

Inducing optimal emotional state for learning in Intelligent Tutoring Systems

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Abstract. Emotions play an important role in cognitive processes and specially in learning tasks. Moreover, there are some evidences that the emotional state of the learner correlated with his performance. Furthermore, it's important that new Intelligent Tutoring Systems involve this emotional aspect; they may be able to recognize the emotional state of the learner, and to change it so as to be in the best conditions for learning. In this paper we describe such an architecture developed in order to determine the optimal emotional state for learning and to induce it. Based on experimentation, we have used the Naïve Bayes classifier to predict the optimal emotional state according to the personality and then we induce it using a hybrid technique which combines the guided imagery technique, music and images.

1 Introduction

Researches in neurosciences and psychology have shown that emotions exert influences in various behavioral and cognitive processes, such as attention, long-term memorizing, decision-making, etc. [5, 18]. Moreover, positive affects are fundamental in cognitive organization and thought processes; they also play an important role to improve creativity and flexibility in problem solving [11]. However, negative affects can block thought processes; people who are anxious have deficit in inductive reasoning [15], slow decision latency [20] and reduced memory capacity [10]. This is not new to teachers involved in traditional learning; students who are bored or anxious could not retain knowledge and think efficiently.

Intelligent Tutoring Systems (ITS) are used to support and improve the process of learning for any field of knowledge [17]. Thus, new ITS should deal with student's emotional states such as sadness or joy, by identifying his current emotional state and attempting to address it. Some ITS architectures integrate learner emotion in the student model. For instance, Conati [4] used a probabilistic model based on Dynamic Decision Networks to assess the emotional state of the user with educational games. In the best of our knowledge; there is no ITS systems dealt with the optimal emotional state.

So, we define the optimal emotional state as the affective state which maximizes learner's performance such as memorization, comprehension, etc. To achieve this goal, we address here the following fundamental questions: how can we detect the current emotional state of the learner? How can we recognize his optimal emotional state for learning? How can we induce this optimal emotional state in the learner?

In the present work we have developed and implemented a system called ESTEL (Emotional State Towards Efficient Learning system) which is able to predict the optimal emotional state of the learner and to induce it, that means to trigger actions so that the learner be in his optimal emotional state.

After reviewing some previous work realized we present ESTEL, architecture of a system intended to generate emotions able to improve learning. We detail all its components and show how we obtained from experiment various elements of these modules. We present in particular this experiment.

2 Previous work

This section will survey some of previous work in inducing emotion in psychology and in computer science domains.

Researchers in psychology have developed a variety of experimental techniques for inducing emotional state aiming to find a relationship between emotions and thought tasks; one of them is the Velten procedure which consists of randomly assigning participants to read a graded set of self-referential statements for example, "I am physically feeling very good today" [19]. A variety of other techniques exists including guided imagery [2] which consists of asking participants to imagine themselves in a series of described situations, for example: "You are sitting in a restaurant with a friend and the conversation becomes hilariously funny and you can't stop from laughing". Some other existing techniques are based upon exposing to participants films, music or odors. Gross and Levenson (1995) found that 16 film clips could induce really one of the following emotions (amusement, anger, contentment, disgust, fear, neutrality, sadness, and surprise) from the 78 films shown to 494 subjects [9]. Researchers in psychology have also developed hybrid techniques which combine two or more procedures; Mayer et al. (1995) used the guided imagery procedure with music procedure to induce four types of emotions, joy, anger, fear, sadness. They used the guided imagery to occupy the foreground attention and the music to emphasize the background.

However, few works in computer science attempted to induce emotions. For instance, at MIT Media Lab, Picard et al. (2001) used pictures to induce a set of emotions which include happiness, sadness, anger, fear, disgust, surprise, neutrality, platonic love and romantic love [14]. Moreover at affective Social Computing Laboratory, Nasoz et al. used results of Gross and Levenson (1995) to induce sadness, anger, surprise, fear, frustration, and amusement [13].

As mentioned previously, emotions play a fundamental role in thought processes; Estrada et al. have found that positive emotions may increase intrinsic motivation [6]. In addition, two recent studies, trying to check the influence of positive emotions on

motivation, have also found that positive affects can enhance performance on the task at hand [11]. For these reasons, our present work aims to induce optimal emotional state which is a positive emotion that maximizes learner's performance.

In the next section, we present the architecture of the ESTEL.

3 ESTEL architecture

In order to answer to the questions mentioned in the introduction, we need to develop a system able to: (1) detect the current emotional state; (2) recognize the optimal emotional state according to the personality of the learner; (3) induce this optimal emotional state; (4) evaluate the knowledge acquisition of the learner in each state of emotions. Furthermore, the corresponding modules able to achieve the previous functionalities are indicated in the architecture shown in Fig. 1.

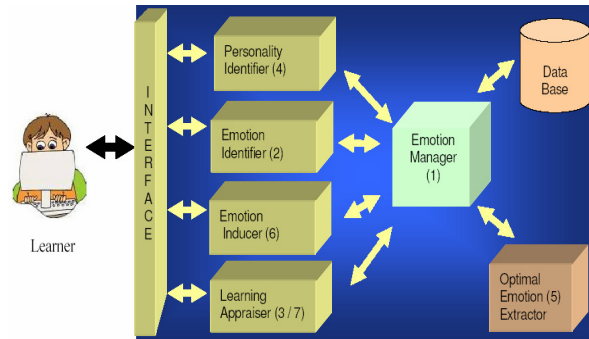


Fig. 1. ESTEL architecture

The different modules of this architecture intervene according to the following sequence; we detail further the functionalities of each module:

- the learner has first to accede to the system through a user interface and his actions are intercepted by the Emotion Manager,
- the Emotion Manager module launches the Emotion Identifier module which identifies the current emotion of the learner (2),
- the Learning Appraiser module receives instruction (3) from the Emotion Manager to submit the learner to a pre-test in order to evaluate his performance in the current emotional state,
- the Emotion Manager module triggers the Personality Identifier module (4) which identifies the personality of the learner,
- in the same way, the Optimal Emotion Extractor (5) is started to predict the optimal emotional state of the learner according to his personality,
- then next module launched is the Emotion Inducer (6), which will induce the optimal emotional state for the learner,

- finally, the Learning Appraiser (7) module will submit the learner to a post-test to evaluate his performance under the optimal emotional state.

The different modules mentioned previously are described below:

3.1 Emotion Manager

The role of this module is to monitor the entire emotional process of ESTEL, to distribute and synchronize tasks, and to coordinate between the other modules. In fact the emotion manager is a part of the student model in an ITS. It receives various parameters from the other modules. As we can see in Fig. 1, ESTEL architecture is centralized, all the information passes by the Emotion Manager module which will successively trigger the other modules.

3.2 Emotion Identifier

The Emotion Identifier module recognizes the current emotional state of the learner; it is based on the Emotion Recognition Agent (ERA). ERA is an agent that has been developed in our lab to identify a user's emotion given a sequence of colors. To achieve this goal, we have conducted an experiment in which 322 participants have to associate color sequences with their emotions. Based on results obtained in the experiment, the agent uses an ID3 algorithm to provide a decision tree which represents the sequence of colors with the corresponding emotions. This decision tree allows us to predict the current emotional state of a new learner according to his choice of a color sequence with 57,6 % accuracy.

3.3 Personality Identifier

Personality traits were identified by applying Abbreviated form of the Revised Eysenck Personality Questionnaire (EPQR-A) [8] which contains 24 items to identify personality from a set of personality traits (Psychoticism, Extraversion, Neuroticism, And Lie Scale). Extravert people are characterized by active and talkative behaviour, high on positive affects. However, Neuroticism is characterized by high levels of negative affects. People with high neuroticism are easily affected by the surrounding atmosphere, get worried easily, quick to anger, and easily discouraged. Psychoticism is characterized by non-conformity, tough-mindedness, hostility, anger, and impulsivity. People with high Lie scale are sociably desirable, agreeable and generally respect the laws in the society [7]. After identifying the personality of the learner, the Personality Identifier module communicates this information to the Emotion Manager which triggers the Optimal Emotion Extractor for determining the optimal emotional state of the learner according to his personality.

3.4 Optimal Emotion Extractor

The Optimal Emotion Extractor module uses a set of rules that we have obtained from the experiment which will be described later. Those rules allow us to determine the learner's optimal emotional state according to his personality. Let us take an example to show how the Optimal Emotion Extractor works; we suppose that the learner's personality is extraversion. To predict his optimal emotional state, the Optimal Emotion Extractor browses the rules to find a case corresponding to the personality of the learner; the rules are represented as:

If (personality = Extraversion) then optimal-emotional-state = joy.

By applying the rule above, the Optimal Emotion Extractor module will identify the learner's optimal emotional state as joy.

After identifying the optimal emotional state of the learner, ESTEL will induce it via the Emotion Inducer module.

3.5 Emotion Inducer

The Emotion Inducer module attempts to induce the optimal emotional state, which represents a positive state of mind that maximizes learner's performance, found by the Optimal Emotion Extractor. For example, when a new learner accedes to ESTEL; the Personality Identifier determines his personality as extraversion, and then the Optimal Emotion Extractor retrieves joy as the optimal emotional state for this personality. Emotion Inducer will elicit joy in this learner by using the hybrid technique which consists of displaying different interfaces. These interfaces include guided imagery vignettes, music and images. The Emotion Inducer is inspired by the study of Mayer et al. [12] that has been done to induce four specific emotions (joy, anger, fear, and sadness). After inducing emotion, the Emotion Manager module will restart the Learning Appraiser module for evaluating learning efficiency.

3.6 Learning Appraiser

This module allows us to assess the performance of the learner in his current emotional state and then in his optimal one. The Learning Appraiser module uses, firstly, a pre-test for measuring the knowledge retention of the learner in the current emotional state. Secondly, it uses a post-test to evaluate the learner in the optimal emotional state. The results obtained will be transferred to the Emotion Manager to find out which of the two emotional states really enhances learning. If the results of the learner obtained in the pre-test (current emotional state) are better than those obtained in the post-test (optimal emotional state), ESTEL will take into consideration the current emotional state of this learner to eventually update the set of possible optimal emotional state for new learners.

As follows, we present the results of the experiment conducted to predict learner's optimal emotional state and to induce it.

4 Experiment & Results

Since different people have different optimal emotional states for learning, we have conducted an experiment to predict optimal emotional state according to the learner's personality. The sample included 137 participants from different genders and ages. First, participants choose the optimal emotional state that maximizes their learning from a set of sixteen emotions (as shown in Fig. 2).



Fig. 2. Emotions Set

After selecting their optimal emotional state, subjects answer to the 24-items of the EPQR-A [8]. The data collected was used to establish a relationship between optimal emotional state and personality.

Table 1. Experiment Results

	Extraversion	Lie	Neuroticism	Psychoticism
Anger	2	0	0	0
Anxious	8	3	3	2
Bored	2	0	2	0
Confident	12	14	8	0
Disgusted	0	1	0	1
Distressed	0	0	3	0
Fear	1	0	0	0
Joy	15	10	7	3
Pride	5	4	11	0
Resentment	0	0	1	0
Self-Gratification	4	7	3	0
Surprised	3	0	1	0
Remorseful	1	0	0	0

As shown in the table above, from the initial set of sixteen emotions given to the 137 participants, just thirteen have been selected. As you notice more than 28% of the participants, who their personality is extraversion, select joy as the optimal emotional state. There are also about 36% of the participants who have the most score in the lie

scale, choose confident for representing their optimal emotional state. Nearly, 29% of the neurotic participants find that their optimal emotional state is pride. Moreover, from the 137, we have found just six psychotic participants, 50% of them have selected joy as the optimal emotional state.

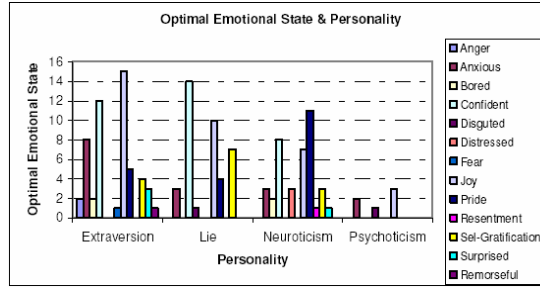


Fig. 3. Optimal emotional state & personality

As shown in Fig. 3, we have learner's personalities and their corresponding optimal emotional states. However, we need to select the most chosen by participants; we have applied the Naïve Bayes classifier to do that. Suppose that personality traits are noted by p_i , and those optimal emotional states variables are noted by o_i , the Naïve Bayes Classifier helps us to find the best class o_i given to p_i in the case of two independent variables [16]. By a direct application of Bayes' theorem, we get:

$$O^* = \text{agr} \max_{o_j \in O} P(o_j) * P(p_i / o_j) . \quad (1)$$

We generally estimate $P(p_i / o_j)$ using m-estimates:

$$P(p_i / o_j) = \frac{n_c + mp}{n + m} . \quad (2)$$

Where:

n = the number of the users who their optimal emotional state is o_j

n_c = the number of the users who their optimal emotional state is o_j and their personality is p_i .

p = a priori estimate for $P(p_i / o_j)$.

m = the size of the sample.

Looking at $P(\text{Joy}/\text{Extraversion})$, we have 53 cases where $p_i = \text{Extraversion}$, and in 15 of those cases $o_j = \text{Joy}$. Thus, $n = 53$ and $n_c = 15$, since we have just one attribute value and $p = 1 / (\text{number-of attribute values})$, so $p = 1$ for all attributes. The size of the sample is $m = 137$, therefore, from formula (2), we get:

$$P(\text{Joy} / \text{Extraversion}) = \frac{15+137}{53+137} = \frac{15}{53} = .28$$

and, $P(\text{Joy}) = \frac{1}{13} = .076$, therefore,

$$P(\text{Joy}) * P(\text{Joy} / \text{Extraversion}) = .28 \times .076 = .021$$

Suppose that we have just two attributes: Anxious and Joy. By applying the same steps for Anxious, we obtained:

$$P(\text{Anxious}) * P(\text{Anxious} / \text{Extraversion}) = .15 \times .076 = .011$$

Using formula (1): since $0.011 < 0.021$, the optimal emotional state predicted according to extraversion is joy.

By applying the Naïve Bayes classifier to all attributes, we have obtained the following tree which allows us to predict the optimal emotional state for a new learner according to his personality (see Fig. 4).

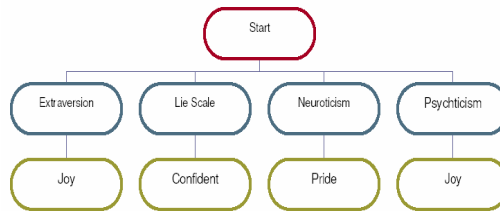


Fig. 4. The predicted optimal emotional state

Furthermore, for each personality we try to induce the corresponding optimal emotional state. The figure bellow (Fig. 5) shows how the hybrid technique allows us to induce joy for the extravert learner, so, we integrate in the interface a guided imagery vignette to engage the foreground attention and in the background we set an image that expresses what was said by the vignette in order to help in the guided imagery, we also put music to improve the background. For example, we say to the learner imagine that “It’s your birthday and friends throw you a terrific surprise party” [12], we show him an image that reflects this situation to help him in his imagination, in the background we put to him a music expressing joy such as Brandenburg Concerto #2 composed by Bach [3]. We use the same principle to induce the two other optimal emotional states.



Fig. 5. Example of interface inducing joy

5 Conclusion and future research

In this paper, we have presented the architecture of our system ESTEL. By which, we proposed a way to predict optimal emotional state for learning and to induce it. We know that it is hard to detect the optimal emotional state for learning. For this reason, we have used the Naïve Bayes classifier which helps us to find the optimal emotional state for each personality. Moreover, we are also aware of the fact that inducing emotions in humans is not easy. That is why we have used the hybrid technique including; guided imagery, music and images attempting to change learner's emotion.

It remains for future research to study the effect of the emotion intensity in thought processes. On one hand, as mentioned previously, positive affects play an important role to enhance learning; on the other hand, the excess of the emotion sensed could go in the opposite direction. So, the learner will be submerged by this emotion and could not achieve the learning tasks in a good way. For this reason, future studies will concentrate on emotion intensities to regulate the emotion induced by ESTEL. So, we are thinking to add a new module called the Emotion Regulator which will be able to control and to regulate the optimal emotional state intensity in order to improve even more the learner's performance.

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