

# Incorporating an Affective Model to an Intelligent Tutor for Mobile Robotics

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**Abstract** - Emotions have been identified as important players in motivation, and motivation is very important for learning. When a tutor recognizes the affective state of the student and responds accordingly, the tutor may be able to motivate students and improve the learning process. We propose a general affective behavior model which integrates information from the student's pedagogical state, affective state, and the tutorial situation, to decide the best tutorial action, considering the tutor preferences from a pedagogical and affective point of view. Our proposal is based on emotions models, personality theories and teachers' expertise. The affective model is implemented as a dynamic decision network, with utility measures on both learning and motivation, and is being incorporated to an intelligent tutor within a virtual laboratory for learning mobile robotics. This paper presents preliminary results in the construction of the affective behavior model.

*Index Terms* - Affective state, decision networks, intelligent tutoring systems, student model, virtual laboratories.

## INTRODUCTION

We have developed an intelligent tutoring system coupled to a virtual laboratory. This environment provides the student with the opportunity to learn through exploration within simulated experiments. Preliminary results show that students who had help of tutor improved their knowledge of the target knowledge objects [1]. During our studies, we detected that motivation is a very important aspect when students use a virtual laboratory, and their learning could be improved if students are motivated by means of appropriate actions. This hypothesis is consistent with what is stated in the literature: motivation is important for learning [2]. Likewise, emotions have been identified as important players in motivation; hence several authors have proposed to use the affective state of the student to give him a more suitable response that fits with his affective and cognitive state [3-6].

Accordingly, we want to improve learning within our virtual laboratory by means of a more personalized environment through recognizing the students' affective state with the aim of reacting appropriately from a pedagogical and affective point of view. We propose an affective behavior model for an intelligent tutoring system, which combines the affective and cognitive state of the student to establish

affective and pedagogical actions. The affective behavior model integrates an affective student model based on the OCC cognitive model of emotions [7] and relies on a probabilistic network. In the construction of the affective student model we use personality questionnaires based on the five factor model [8]. To select the tutorial actions, we propose the use of a dynamic decision network with two utilities measure on both learning and affect. By using the decision network, the tutor selects the best pedagogical and affective response considering the current state of the student. We have refined our model by means of questionnaires presented to university teachers. In the questionnaires we presented several scenarios of tutoring and we asked the teachers to select the appropriate pedagogical action for each scenario.

The rest of the paper is organized as follows. First, we summarize related work in affective tutors. Then we describe the proposed affective model. Next, we present preliminary results in the incorporation of the affective behavior model to a tutor for mobile robotics. Finally, we discuss our ongoing and future work.

## RELATED WORK

The affective state has been recognized as an important component in learning [2]; consequently, several authors have proposed to incorporate the affective state in the user model, to give a response according to the affective and cognitive state. One of first steps towards this end, has been the OCC Cognitive Model of Emotions [7], proposed by Ortony, Clore and Collins, with the aim to give artificial intelligence programs the capability to reason about humans emotions. This model considers that emotions arise as a result of a cognitive appraisal between goal and the situation. The OCC model has been used in artificial programs for education.

One of the most detailed affect models is presented in [3, 9]. This affect model has two ways to establish the affect; on one hand, in a predictive way, they considered that emotions arise as OCC stated; and on the other hand, in a diagnostic way, they consider that emotions have an impact in biological signs and facial expressions. This model is developed as a probabilistic model and has been applied to an educational game for learning number factorization. The OCC model has been also used to generate emotions. For example, in [10] a robotic character with the ability to display facial expressions denoting an affective state is described.

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There are another proposals based on students' interaction. For example, [4] describes a motivational model based on students' traits and on their cognitive state during the tutoring interaction. This work establishes the motivation state as a function of trait and state variables, such as: control, challenge, independence, fantasy, confidence, sensory interest, cognitive interest, effort and satisfaction. They have conducted a study and they generated a set of rules for diagnosis of the motivational state of students in an intelligent tutoring system to learn Japanese numbers. Other approach to detect motivation in students is presented in [11]. This model is based on observations from human tutors coaching students in on-line learning tasks. It takes into account the students' focus of attention, current task, and expected time required to perform the task. This information is obtained from the students' eye gaze and interface actions; and it is combined with information about the students' activities.

An interesting work on tutoring dialogs is presented in [6]. They are adapting a linguistic theory of social interaction to generate linguistic expressions in a tutor for teaching the basics of electricity and electronics. In this work they take into account social variables when they generate feedback.

An approach to select optimal tutorial actions for a tutor in a calculus domain is presented in [12]. This model is based on a dynamic decision network and its representation for the student includes problem-related knowledge, focus of attention, independence and morale. This model has been developed to emulate turn taking in human tutoring dialogs, and its aim is to predict the impact of the tutorial action in the student state, selecting the action with highest expected utility.

Although emotions have been recognized as an important aspect on learning, and there are several proposals to include emotions processing in intelligent tutoring systems, there are still many questions about emotions without response, such as which affective states are relevant for learning. In particular, the relationship between learning and tutorial actions has been not established. In the next section we describe our proposal to include affective behavior in an intelligent tutoring system.

**AFFECTIVE BEHAVIOR MODEL**

An Intelligent Tutoring System (ITS) is a computer-based educational system that provides individualized instruction like a human tutor. An ITS decides how and what to teach based on the student pedagogical state. However, it has been demonstrated that an experienced human tutor manages the emotional state (besides the pedagogical state) of the student to motivate him and to improve the learning process. Therefore, the student model structure needs to be augmented to include knowledge about the affective state. The ITS needs the ability of reasoning about the affective state to provide students with an adequate response from a pedagogical and affective point of view; in this sense, a model of affective behavior for the tutor is required; this model has to enable a mapping from the affective and pedagogical student model to the pedagogical responses of the tutor.

We propose an *affective behavior model* for intelligent tutoring systems. In the context of this work, the affective

behavior has two main functions: 1) to infer the affective student state; and 2) to establish the optimal tutorial action considering the student affective state. In this way, the ITS provides students with a tutorial action according to their pedagogical and affective state. A flow diagram of the affective behavior model (ABM) is presented in Figure 1.

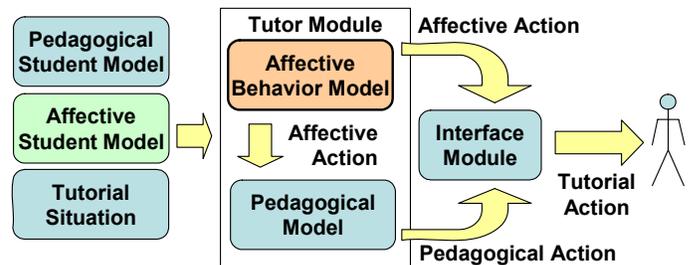


FIGURE 1  
FLOW DIAGRAM IN THE AFFECTIVE BEHAVIOR MODEL

The ABM considers the student models and the tutorial situation to establish the affective action. The affective action helps the pedagogical model to establish the next pedagogical action, and it also helps to the interface module to establish the physical realization of the pedagogical action. So the student receives a tutorial action with an affective component and a pedagogical component.

The ABM is being integrated to an ITS coupled to a virtual laboratory for teaching mobile robotics, which is described later. In Figure 2, the architecture of the affective ITS for mobile robotics is presented, the affective components are shown shaded.

The affective analysis module obtains the indicators used to infer the affective state and to update the affective student model. With this last structure, the affective behavior model will determine the affective action to be delivered by the affective tutor model. We take the indicators for the affective state from the personality, interaction and performance of the student in the virtual laboratory. In the next section the affective student model is presented and then we describe the affective tutor model.

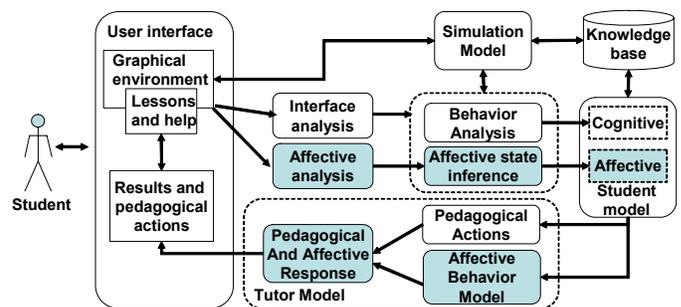


FIGURE 2  
ARCHITECTURE OF THE AFFECTIVE INTELLIGENT TUTORING SYSTEM FOR MOBILE ROBOTICS

*I. The Affective Student Model*

The student model must contain knowledge about the affective state of the student, in addition to knowledge about his pedagogical state, in order to give him an affectively

adequate response and at the pedagogically appropriate time. To determine the student affective state we use the following factors: 1) student personality traits, 2) student knowledge state, 3) goals and 4) tutorial situation. Since the process of establishing the affective state involves uncertainty [3], we represent the affective student model by a dynamic Bayesian network as it is shown in Figure 3. This network is a high level representation of the model, thus the nodes in the figure are actually a sets of nodes in the detailed model.

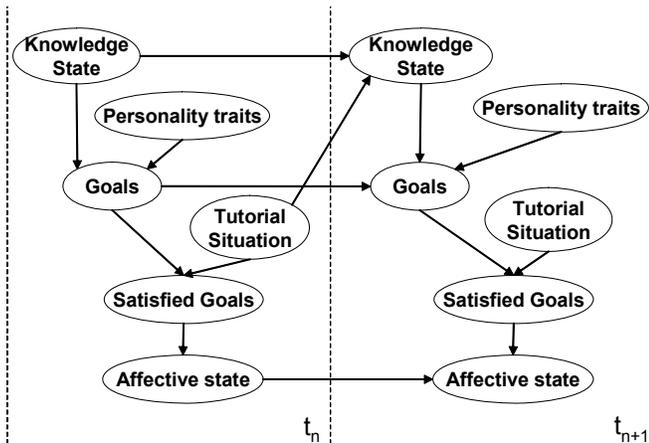


FIGURE 3

HIGH LEVEL BAYESIAN NETWORK FOR THE AFFECTIVE STUDENT MODEL

The affective state is not static, but it changes over time as a result of the changing environment and the particular interpretation of each individual. To have a realistic model of the affective state, we also need to consider the previous affective state. Consequently, we use dynamic Bayesian networks to model the dynamic nature of the affective state and its influence in the next state. In our dynamic network, we maintain two time slides, a slide is added and a slide is discarded after each student's experiment. To infer the affective state at  $t_n$  we use the knowledge state of the student, the tutorial situation and the personality traits of the student; this is used to predict the affective state at  $t_{n+1}$ . For the tutorial situation we take into account the results of the experiment conducted in the virtual laboratory, such as: if the student meets the goal, the experiment duration, if the student had control over the robot, and so on.

Our proposal for inferring the affective state is based on the OCC Model [7] which establishes emotional state as a cognitive appraisal between goals and situation, i.e. how the current situation fits with the student's goals. We represent it with a relationship between *goals* and *tutorial situation* nodes through the *satisfied goals* node, and a relationship between the *satisfied goals* node and the *affective state* node. From the complete set of emotions proposed by the OCC model, we only use six emotions: *joy-distress*, *pride-shame*, and *admiration-reproach*. Since in each pair of emotions, each emotion is a complement of the other one, we use consider each pair as one dimension (one variable), therefore we have three types of emotions.

According to the OCC model, the goals are fundamental to determine the affective state. To establish the student goals, we had two options: to ask the student, or to infer them. We think that asking the student is not a good option because people, in general, tend to be polite and probably the responses are not completely true, even if the counterpart is a computer [14]. Consequently, we decided to infer goals by means of personality traits and the knowledge the student has about the subject matter. We have established three goals for our domain: 1) to learn the topics related to the experiment, 2) to perform the experiment successfully, and 3) to complete the experiment as fast as possible.

We based the personality traits on the Five-Factor Model [9], which considers five dimensions for personality: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. Currently, we use only two of them (*conscientiousness*, *neuroticism*) to establish goals, because a relationship has been established between these two dimensions and learning; however, a relation between learning and *openness* has been stated, but it has not been proved [13]. To obtain the information for the personality traits variable, the students answer a personality questionnaire based on the five-factor model [14].

The information for the *knowledge state* and *tutorial situation* nodes comes from the pedagogical student model and the experiment results. The dependency relations in the Bayesian dynamic network, Figure 3, have been established based on the literature [13, 14], questionnaires applied to students and intuition. The structure just described is used by the affective tutor model which is presented in the next section.

## II. The Affective Tutor Model

Once the affective student model has been obtained, the tutor has to respond accordingly, and in order to do that, the tutor needs an affective behavior model which establishes parameters that enable a mapping from the affective and cognitive student state to actions of the tutor. As is shown in Figure 1, the ABM receives information from three components: the affective student model, the cognitive student model and the tutorial situation. The proposed model translates these components into affective actions towards the tutor and interface modules. The affective action contains knowledge about the overall situation that will help the tutor module to determine the next response to the student, and also it will advise the interface module to express the response in a suitable way. Based on the affective action, the tutor module can decide if it is necessary to provide another exercise or to change the topic in turn. For example, if the student's response is incorrect and his affective state is happy, the tutor can encourage the student with another exercise more suitable to the situation in order to maintain motivation at a high level.

Our main hypothesis is that the tutor action has a direct influence on learning and the affective state of the student, and selecting the appropriate tutorial action (i.e. according to the current student state), the tutor could improve the learning process and the affective state in students. Given this

hypothesis, we want to help students to learn and at the same time to foster a good affective state. Towards this aim, we use decision theory considering a trade-off between learning and affective state. We are developing the model based on multi-attribute utility theory [12, 15].

The ABM is represented as a dynamic decision network (DDN). Decision networks are an extension of the Bayesian networks and they are also called influence diagram. Dynamic decision networks, in a similar way as DBNs for BN, extend decision networks to represent dynamic decision problems. In Figure 4, we present a high level representation of the ABM as a dynamic decision network. The dynamic Bayesian network implicit in the DDN model, is used to predict how the tutorial actions influence the affective and pedagogical state of the student, considering the current affective and pedagogical states. This prediction is used to establish the utility of each tutorial action for the current state.

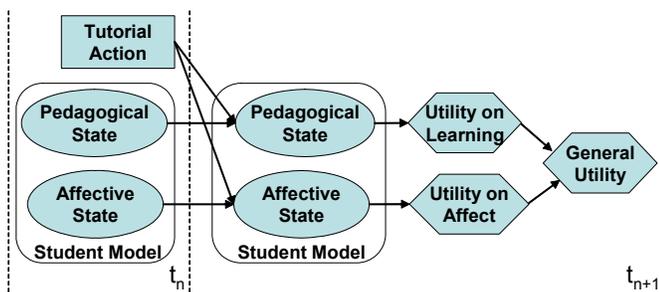


FIGURE 4

HIGH LEVEL DYNAMIC DECISION NETWORK FOR THE AFFECTIVE TUTOR MODEL

We consider the effects of the tutorial actions in each state individually, and then we consider a general effect in the tutoring process. The dynamic decision network establishes the pedagogical action considering two utilities measures, one on learning and other on affect, which are combined to obtain the global utility by a weighted linear combination. This utility functions represents the tutor preferences.

After the student completes an experiment in the virtual laboratory (described in the next section), i.e. after the student model is updated (time  $t_n$ ), a new time slide is added (time  $t_{n+1}$ ). In the time  $t_n$  we have the current student state (affective and pedagogical) and the possible tutorial actions; in time  $t_{n+1}$  we have the prediction of how the tutor action influences the student affective and pedagogical state, from which we estimate the individual (affect and learning) and global utilities.

Each affective and pedagogical node in the high level dynamic decision network (Figure 4) is actually a Bayesian network. The Bayesian network for the affective state was described in last section (See Figure 3, and for a detailed description see [16]). A detailed description of the Bayesian network for the pedagogical state is described in [1].

The utility of the pedagogical action is calculated given the tutor preferences, which are based on the expertise of a group of teachers. We conducted a study with teachers to validate our assumptions and refine our model. In this study we asked them to rate the pedagogical actions for each

affective and pedagogical state. We describe the results of this study below, in the section “Current and Future Work”.

For learning, we measure the utility in terms of how much the learning could be increased with the tutorial action given the current pedagogical state. The utility on learning is always a number greater or equal than 0, because currently we do not model forgetting. For example, for a node which represents the knowledge about a topic, we have the utility on learning as the result of subtracting the probability of knowing the topic in the time  $t_n$  from the probability of knowing the topic in the time  $t_{n+1}$ . In the same way, for the affective state, we measure the utility in terms of how much the affect could be improved with the tutorial action given the current affective state. In this case, the utility can be a number lower than 0 because the tutorial action can have a negative effect on the affective state of the student. For example, we have the utility on a specific emotion as the result of subtracting the probability of having that emotion in the time  $t_{n+1}$  from the probability of having that emotion in the time  $t_n$ . Finally, for the overall utility, we obtain a weighted sum of the utility on learning and the utility on affect. In this way, 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 slide  $t_{n+1}$  is discharged. This is because, currently, 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; waits for the next student action and the student model is updated. In this way the cycle is repeated for each student action.

The decision network can select among seven pedagogical actions: 1) exercise in a new category, 2) present another exercise with a higher difficulty level, 3) Present another exercise with same difficulty level, 4) Present another exercise with a lower difficulty level, 5) Give a lesson about a basic concept, 6) Give a lesson about a sub-topic y 7) Give a lesson about a topic. In next section, we describe the virtual laboratory and the intelligent tutoring system, and present the application of the affective behavior model to this domain.

#### THE VIRTUAL LABORATORY AND THE INTELLIGENT TUTORING SYSTEM

Our application domain is a simulated mobile robotics laboratory. The virtual laboratory for mobile robotics is used in an undergraduate course. The students interact with the virtual laboratory based on 3-D simulations, which enables the students to explore the basic concepts in the course: mechanical design, sensors, and control; before they start building a physical robot. An intelligent tutoring system guides the students during their interactions within the virtual laboratory.

The experiments within the virtual laboratory consist of aspects associated to a mobile robot competition (i.e., line following), which requires some basic knowledge of mechanical design, sensors, control theory and programming. We have designed several experiments focused on these

knowledge items. Figure 5 shows a screen shot of the virtual laboratory. The experiment in Figure 5 involves robotics' mechanical design concepts and enables students to explore three different kinematics models and several parameters for each model. When a student performs an experiment in the virtual laboratory, the experiment results and student exploration behavior are used in the student model to estimate the probability of the student's command of each *knowledge item* related to the experiment.

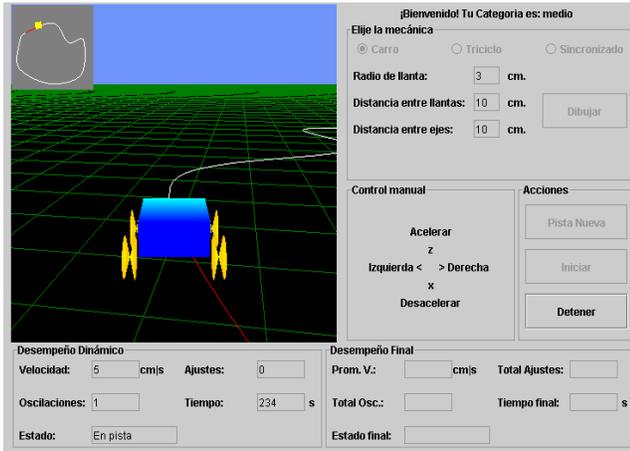


FIGURE 5  
A SCREEN SHOT OF THE VIRTUAL LABORATORY

The pedagogical student state is modeled as a Bayesian network representing the relationships among themes, sub-themes and basic concepts of the experiment. The student model is updated based on the results of the experiments and the exploration behavior. Figure 6 shows a Bayesian network representing the pedagogical student model. This network illustrates the dependency relations between the experiment performance and behavior (bottom), with the knowledge items, sub-themes and themes, and finally with the student's category (top). Based on this structure and using standard probability propagation techniques, the evidence from the performance and behavior of the student in an experiment is used to update the student pedagogical model, the principal component of the ITS.

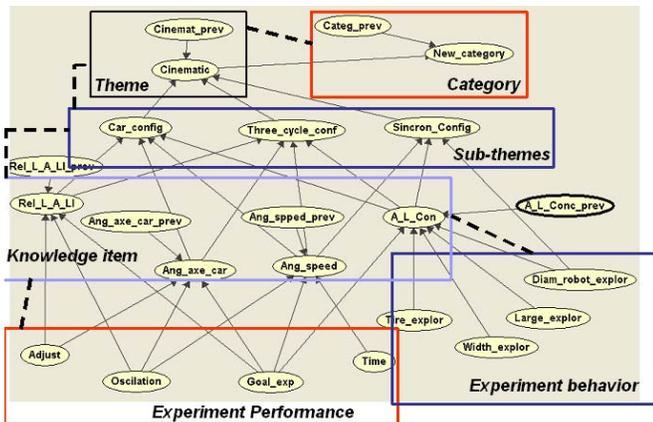


FIGURE 6

A BAYESIAN NETWORK REPRESENTING THE PEDAGOGICAL STUDENT MODEL

In the next section we described how the affective behavior model described above is integrated in the intelligent tutoring system.

*I. Integrating Affective Behavior*

When a student performs an experiment in the virtual laboratory, the ITS updates the pedagogical student model based on a Bayesian network as the one shown in Figure 6. At the same time, the affective student model is also updated, using also a Bayesian network model, depicted in Figure 7. The shaded nodes in Figure 7 represent sets of nodes taken from the pedagogical student model in Figure 6.

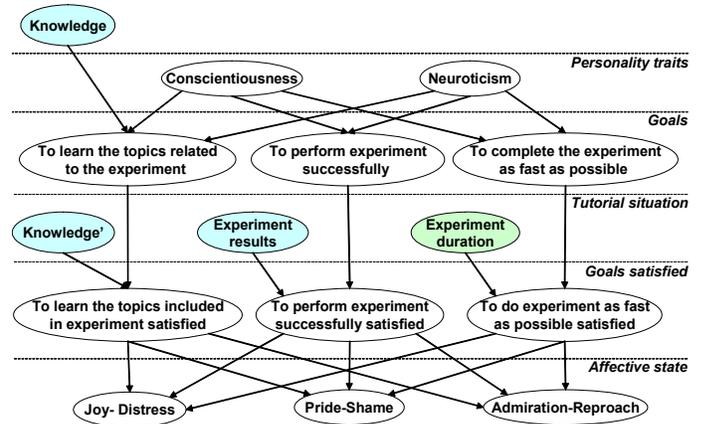


FIGURE 7

BAYESIAN NETWORK REPRESENTING THE AFFECTIVE STUDENT MODEL

Once, the affective and pedagogical student models have been updated, the tutor has to select the optimal pedagogical action to be delivered to the student. Then, both Bayesian networks are linked to the decision network in the slide  $t_n$  (Figure 4), which in more detail for this domain is shown in Figure 8.

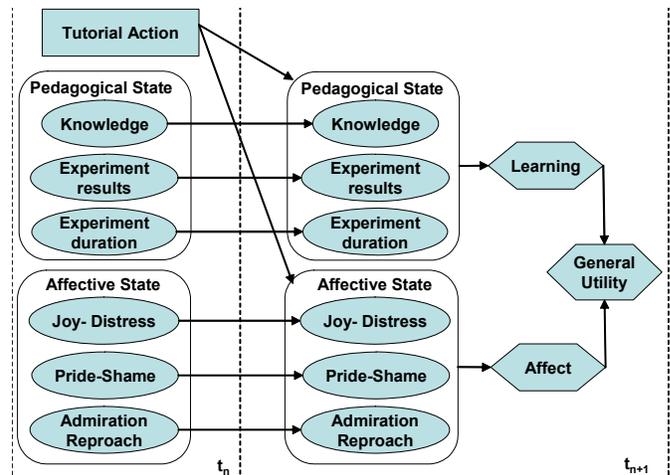


FIGURE 8

DYNAMIC DECISION NETWORK FOR THE AFFECTIVE TUTOR MODEL

At this point, the slide  $t_{n+1}$  is added to the decision network in order to predict the impact of each tutorial action on learning and on the affect of the student, and to select the

tutorial action with the maximum expected utility. When the tutorial action is selected, it is delivered to the student; and a new time slide is added to both, pedagogical and affective student models.

### PRELIMINARY RESULTS

We implemented a first version of the ABM. The Bayesian and decision networks were implemented in the Elvira System [17], a development environment for graphical models. The probabilistic relationships were established with base on the expertise of teachers. Then we evaluated this first version.

For evaluating the model we constructed several scenarios of tutoring, for a detailed description of the evaluation see [16]. A tutoring scenario consists of the personality of the student, the knowledge that the student has before the experiment, and the tutorial situation, i.e. the results of the experiment. We presented the eight cases to a group of teachers with between 8 and 26 years of experience. In this study, the teachers could choose one of the possible pedagogical actions previously defined, or they could determine a different pedagogical action. In this last case, we asked the teacher to explain the other pedagogical action, and the reasons to establish it.

We compared the results of model with the teachers' answers; and in the 57% of the cases, the pedagogical action established by the teachers agreed with the pedagogical action established by the model. An interesting finding is that there are more matches between the system and teachers who had less years of experience; so it seems that our system is *similar* to an inexperienced teacher. We analyzed the teachers' answers for each case in order to obtain some insight to improve the affective behavior model.

We obtained motivating results in the estimation of the affective state and in establishing the pedagogical action. The results of this study help us to refine our model, by means of changing the probabilities and some relationships of the variables included in the model. As a result, we established our current affective behavior model. Currently, we are implementing the changes in the ABM, and we are planning a new study to evaluate the model. In this new study, we will ask the teachers to observe the students while they interact with the system.

### CONCLUSIONS

In this paper, we proposed an affective behavior model for an intelligent tutoring system. The affective behavior model is composed by: (i) the affective student model, and (ii) the affective tutor model. Our main contribution is establishing a tutorial action considering the affective and pedagogical state of the student. The general model relies on a probabilistic model using dynamic Bayesian networks and dynamic decision networks. We have presented an initial version of the affective behavior model and how the model is being refined by means of teachers' evaluations. The intelligent tutoring system for the virtual laboratory without affective components is already in use. The next phase is to integrate the affective behavior model to the ITS. Then, we will conduct some

experiments to compare the improvements in learning and affect of the students with the incorporation of the affective components, against the ITS without affective components.

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