Modeling Students' Emotions to Improve Learning with Educational Games

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Abstract

We describe preliminary research on intelligent pedagogical agents designed to maximize students' learning from educational games, while maintaining the high level of positive emotional engagement that games usually trigger. The agents' behavior is based on a decision theoretic model, dictating that agents act so as to maximize the expected utility of their actions. In our framework, a pedagogical agent's utility function is defined to take into account both a user's learning and emotional state. In this paper we will first describe this general decision-theoretic model. We will then illustrate in detail how the user's emotional state is assessed within the model by taking into account the interaction with the game, the user's personality and the user's bodily expressions that are known to be directly influenced by emotional reactions.

Introduction

Several authors have suggested the potential of video and computer games as educational tools (e.g., [9, 17]). However, empirical studies have shown that, while educational games are usually highly engaging, they often do not trigger the constructive reasoning necessary for learning [3] [8].

An explanation of these findings is that it is often possible to learn how to play an educational game effectively without necessarily reasoning about the target domain knowledge [3]. Possibly, for many students the high level of engagement triggered by the game activities acts as a distraction from reflective cognition, especially when the game is not integrated with external activities that help ground the game experience into the learning one. Also, educational games are usually highly exploratory in nature, and empirical studies on exploratory learning environments have shown that these environments tend to be effective only for those students that already possess the learning skills necessary to benefit from autonomous exploration [16].

To overcome the limitations of educational games, we are working on designing intelligent educational agents that, as part of game playing, can generate tailored interventions aimed at stimulating student's reasoning if they detect that a student is failing to learn from the game. "As part of game playing" is the key point in the design of these agents. The main advantage of educational games versus more traditional computer-based tutors is that the former tend to generate a much higher level of students' positive emotional engagement, thus making the learning experience more motivating and appealing. In order not to lose this advantage, it is crucial that the interventions of pedagogical agents be consistent with the spirit of the game and consider the players emotional state, in addition to their learning.

In this paper, we first describe a general decision-theoretic model to guide the behaviour of intelligent pedagogical agents for educational games. We then provide further details on the part of the model that provides a probabilistic assessment of the player's emotional state during the interaction with the game, by integrating in a principled way different sources of ambiguous information on the user's emotional state.

Decision-theoretic pedagogical agents

As we mentioned in the previous section, we want to devise pedagogical agents that can act so as to improve students' learning with educational games, while maintaining as much as possible a high level of user's positive emotional engagement. We chose to formalize this behavior by following the decision-theoretic approach to agents' design presented in [15], dictating that a rational agent acts so as to maximize the expected utility of its actions [6]. In a decision-theoretic model, an agent's preferences over world states S are expressed by a utility function U(S), which assigns a single number to express the desirability of a state. Furthermore, for each action *a* available to the agent, and for each possible outcome state S' of that action, P(S'|E, *a*) represents the agent's belief that action *a* will result in state S', when the action is

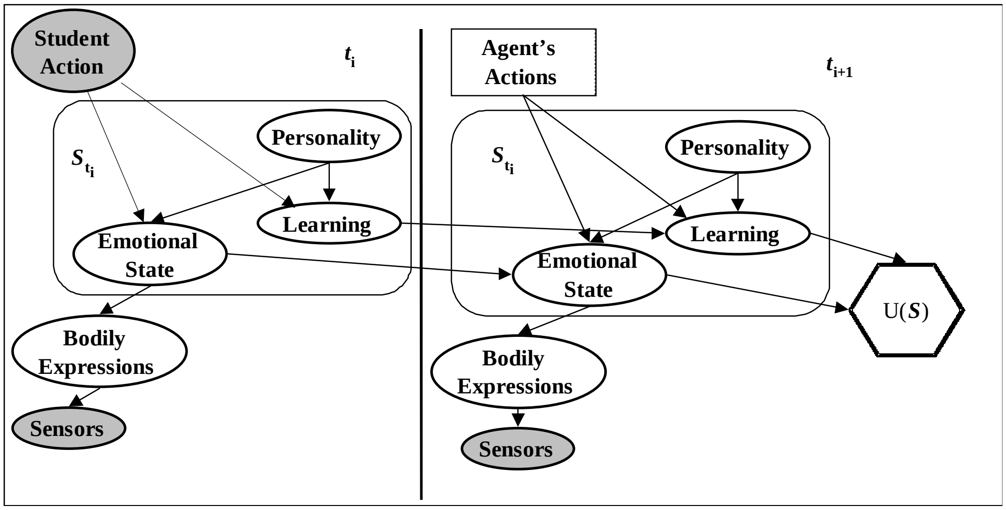

Figure 1: DDN to model the decisions of a pedagogical agent

performed in a state identified by evidence E. The expected utility of an action *a* is then computed as

$$EU(A) = \Sigma_{S'} P(S'|E, a)U(S')$$

A decision-theoretic agent selects the action that maximizes this value when deciding how to act.

Decision Networks (DNs), or *influence diagrams*, are an extension of Bayesian Networks [13] that allow modeling decision-theoretic behavior. In addition to nodes representing probabilistic events in the world, a DN includes nodes representing an agent's utilities and decision points. By relying on propagation algorithms for Bayesian networks, DNs allow computing the agent's action (or sequence of actions) with maximum expected utility given the available evidence on the current state of the world.

Dynamic Decision Networks (DDNs) add to DNs the capability of modeling environments that change over time. Figure 1 shows how a DDN can be used to define the behavior of pedagogical agents that take into account both the player's learning and emotional reactions when deciding how to act. This DDN models behavior over two *time slices*, to answer the question: given the student state S_{ti} at time t_i, which is the agent's action that will maximize the agent's expected utility at time t_{i+1}, defined in terms of the student's learning and emotional state at that time?

The links between variables in different time slices indicates that the values of these variables evolve over time and that the value at time t_i influences the value at time t_{i+1}. In our model, this is the case for the random variables *Learning* and *Emotional States* representing a student's learning and emotional state respectively. These links model, for example, the fact that a student is likely to know a given concept at time t_{i+1} if she knew it at time t_i. Or that a student is more likely to feel a given emotion at time t_{i+1} if something that can trigger that emotion happens and the student was already feeling that emotion at time $t_{i.}$

The shaded nodes in each time slice represent random variables for which evidence is available to update the student model at that time. In Figure 1, this evidence includes the student's game action at time t_i, as well as the output of sensors for monitoring the student's affective response at both time t_I and t_{i+1} (we will say more about these sensors in a later section). The rectangular node in time slice t_{i+1} represents the agent's available actions at that time, while the hexagonal node represents the agent's utility.

The link from the Learning and Emotional State nodes to the utility node in Figure 1 indicate that an agent's utility function is defined over the student's learning and emotional states. By varying their utility function, we can define agents that play different pedagogical roles in the game. So, for instance, the utility function of a *tutoring-oriented* agent will assign higher values to states characterized by high levels of student's learning, giving less importance to the student's emotional engagement, opposite to the utility function of a more *game-oriented* agent, concerned primarily with triggering positive emotional engagement in the student.

In the rest of the paper, we will concentrate on illustrating the part of the DDN that assesses the user's emotional state, to show how a probabilistic model can deal with the high level of uncertainty involved in this still largely unexplored user modeling task. For simplicity, we will ignore any relation between emotional state and learning, as well as details on how assessment of learning is performed.

Other researchers have been investigating a decision theoretic approach to devise intelligent tutors for complex problem solving [11] and for English capitalization and punctuation [10]. However, the model in [10] includes in the tutor's utility function only variables related to student's learning, while [11] includes also a variable representing students' morale but currently does not provide any detailed description of how this variable is assessed.

Probabilistic assessment of relevant emotions during game playing

Emotional states can be detected because they often affect both visible bodily expressions, such as facial expressions, voice intonation, posture and gestures, as well as less observable ones, such as heart rate, blood pressure, skin conductance, color and temperature [14]. Often a single emotion affects multiple bodily expressions, but several studies indicate that a single bodily expression by itself is usually not sufficient to recognize a specific emotion. For instance, skin conductivity is a very good indicator of general level of arousal (i.e., the intensity of the emotion), but cannot identify the valence of the emotion that caused the arousal (i.e., whether the emotion relates to positive or negative feelings) [14]. Emotions with negative valence tend to increase heart rate more than emotions with positive valence [2], but heart rate provides little information about specific emotions [4]. Also, which bodily expressions an emotion affects can depend on the intensity of the emotion, on the user's temperament and personality, as well as on the context in which the emotion is aroused.

The above factors make emotion recognition a task frequently permeated with uncertainty, especially if the interaction context can induce a variety of different emotional states in different users. Most of the research done so far on modeling users' emotional state has reduced this uncertainty either by considering tasks in which it is relevant to only monitor the presence or absence of a specific emotion [6] or by focusing on monitoring lower level measures of emotional reaction, such as the intensity and valence of emotional arousal [1]. In educational games, neither of these approaches is appropriate, for two main reasons. First, an educational game can arouse different emotions in different players. For instance, the exploratory nature of the game can be very exciting for people with a high level of curiosity and confidence, while it may cause frustration or anxiety in learners that are more passive and less confident. Second, detecting the student's specific emotions is important for an agent to decide how to correct possibly negative emotional states. DDNs allow us to deal with the high level of uncertainty involved in monitoring a user's emotional state during the interaction with an educational game by relying on the sound foundations of probability theory.

Figure 1 shows a high level description of our probabilistic model of emotions, in which only the general factors involved in assessing a user's emotional states are represented. The model indicates that the student's emotional state at time t_{i+1} is directly influenced by: (i) the agent's action at that time; (ii) the student's personality traits; (iii) the emotional state at time t_i, which summarizes the effect that the interaction with the game has had on the student's emotions up to that point. The user's emotional state influences her bodily expressions which, in turn, influence the measurements taken with the available sensors. The advantage of having a model based on a DDN is that it can leverage any evidence available on the variables related to emotional states to make predictions for any other variable in the model. So, for instance, available information on the user's personality can improve the assessment of the user's emotional state, even in absence of reliable sensors. Or, we can assess both emotional state and personality traits from reliable sensors, agent behavior's and previous emotional state when we have no evidence on a user's personality.

We now show an illustrative example of how the general model in Figure 1, at time slice t_{i+1}, can be refined and used to monitor a player's emotional state. We remind the reader that in this paper we will not consider the part of the model related to student's learning.

Model variables and structure

For the sake of simplicity, the model described in this example (shown in Figure 2), only includes a subset of the variables that could be used to refine the general model in time slice t_{i+1} of Figure 1. We chose this subset to give the reader a sense of how the model is built and of its workings, but several additional variables should be included to accurately model a real interaction.

Agent's actions. We will consider a simplified agent that has only two available actions: (1) provide help when the student makes a mistake and (2) do nothing

Variables describing the user's emotional state. As suggested by the Orthony, Clore and Collins (OCC) cognitive model of emotions **[12]**, three of the emotional states that may arise as a consequence of an agent's action are: (i) *reproach* if the agent's action interferes with a player's goal; (ii) *shame*, if the agent's action makes the player self-conscious about her own errors; (iii) *relief* if the agent's action helps the student overcome a problematic situation (see *user's emotional state* cluster in Figure 2). These are the three emotional states that we

explicitly represent in our illustrative model. We also add to the emotional state cluster nodes representing emotion *valence* (nodes *PosValence* and *NegValence*, in Figure 2) and level of *arousal*.

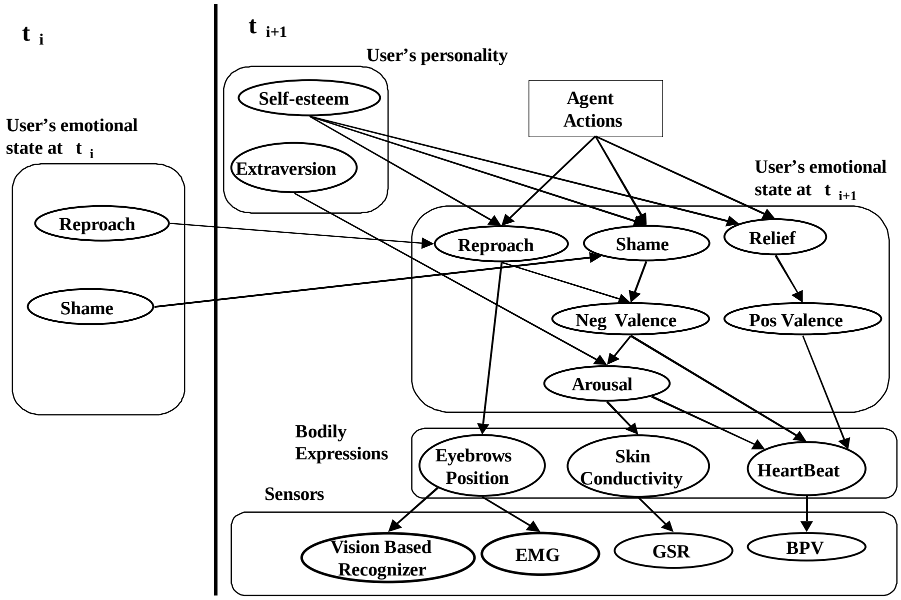

Figure 2: Sample model of emotion assessment

Variables describing the user's personality traits. We consider only two personality traits in this example: *self-esteem* and *extraversion*. As shown in Figure 2, self-esteem directly influences the emotional states that the agent's actions can induce. The conditional probability table (CPT) for the variable *reproach*, for instance, models the fact that the player is likely to feel reproach if she has high self-esteem and the agent provides help after an erroneous action, because the agent's intervention may interfere with the student's beliefs that she can discover by herself how to play adequately[1]. The probability of the player feeling reproach is even higher if she was already feeling reproach toward the agent before its last intervention. On the other hand, if the player has low self-esteem, the agent's provision of help can make the player self-conscious about his bad move, thus generating shame. This is even more likely if the player was already feeling shame before this last action. There is also a chance that the same agent's action could generate relief, because it allows a low self-esteem player to recover from a situation that he might feel unable to handle alone.

The second personality trait that we include in the model is *extraversion*. The corresponding variable directly influences level of arousal. The CPT for extraversion encodes the finding that introverts are known to reach a higher level of arousal than extroverts, given the same stimuli [7].

Variables describing bodily expressions and sensors. Let's suppose that we have sensors to detect three types of bodily expressions: (i) *eyebrow position*, by using, for instance, vision software to detect facial expression and electromyogram (EMG, a way to detect muscle contraction); (ii) *skin conductivity*, through a sensor that detects galvanic skin response (GSR); (iii) *heart rate*, through a sensor measuring blood volume pressure (BPV). The EMG, GSR and BPV sensors are all easily wearable by the user in a non-intrusive way [14]. Each bodily expression B is linked to each sensor S that can detect it, as shown in Figure 2, and if multiple sensors are available, the decision network propagation algorithms can automatically integrate evidence data coming from all of them. By encoding the probability of a sensor's value S given each value of bodily expression B, the conditional probability P(S|B) specifies the reliability of each sensor. Because this measure can be independently specified for each sensor and for the bodily expression that it detects, the model allows one to easily include new sensors as they become available.

Likewise, each conditional probability $P(B|E_1,..,E_n)$, indicates how a set of emotional states $E_1,..,E_n$ affects a given bodily expression B. As information on a bodily

[1] All the conditional probabilities in the model are based on the author's estimates, derived from findings described in literature on emotions.

expression not yet considered in the model becomes available, a new variable for this expression can be added to the model and linked to the emotion variables that influence it, thus increasing the amount of evidence that can be used to detect these emotions. The conditional probabilities linking emotions and bodily expressions in our example model represent the following findings [14]:

1. Frowning eyebrows are a very good indicator of negative emotions in the anger range, including reproach.
2. Skin conductivity is a very good indicator of the level of arousal.
3. Heartbeat increases with arousal, and more so in the presence of emotions with negative valence.

Sample assessment

We now give an example of how the model in Figure 2 can incrementally refine the assessment on the user's emotional state as more relevant user data become available, thus providing the agent with increasingly accurate information to decide how to act to help the user interact best with the game.

Let's suppose that, at some point during the interaction with the game, the player performs an incorrect action that reveals lack of understanding of a piece of the knowledge that the game tries to teach. Let's also suppose that the agent decides to provide help and the only sensor signal available at this time is high BVP. When this evidence is inserted in the model in Figure 2 and propagated, it increases the probability that the player's heart rate is high. High heartbeat in turn increases the probability that the player is in an emotional state with negative rather than positive valence (because of the conditional probability representing finding 3 listed in the previous section). Although the available evidence cannot discriminate between the player feeling reproach or shame, knowing that the user feels a negative emotion may influence the model so that the action with the highest expected utility at the next decision cycle is one that already tries to deal with the player's negative emotional state.

Let's now suppose that, in addition to high BVP, we also detect high GSR. When propagated in the model, this evidence increases the probability of a high level of arousal (because of the conditional probability representing finding 2 in the previous section), and consequently the probability that our player is an introvert (because of the finding, mentioned in the previous section, that an introvert tends to reach a higher level of arousal than an extrovert given the same stimulus). This assessment may result, in the next decision cycle, in selecting an agent's action that deals specifically with overcoming a user's negative emotional state when the user is an introvert (provided that the agent has such action).

Lastly, if our sensors also detect that the user is frowning, the probability of the player feeling reproach rather than shame increases (because of the conditional probability representing finding 1 in the previous section). This provides further information for the agent to decide what to do to overcome the player's reproach at the next decision cycle. Indication that the player feels reproach also increases the probability that the player has high rather than low self-esteem (because of how we defined the CPT for the variable Reproach). This information may result in the next selected action to be one that deals specifically with overcoming reproach in a high-self-esteem person.

Notice that the model would have given a high probability to the user feeling reproach even if, instead of having evidence about the user frowning, it had evidence about the user having high self-esteem, collected, for instance, from the user's data available before the interaction with the game.

If contradictory evidence arises, such as knowledge that the player has low self-esteem but frowns upon provision of help from the agent, the model assessment will depend on the relative strength assigned to the different kinds of evidence by the model CPTs. However, in general the model probabilities will reflect a higher level of uncertainty on the user's emotional state, which also represents valuable information that the agent can use to decide how to act.

Model specification

One of the major difficulties in using probabilistic models like decision and Bayesian networks is defining the required prior and conditional probabilities. In the model in Figure 2, the only prior probabilities are those for variables representing the player's personality, which can be defined through existing statistics, specialized tests and stereotypes, or set to indicate lack of specific information. The conditional probabilities for the model have been defined by the author to encode the general qualitative information available in the literature, and can be refined for a particular application and user population through empirical evaluations.

We plan to continue combining the initial model specification based on existing findings with empirical model calibration, in order to include in our model additional personality traits, emotional states and bodily reactions that will provide a more complete model of the student's emotional arousal for this particular type of interaction.

Conclusions and Future Work

We have described preliminary research on designing decision-theoretic pedagogical agents to improve the effectiveness of educational games. The key feature of these agents is that they consider a player's emotional state, in addition to the state of her learning, to decide when and how to support the student to learn at best from the game.

We have illustrated how these agents' behavior can be modeled using a dynamic decision network. The network represents how a student's learning and emotional state evolve during game playing and how they determine the agent's utility. We then presented an example of how the network provides a probabilistic assessment of a player's emotional state by integrating information on the possible causes of emotional arousal (e.g., the interaction with the agent and the player's personality traits), as well as the behavioral effects of this arousal (e.g., the player's bodily expressions).

The next step in this research is to identify other emotions that actually arise during the interaction with educational games, along with the bodily expressions that accompany them. To do this, we have collected videotapes of students playing with Prime Climb, one of the educational games developed in our lab. We are also designing Wizard of OZ experiments, to observe the students' interaction with a version of Prime Climb that includes an intelligent help agent similar to the one sketched in this paper. From the results of these studies, we will then decide which sensors to use to detect the relevant bodily expressions, and we will use this information to revise and complete the model of emotional assessment described in this paper.

We also plan to integrate in the model the assessment of a student's learning, as well as more temporal information, such as for how long a player has been in a given emotional state.

References

1. Ball, G. and J. Breese. Modeling the emotional state of computer users. in *Workshop on 'Attitude, Personality and Emotions in User-Adapted Interaction', UM '99*. 1999.
2. Cacioppo, J.T., G.C. Berntson, K.M. Poehlmann, and T.A. Ito, The psychopysiology of Emotions, in *Handbook of Emotions (2nd edition)*, M. Lewis and J.M. Haviland-Jones, Editors. 2000, The Guilford Press.
3. Conati, C. and J. Fain Lehman, EFH-Soar: Modeling education in highly interactive microworlds, in *Lecture Notes in Artificial Intelligence*. 1993, Springer-Verlag: New York.
4. Ekman, P., R.V. Levenson, and V.W. Friesen, Autonomic nervous system activity distinguishes among emotions. *Science*, 1983. **221**: p. 1208-1210.
5. Henrion, M., J. Breeze, and E. Horvitz, Decision Analysis and Expert Systems. AI Magazine, 1991.
6. Hudlika, E. Increasing SIA architecture realism by modeling and adapting to affect and personality. in *Fall AAAI Symposium on Socially Intelligent Agents: the Human in the Loop*. 2000. North Falmouth, MS, USA.
7. Kahneman, D., Arousal and attention, in *Attention and effort*. 1973, PrenticeHall: Englewood Cliffs, N.J. p. 2-49.
8. Klawe, M. When Does The Use Of Computer Games And Other Interactive Multimedia Software Help Students Learn Mathematics? in *NCTM Standards 2000 Technology Conference*. 1998. Arlington, VA.
9. Malone, T.W. and M.R. Lepper, Making learning fun: A taxonomy of intrinsic motivations for learning, in *Aptitude, learning and instruction: Volume III Conative and affective process analyses*, R.E. Snow and M.J. Farr, Editors. 1987, Erlbaum: Hillsdale, NJ.
10. Mayo, M. and A. Mitrovic, Optimising ITS behaviour with Bayesian networks and decision theory. International Journal of AI in Education, 2001. **12**.
11. Murray, C. and K. VanLehn. DT Tutor: A decision-theoretic dynamic apprach for optimal selection of tutorial actions. in *ITS 2000*. 2000. Montreal, Canada.
12. Orthony, A., G.L. Clore, and C. A., The cognitive structure of emotions. 1988: Cambridge University Press.
13. Pearl, J., Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. 1988, San Mateo, CA: Morgan-Kaufmann.
14. Picard, R., Affective Computing, ed. M. Press. 1997.
15. Russell, S. and P. Norvig, Artificial Intelligence: A Modern Approach. 1995, Los Altos, CA: Morgan-Kaufman.
16. Shute, V.J., A comparison of learning environments: All that glitters..., in *Computers as Cognitive Tools*, S.P.L.a.S.J. Derry, Editor. 1993, Lawrence Erlbaum Associates: Hillsdale, NJ. p. 47-73.
17. Silvern, S.B., Classroom Use of Videogames. *Educational Research Quarterly*, 1986: p. 10-16.