Incorporating an Affective Behavior Model into an Educational Game

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Abstract

Emotions are a ubiquitous component of motivation and learning. We have developed an affective behavior model for intelligent tutoring systems that considers both the affective and knowledge state of the student to generate tutorial actions. The affective behavior model (ABM) was designed based on teachers' expertise obtained through interviews. It relies on a dynamic decision network with a utility measure on both student learning and affect to generate tutorial actions aimed at balancing the two. We have integrated and evaluated the ABM in an educational game to learn number factorization. We carried out a controlled user study to evaluate the impact of the affective model on learning. The results show that for the younger students there is a significant improvement on learning when the affective behavior model is incorporated.

Introduction

Emotions have been recognized as an important component in motivation and learning. There is evidence that experienced human tutors monitor and react to the emotional state of the students in order to motivate them and to improve their learning process (Johnson, Rickel and Lester, 2000). Recently there has been extensive work on modeling student emotions in intelligent tutoring systems, see (Conati and Mclaren, 2009); however, there have been only limited attempts to integrate information on student affect in the tutorial decisions, e.g. (Zacharov and Mitrovic, 2008; Faivre, Nkambou and Frasson, 2003; Murray and VanLehn, 2001). If we want to consider the student affective state in the tutorial actions, an important problem is to identify the best tutorial action given both the students' affective and knowledge state. In this paper we describe an approach to tackle this problem. We have developed an affective behavior model (ABM from now on) that considers both the affective and knowledge state of the student to generate tutorial actions. The affective student model used by the ABM is based on a probabilistic affective model previously developed by researchers at the University of British Columbia, (Conati and Zhou, 2002; Conati and Mclaren, 2005). The ABM selects the tutorial actions with the best expected effect on a student's affect and knowledge by using a dynamic decision network with a utility measure on both, learning and affect. We have designed the ABM based on interviews with qualified teachers aimed at understanding which actions the teachers select according to the state of a student's affect and knowledge. The ABM has been integrated into an educational game to learn number factorization, Prime Climb. This game includes a pedagogical agent with a model of student's knowledge (Manske and Conati, 2005). We conducted a user study to evaluate the affective behavior model, showing that for younger students there is positive impact on learning.

The Prime Climb educational game

Prime Climb (see figure 1), is an educational game to help students to learn number factorization. Two players have to climb mountains in a collaborative way. Each mountain is composed by hexagons labeled with numbers. Players have to move to a number that does not have common factors with the partner's number, if not they fall off the mountain.

To give adequate instruction, Prime Climb relies on a Bayesian pedagogical student model (Manske and Conati, 2005). The student model assesses the evolution of a student's factorization knowledge during interaction with the game. The pedagogical student model is used by an animated agent to deliver hints when it has evidence that the student is not learning from the game. The animated pedagogical agent is implemented through the Merlin character of Microsoft agent (Microsoft, 2005).

The affective behavior model

The affective behavior model we have developed for intelligent tutoring systems (ABM) takes affect into account when interacting with a student by i) inferring the affective state of the student (affective student model); and ii) by establishing the optimal tutorial action based on the student's current affective and knowledge state (affective tutor model). A flow diagram of the ABM is presented in figure 2.

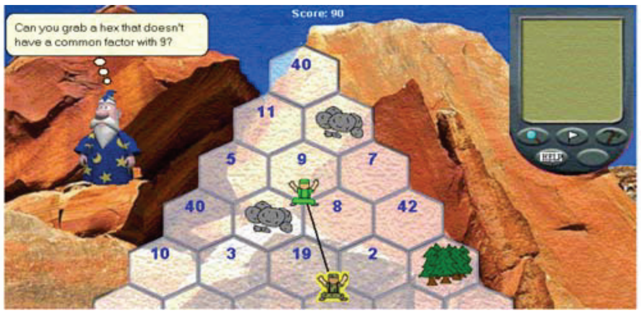

Figure 1. Prime Climb interface.

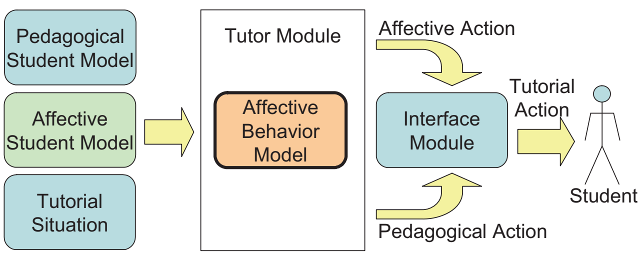

Figure 2. General diagram of the affective behavior model.

To generate a tutorial action, the ABM considers the affective and knowledge state of the student (as assessed by the corresponding student models), as well as the tutorial situation. The tutorial action is viewed as consisting of two components. The first component targets mainly the student's affective state (affective component) and consist of agent's animations, as we'll described in a later section. The second component (pedagogical component targets mainly the student's knowledge and consists of verbal hints (also described later). Thus selecting a tutorial action involves selecting these two components. Finally, the interface module establishes the physical realization of the tutorial action. To assess the affective state of the student, the ABM relies on a probabilistic student model that bases its predictions on information about a student's personality and interaction behavior. In the next section we describe this model.

The affective student model

Our affective student model uses the OCC model (Ortony, Clore and Collins, 1988) to provide a causal assessment of student's emotions based on contextual information. The OCC model defines emotional state as the outcome of the cognitive appraisal of the current situation with respect to one's goals. The general structure of our model is based on a model previously defined for Prime Climb by (Conati and Zhou, 2002; Conati and Mclaren, 2005; Conati and Mclaren, 2009). This model consists of a dynamic Bayesian network (DBN) that probabilistically relates student personality, goals and interaction events with student's affective states, based on the theory defined by the OCC model. Figure 3 shows a high level representation of the model, where each node in the network is actually a set of nodes in the actual model.

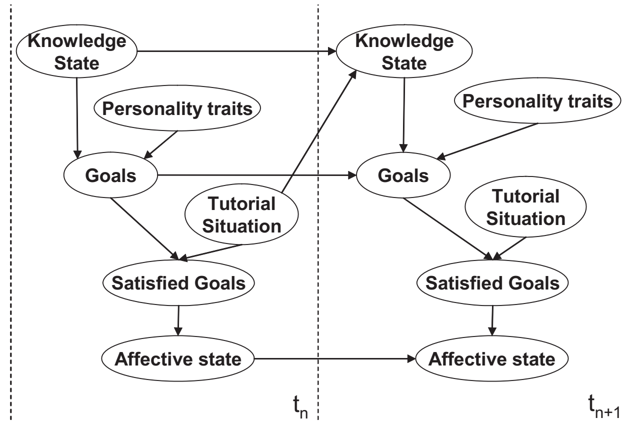

Figure 3.High level DBN for the affective student model.

The DBN models the dynamic nature of the student's emotions. To infer the affective state at t_n, it considers the student's knowledge, personality, and the tutorial situation at that time, as well as the student affective state at t_{n-1}. The use of the student's knowledge state is novel in this model, since it was not part of the model proposed in (Conati and Zhou, 2002; Conati and Mclaren, 2005). The tutorial situation is defined based on the results of the student actions (e.g., a fall or a successful move).

The student's appraisal of the current situation given her goal is represented by the relation between the *goals* and *tutorial situation* nodes through the *satisfied goals* node. The influence of the appraisal process on the student's affect is represented by the link between the *satisfied goals* node and the *affective state* node. From the complete set of emotions proposed by the OCC model, the affective model only includes six emotions: *joy*, *distress*, *pride*, *shame, admiration* and *reproach*. These are represented as three pairs of mutually exclusive emotions: *joy-distress*, *pride-shame* and *admiration-reproach*, each represented by a binary node in the network.

According to the OCC model, one's the goals are fundamental to determine one's affective state, but asking the students to express these goals during game playing would be too intrusive. Consequently, the goals in our network are inferred from indirect sources of evidence. Like (Conati and Zhou, 2002) we use personality traits as a predictor of the student's goals, but we also include the student's factorization knowledge. Note that, while (Conati and Zhou, 2002) included five goals in their model, we use a simplified version that has only three: 1) *to learn the topics*, 2) *to succeed in game playing*, and 3) *to be as fast as possible*. The reasons for establishing these goals are based on the nature of the task: to play a game to learn math. The first goal can be present because it is the main aim of the task: to play for learning; the second goal can be present because in a game players try to win; the third goal can be present because generally children want a quick reward.

The personality traits we included in the model are based on the five-factor model (Costa and McCrae, 1992), which considers 5 dimensions for personality: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. While (Conati and Zhou, 2002) used 4 of these 5 factors in their model, we include only 2, *conscientiousness* and *neuroticism*, to establish goals, because these are the ones for which a stronger relationship was found with learning (Heinström, 2000). To obtain priors on the personality nodes in the network, we conducted a study with 58 university students. The students had to answer a personality questionnaire (Boeree, 2005) based on the five-factor model. The information on the student's knowledge state and tutorial situation nodes comes from the model of student's knowledge and from the outcome of student's actions.

The dependency relations in the DBN (Figure 3) have been established based on the literature (Boeree, 1998; Heinström, 2000) and on insights from teachers. For example, if the student has a conscientiousness personality and limited understanding of number factorization, the probability of having the goal to learn number factorization through Prime Climb is high, because she is a responsible person who cares for her duties. On the other hand, if the student is a neurotic person, there is a higher probability of having the goal to succeed in game playing than to learn, because a neurotic person wants to have immediate and tangible success.

Selection of the tutorial action

Once the affective student state has been determined, the tutor has to respond accordingly. To do that, the tutor needs a model which establishes parameters that enable a mapping from the affective and knowledge student state to tutorial actions. The tutorial actions are composed by an affective and a pedagogical component. In Prime Climb, the pedagogical component consists of textual hints, while the affective component is realized via one of the Microsoft agent's animations. For example, Merlin can explain what a common factor is via a text appearing in a speech bubble (pedagogical component) while making a conciliating face and extending his arms to better trigger the student's attention and motivation (affective components). The affective component of a tutorial action tries to promote a positive affective student state and the pedagogical component aims to convey knowledge. Figure 4 shows more examples of Merlin's tutorial actions (the text in the bubbles is in Spanish). The first and second example relate to a situation in which the student is doing well. Merlin then congratulates the student verbally by saying "Very well!" or "Congratulations!" They also include animations aimed at conveying enthusiasm by either showing a trophy (first example) or clapping (second example). The third and fourth examples relate to a situation in which the student has made a mistake. The third one gives a rather general verbal tip ("Think about how to factorize both your number and your partner's number"), while the fourth example gives more specific help ("factors of a number are numbers that when multiplied give the original number"). In both cases, the tutorial actions include animations aimed at attracting the student's attention and reinforcing the verbal hints.

Figure 4. Some of Merlin's tutorial actions

Because we want that the agent's tutorial actions both help students learn and foster a good affective state, we use decision theory to achieve the best balance between these two objectives. The decision process is represented as a dynamic decision network (DDN), shown in figure 5. The DBN included in the DDN model is used to predict how the available tutorial actions influence a student's knowledge and affect given her current state. This prediction is used to establish the utility of each tutorial action for the current state.

Our model uses multi-attribute utility theory to define the necessary utilities (Clemen, 2000; Murray and VanLehn, 2001). That is, the DDN establishes the tutorial action considering two utility measures, one on learning and one on affect, which are combined to obtain the global utility by a weighted linear combination. These utility functions are the means that allow educators adopting the system to express their preferences towards learning and affect.

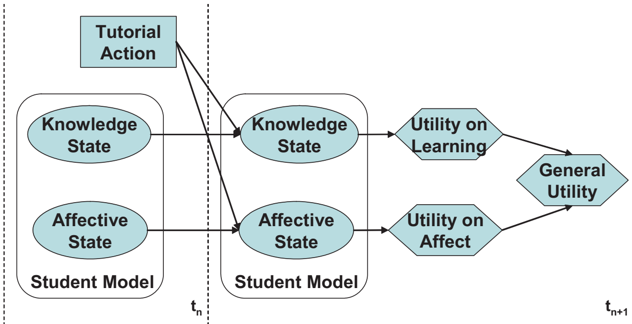

Figure 5. High level DDN for the affective tutor model.

After the student performs an action, i.e. after the student model is updated (time t_n), a new time slice is added (time t_{n+1}). At time t_n we have the current student state and the possible tutorial actions; at time t_{n+1} we have the prediction of how the tutor action influences the student's affect and knowledge, from which we estimate the individual and global utilities. The *affective state* in figure 5 is assessed by the affective model described in the previous section. The student's knowledge is assessed by another probabilistic model described in (Manske and Conati, 2005). The influence of each tutorial action on student's knowledge and affect, and the corresponding utility, are based on the teachers' expertise.

The utility for learning is measured in terms of how much the student's knowledge is improved by the tutorial action given her current knowledge. Similarly, the utility for affect is measured in terms of how much the student affect improves as a result of the action. Finally, the overall utility is computed as a weighted sum of these two utilities Thus, the tutor calculates the utility for each tutorial action considering the current state, and it selects the tutorial action with the maximum expected utility.

When the tutorial action has been selected, the decision network has finished its work and the time slice t_{n+1} is discharged. This is because the tutorial action is not used to update the student model but only to predict the impact of the tutorial action. At this point, the tutor delivers the selected action to the student and then uses the resulting student's response to update the student models. This cycle is repeated for each student action. The parameters of the DDN are based on the teachers study described in the next section.

The teachers study

The goal of this study was to understand which actions the teachers perform based on the state of a student's affect and knowledge, and why they select those actions. Eleven math teachers participated in the study. They had an average teaching experience of 17.63 years. We explained to the teachers the objective of this study, and our main motivations and hypothesis. The study included two phases. In the first phase, the teachers interacted with Prime Climb and selected the animations that they deemed to be generally appropriate to convey affective elements via the Prime Climb agent. In the second phase, they mapped appropriate affective actions to specific student states and tutorial situations. In the first phase of the study, the teachers first interacted freely with Prime Climb to familiarize themselves with the game. Then they were shown the Microsoft agent animations, and were asked to say which animations they considered suitable to provide affective tutorial feedback in Prime Climb. Based on the teachers' responses, we selected 14 of the available 58 animations as those most potentially effective as affective components of Merlin's interventions. These 14 actions are listed in table 1.

Affective action
A1-Acknowledge
A2-Announce
A3-Congratulate
A4-Congratulate2
A5-DoMagic1
A6-DoMagic2
A7-Greet
A8-Hide
A9-Pleased
A10-Alert
A11-Confused
A12-Explain
A13-GetAttention
A14-Surprised

Table 1. Merlin's animations selected in the teachers study as affective elements of a tutorial action.

In the second part of the study, the teachers viewed a video of the interaction of one student with Prime Climb. The interaction lasted approximately five minutes, during which the student climbed three mountains (levels). This specific video was selected because it showed a variety of tutorial situations based on a mix of student's correct and incorrect behaviors. While it would have been more principled to show the teachers interactions of several different students with Prime Climb, this was not possible because of constraints on the teachers' availability.

Teachers were provided with facilities to replay the video. After each student's move, they were asked to rate the student's affective state and to establish the pedagogical and affective components of the tutorial action that they considered adequate at that particular point. We also asked teachers to say how they thought the selected action improved the student's affect and knowledge. An example teacher's report is presented in table 2.

To rate the affective state, the teachers had a slider for each emotion pair: *joy-distress*, *pride-shame* and *admiration-reproach.* Moving the slider from left to right allowed teacher to rate each emotion pair on a scale from **1** to **100**, where **100** means *joy*, *pride* or *admiration* and **1** means *distress*, *shame* or *reproach*. The teachers selected the preferred pedagogical and affective component of an action from combo boxes showing all the available textual hints and animations. They could enter explanations and comments on their selections in the open text field shown at the bottom of table 2.

Affective:	**Pride/Shame**	75/25
	Admiration/Reproach	70/30
	Joy/Distress	73/27
Knowledge state:	Student knows the numbers factorization	
Pedagogical action	Right, these numbers do not share factors	
Animation	Congratulate_2	
Pedagogical action explanation	Student made a correct click	
Animation explanation	Student is having success	
Comments	I try to motivate the student	

Table 2. Example of a teacher's report from the second phase of the teachers study.

This phase of the study is the most important because it provides information about how the teachers choose their actions considering the affective and the knowledge states of the students. Assuming that teachers selected actions that they believed would improve a student's affective state and knowledge, we used the teachers' reports to establish the probabilities describing the impact of the various affective and pedagogical components of an action on knowledge and affect, given the current student's state and outcome of student's action. These are the probabilities used by the DDN in the ABM to calculate the expected utility of actions.

For example, when a student made a successful move but seemed not to know the numbers factorization, teachers often selected the verbal hint "You're right again! But do you know why? Here's an example", where the example is an explanation about the factorization of the relevant numbers. Thus, the CPTs describing the factorization knowledge of the numbers involved in a student's correct move at time t_n are set so that, if the knowledge is predicted to be low at time t_{n-1} and the selected action is the hint plus example, then the probability that the relevant numbers are known is increased by a fixed percentage.

The user study

To evaluate the performance of the ABM, we conducted a user study in a school in Mexico, with students from grade 6 in primary school, and 1-3 in secondary school (grades 6-8 in elementary school in the American system). Sixty two students participated.

In this study, we set the personality nodes in the affective model using the priors generated by a previous study with university students. We did so because the personality tests we had available were not suitable for younger subjects.

For each grade, the students were randomly divided into two groups; the first group (control) played with a version of Prime Climb that only included the model of student knowledge and the agent generating verbal hints with no animations. The second group played with Prime Climb with the affective behavior model (experimental group). Each student was previously instructed on how to interact with Prime Climb and about the rules of the game. Table 3 shows the sizes of the various groups in our study.

Grade		Avg Age	No. of students		
			Cntrl Gr.	Exp. Gr.	Total
Primary	6	11.9	8	9	17
Secondary	1	12.6	10	10	20
	2	13.8	6	5	11
	3	14.8	7	7	14

Table 3. Students participating in the study.

For each group, we gave each student a pre-test to evaluate her knowledge on factorization. Then the students played with Prime Climb for 40 minutes. After game playing, students took a post-test equivalent to the pretest. The students spent 5 minutes on average to complete the exams. Students were observed during their interaction with Prime Climb and they also filled a questionnaire on their experience with Prime Climb after game playing.

Grade		Control Group			Experimental Group		
		Pre	Post	Gain	Pre	Post	Gain
6	Avg	3.63	4.25	0.63	3.44	4.89	1.44
	StdDv	0.52	0.46	0.92	0.53	0.33	0.53
1	Avg	2.80	3.00	0.20	3.10	3.60	0.50
	StdDv	1.48	1.56	2.39	1.73	1.43	1.18
2	Avg	3.83	3.50	-0.33	3.40	3.00	-0.40
	StdDv	0.98	0.84	1.37	1.14	1.22	0.89
3	Avg	4.29	3.86	-0.43	4.00	4.14	0.14
	StdDv	0.76	0.69	0.53	1.41	1.46	1.46

Table 4. Test results (average and standard deviation) for the control and experimental groups, per grade.

G.	Control Group Pre-test/post-test		Exp. Group Pre-test/post-test		Learning gains Cntl grp/Exp grp	
	t	p (1-tailed)	T	p (1-tailed)	t	p (1-tailed)
6º	**2.55**	**0.09**	**6.95**	**0.000036**	**8.10**	**0.04**
1º	0.29	0.80	0.70	0.21	0.36	0.69
2º	0.63	0.58	0.53	0.37	0.09	0.93
3º	1.10	0.08	0.19	0.80	0.97	0.28

Table 5. Statistical analysis of the learning gains in each group: control and experimental, and between groups.

We compared the learning gain between the control and experimental groups, shown in table 4. In general trends are in favor of the experimental group. However, the difference between pre-test and post-test is statistically significant just for grade 6 for both groups. The difference between learning gains in the control and experimental groups is also statistically significant just for grade 6 (see Table 5). These results seem to indicate that in general Prime Climb was not a good tool for students in higher grades. However, when the game was appropriate, (as it seems to be the case for students in grade 6) the addition of the ABM generates significantly more learning. We believe that the reason for the different effectiveness of

Prime Climb in the different grades is due to the fact that students in the higher grades would not be tested directly on factorization knowledge as part of their regular curriculum, and thus did not try to learn from Prime Climb as much as the students in grade 6 did. Unfortunately we have no evidence to support our intuition, but we plan to perform an in-depth analysis of the interaction logs of all groups to see if we can understand why they learned differently from the game.

From a preliminary analysis of the students' questionnaires, we saw that most of the students liked playing Prime Climb. The version of Merlin that included the animations generated based on the ABM was rated higher than the version used in the control group. Students in the experimental group stated that they found Merlin movements funny and they felt that the animated character was helping them learn. Most students in the control group affirmed that they were not sure if Merlin was helping them to learn.

Conclusions and future work

We have developed an affective behavior model for intelligent tutoring systems that integrates information on a student's affect and knowledge to select the best tutorial actions. The affective behavior model was designed based on teachers' expertise and it is represented as dynamic decision network with a utility measures on learning and affect. We have integrated and evaluated the affective behavior model in an educational game to learn number factorization. A controlled user study shows that for students in grade 6 (primary school) there is a significant improvement on learning when the affective behavior model is incorporated. We found no effects with older students (grade 1-3 in secondary school). Students generally preferred the animated agent whose behavior is generated by considering both their knowledge and affective state.

Our main contributions are: (i) a decision-theoretic affective model which selects a tutorial action considering the affective and the knowledge state of the students, (ii) a teachers' study that allowed the refinement and parameterization of the model, and (iii) a controlled user study that evaluated the impact of the affective model on learning.

We plan to do a more detailed analysis of the user study based on data mining techniques to try to understand better what students did and why they did that; and also to understand the differences in performance between younger and older students. We also plan to incorporate the affective behavior model to a tutor for learning robotics for college students, and evaluate its impact in this domain.

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