agents has explored their affective responsiveness to biofeedback information and the communicative context (Prendinger & Ishizuka, 2005). Additional work has supplemented empathetic virtual agents capable of mimicking the emotional state of students with motivational statements that provide feedback regarding students success and efforts (Arroyo et al., 2009). It has also yielded agents that interact with one another and with the user in a virtual learning environment to elicit empathetic behaviors from its users (Paiva et al., 2005).

Affective Reasoning in Crystal Island

Crystal Island (Fig. 1) is a narrative-centered learning environment that is being created in the domain of microbiology for middle school students. It features a science mystery set on a recently discovered volcanic island where a research station has been established to study the unique flora and fauna.

The user plays the protagonist, Alex, who is attempting to discover the source of an unidentified infectious disease at the 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. She is free to

Fig. 1 CRYSTAL ISLAND learning environment

explore the world and interact with other characters while forming questions, generating hypotheses, collecting data, and testing her hypotheses. Throughout the mystery, she can walk around the island and visit the infirmary, the lab, the dining hall, and the living quarters of each member of the team. She can pick up and manipulate objects, and she can talk with characters to gather clues about the source of the disease. In the course of her adventure she must gather enough evidence to correctly identify the type and source of the disease that has infected the camp members.

The approaches to affective support used in CRYSTAL ISLAND are based on the widely accepted appraisal theory of human emotions and one that is particularly well suited for computational modeling (Marsella & Gratch, 2009; Smith & Lazarus, 1990). According to this model (Fig. 2), individuals compare events in the environment to their goals and beliefs to develop an understanding of how these events impact their personal situation. This appraisal results in an emotional state as well as associated action tendencies and physiological responses. Upon experiencing this emotion, individuals are then likely to engage in emotion regulation behaviors (*coping*). Since the emotional state was determined by an interaction of the environment and the individuals' beliefs, one of these must be altered in order to attenuate the affective state. This distinction leads to two separate types of coping strategies: emotion focused and problem focused. These strategies attempt to alleviate emotional experiences by attempts to alter either one's own beliefs or the external environment, respectively.

Affective support in CRYSTAL ISLAND attempts to mirror this process of appraisal. The system itself has its own internal goals and beliefs that are often based on empirical data-driven models of user interaction. The system compares its own goals (e.g., student learning, positive affect, etc.) with the variables it is able to observe in the environment to create an assessment of the current situation of the user interaction. Based on this assessment it considers multiple strategies of intervening to aid student development. These strategies also take on a problem-based or

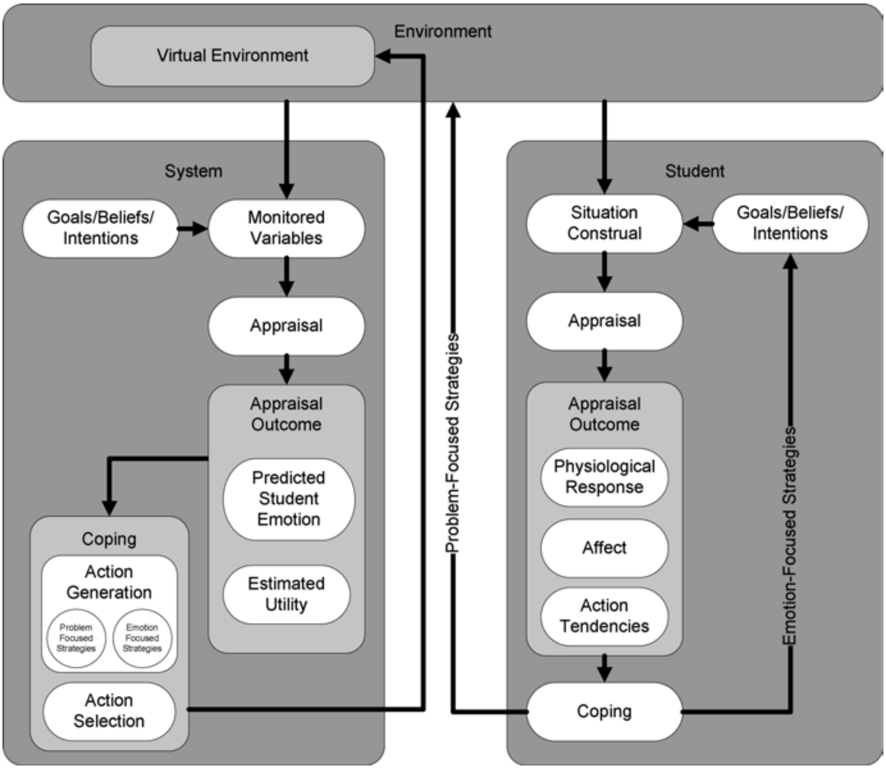

Fig. 2 Affective support in Crystal Island

emotion-based focus, mirroring the coping strategies individuals use during affective appraisal. However, the system cannot directly affect the appraisal process of the individual student. Instead, it must affect the environment in some way, such as through character-driven feedback, in order to encourage coping strategies and consequent reappraisal in students.

Empirical Findings

In order to examine the necessity and direction of affect sensitivity in narrative-centered learning environments, it is important to first focus on categorizing the affective experiences of students as they interacted with the Crystal Island environment. Primarily, it is important to distinguish how these affective experiences differed from those reported in more typical tutoring environments and problem solving non-narrative games. An initial study showed some interesting similarities and differences between the affective experiences in Crystal Island (McQuiggan et al., 2010), The Incredible Machine: Even More Contraptions (Baker et al., 2007), and AutoTutor (D'Mello et al., 2008). The Incredible Machine is a commercially available problem solving game in which students attempt to accomplish goals by building machines out of many everyday items while AutoTutor is a natural language-based intelligent tutoring system that aids students solving computer literacy and physics problems.

While the three environments are very different, several important findings were replicated in all three settings. First, the emotion of *flow* is the most commonly reported emotion in each environment, accounting for between 28 and 61% of all reports in individual studies. Interestingly, in the tutoring environment the reported levels of *flow* were only marginally higher than those of *boredom* and *confusion*, each accounting for nearly a quarter of all reports. In the two game-based environments, however, *confusion* and *boredom* together accounted for less than 20% of reports. The similarities and differences between affective experiences between the environments indicate both that it is important to examine narrative-centered learning environments for their specific impact on student affect and also that the results of these findings may provide insight to other learning environments despite the different approaches to instruction.

This initial study also replicated the finding that students tend to remain in the same emotional state over time. D'Mello et al. (2007) refer to this tendency as a *virtuous* or *vicious cycle*, depending on whether the persisting affective state is positive or negative. The continued support for this finding in very different learning environments suggests that affective intervention strategies should be developed to promote virtuous cycles and to prevent vicious ones.

Affect Recognition

In our laboratory we have investigated inductive approaches to recognizing student affective states, levels of self-efficacy, and several other cognitive and affective constructs. By recognizing student affect we hope to inform pedagogical planning and control modules of learning environments, such as Crystal Island, to improve tutorial and affective interactions. Likewise, by diagnosing self-efficacy we hope to better inform the pedagogical decisions bearing on the selection of problem difficulty by ensuring that the student has not only mastered the concept but believes in his or her abilities to utilize acquired knowledge.

Various models of emotion have been induced from observations of student behavior in Crystal Island to predict student self-reported affective states. We have investigated models that predicted affective state from a set of six emotional states (*excitement, fear, frustration, happiness, relaxation,* and *sadness*) using naïve Bayes and decision trees resulting in the best performing model with 95% accuracy. We then investigated approaches to early prediction of student frustration by collapsing the dataset to two states: *Frustration* and *Not Frustration*. To create models that make accurate predictions of student frustration as early as possible, we again use training data collected from observations of students interacting with Crystal Island. From this data, we then induced *n*-gram models, naïve Bayes, support vector machines, and decision trees to make early predictions of student frustration. These induced models were able to predict student frustration up to 30 s before confirmation of student frustration (self-reported frustration), with the best performing model achieving 89% accuracy (McQuiggan et al., 2007).

A foundational study to investigate the prospect of using the inductive approach to model self-efficacy in an online tutorial system produced models that were able to classify student self-efficacy as *High Efficacy* or *Low Efficacy* with 87% accuracy (McQuiggan, Mott, & Lester, 2008). Models were constructed from representations of ongoing situations in the online tutorial system. A second empirical study was designed to investigate the potential and the value of creating models of self-efficacy in more complex interactive learning environments (McQuiggan, Mott, & Lester). Models of self-efficacy were induced from observations of student behavior in the Crystal Island environment including representations of subject actions, locations, and other world state information. The highest performing induced naïve Bayes models correctly classified 85.2% of instances in the first empirical study and 82.1% of instances in the second empirical study. The highest performing decision tree models correctly classified 86.9% of instances in the first study and 87.3% of instances in the second study.

Affective Feedback

Recognizing student's affective states in real time provides little benefit without being able to provide intelligent responses aimed at improving the student's emotions during the learning experience. To this end we have examined a variety of methods for determining how best to provide affective feedback to students that is both natural and helpful in maintaining affective states that are conducive to learning. Given the rich interactive and social nature of Crystal Island's virtual characters, endowing these agents with the ability to respond directly to students' emotional states seemed to be a promising mechanism for emulating natural human–human affect sensitivity. While virtual character feedback is currently limited to text-based responses to self-reported affective states, a variety of types of feedback within this paradigm have been explored to gain understanding of the most effective mechanisms for supporting students' affective experience.

The first attempts to model ideal affective feedback examined students reactions to parallel and reactive empathy (McQuiggan, Robison, et al., 2008; McQuiggan et al., 2010), where parallel empathy occurs when the virtual character mimics the student's emotional state in an attempt to demonstrate an understanding of the situation and the student's perception of it. Alternatively, reactive empathy occurs when the character attempts to motivate the student to enter a more positive state. In this case, the character may not directly mimic the student's own emotional state but will still demonstrate an understanding of the situation and use this as a basis for motivating a more positive emotional state (Davis, 1994). An initial model of agent feedback was developed using machine learning techniques and a corpus of data collected from students interacting with empathetic virtual agents (McQuiggan, Robison, et al., 2008). In this study, subjects were given the opportunity to rate whether each empathetic response was helpful and appropriate in real time. This data was then used to determine the instances in which parallel or reactive empathetic statements should be used.

However, it seemed that perhaps students ranking of the quality of responses might not be indicative of whether the responses were actually useful in improving students' affective experiences. Therefore, transition models were created to determine if parallel and reactive empathetic statements would differentially impact the consequent emotional state of the student, and, if so, how they would be different. The results of this analysis revealed very interesting trends. In general, it appeared that parallel empathetic responses in which the character mimics the same emotional state to the student had a strong tendency to encourage virtuous and vicious cycles. Students feeling positive would remain positive and vice-versa for students experiencing negative states. Alternatively, when subjects received motivating, reactive empathetic statements they tended to reverse affective states. This meant that a student feeling negatively would respond to the motivation and had a higher likelihood to report subsequent positive affective states. However, when a student in a positive state received motivating empathetic feedback, they would react negatively and had a high likelihood of transitioning into a negative state. It is hypothesized that the source of this response lies in an adverse response toward being told to "feel better" when one is already feeling relatively well. Based on these findings, a simplified model of empathetic feedback was developed in which agents would respond with parallel empathy to positive emotional states and reactive empathy to negative states.

While empathetic statements seemed useful for supporting student emotion, they seemed to focus too much on the affective state of the student, perhaps neglecting the important cognitive processes of the student. The emotional states of the students in the learning environment are likely strongly impacted by their ability to understand and maneuver the virtual learning environment, and it may be the case that providing additional cognitive support could alleviate some of the same negative emotions perhaps more effectively than affect-focused empathetic statements. Therefore, a follow-up study examined the use of task-based feedback (in addition to empathetic feedback) that guided students through the learning task and reinforced their past successes. Using a methodology similar to the one in the initial, empathy-only study, models were learned based on of students' ratings of the quality of empathetic and task-based feedback.

Risk and Utility of Affect-Sensitive Behavior

The initial findings of the differential responses of affective feedback indicated the power that the virtual characters had in influencing student affective states. It became clear that it was plausible that in trying to support student emotional experiences it could also risk inducing unintended negative emotions. Just as responding to another individual's emotional states in human–human communication is full of uncertainty, the same uncertainty is magnified in human–agent interactions, which lack access to many of the important cues available to human interlocutors. Quantifying this uncertainty became the next important step in informing affective behavior.

In order to take a first step toward quantifying the expected risk or utility associated with affective feedback we first analyzed the emotional transitions students were likely to experience when presented with varying qualities of emotional feedback (Robison, McQuiggan, & Lester, 2009). This analysis yielded interesting results that confirmed the need for measuring uncertainty and risk. The results indicated that providing affective feedback to students in a positive state was highly risky and should be avoided. While an appropriate response could support positive emotions, inappropriate feedback could cause students to transition into very negative emotional states. Because students are likely to stay positive when left on their own, it is best to avoid intervention. When students are in a highly negative emotion, the converse holds: though an inappropriate response may prolong a negative state, the chance to perhaps improve their state offers such a great benefit that it is worth attempting an intervention, even when the system is unsure of the best type of feedback to give. While these findings are simple, the types of responses given to moderately negative emotions (i.e., *boredom*) require further study. For these states, students are likely to transition to positive states with appropriate feedback, but will transition to more negative states when feedback is inappropriate. In this case, the ability to measure uncertainty in the best type of feedback and weigh this with expected utility values becomes important in developing affect-sensitive virtual characters.

Conclusions and Future Work

The capability to recognize, understand, respond to, and express affect offers significant potential for improving the quality of interaction in interactive learning environments. In interactive learning environments, there is potential to create effective learning experiences through adaptations that account for student emotion and efficacy and can respond effectively through complex socio-constructs such as empathy. By endowing these systems with the ability to detect and properly respond to student affect, we may be able to encourage positive states for both immediate and long-term learning gains.

While current results are promising and provide some insight into how to properly support students' affective experiences and the importance of these efforts, there are many areas that are yet to be explored. For instance, initial work has examined *which* affective states students report while engaging in learning activities. Future work will examine *when* and *why* these states occur. If a student is experiencing frustration, it is likely very important to understand the source of that frustration in order to properly respond to it. The student may be experiencing difficulties with the learning material or the controls of the environment, or she may simply be irritated by characters who are attempting to provide feedback. Understanding the sources of affective states will not only help identify the most appropriate interventions but will also contribute to better designs that will enable negative emotions to be effectively managed.

Another important line of work will be understanding how the affective experiences of students influence learning gains and interactions in the environment. For instance, it is hypothesized that when a student experiences a negative emotion he or she may disengage from the learning aspects of the environment, focusing exclusively on the narrative features. This may or may not hinder overall learning as it may indicate successful emotion regulation or metacognitive behaviors. Understanding emotional impacts on learning will also contribute to the development of an empirically based utility measure of emotion that can be used in conjunction with measures of risk and benefit associated with interactive interventions. In this way, agent behavior can be driven by long-term learning goals rather than just short-term affective goals.

In addition to understanding how emotion impacts learning and student game-play, it will be important to examine how individual traits and beliefs may guide these phenomena. Previous work has already indicated the strong impact that personality traits and learning beliefs can have on emotional experiences of students. Examination of factors such as goal orientation, personality, self-efficacy and beliefs about the nature of learning in conjunction with student affect will help to provide systems that can tailor support to individual student needs and experiences.

Finally, combining the aspects of emotion recognition and expression discussed above into a unified system will provide insight into how affect-sensitive virtual environments might contribute to student learning. To date, each of the systems and findings discussed has been examined in isolation, focusing on one small piece of a large and complex puzzle. The ability to utilize each component of knowledge in an affect-sensitive learning environment offers significant promise for promoting effective learning that is accompanied by positive affective experiences.

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