

# Predicting the Learner's Emotional Reaction towards the Tutor's Intervention

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## Abstract

*The tutor tries, by using feedbacks, to keep the learner's attention and to increase his motivation and then his performance. However, the effectiveness of the tutor's feedbacks on the learner varies from one learner to another. It depends essentially on the learner's traits and it is reflected in the learner's emotional reaction. Consequently, it is important to detect the learner's emotional reaction following the tutor's intervention in order to personalize the feedback type. Our proposal consists of a methodology, based on machine learning technique, able to predict the learner's emotional reaction starting from the analysis of descriptive variables of the learner's current situation, such as: personality, motivation and tutor's feedback type.*

## 1. Introduction

Lately emotions have received considerable attention from several researchers especially in the computer science domain. In fact, human beings use emotions to communicate. In addition, Nass and Reeves claimed that emotions are widely related to communication and social activities, and that human beings interact with computers in an emotional way [13]. Indeed, emotions are also important in cognitive processes. For instance, Damasio has proved the influence of emotions on reasoning, memorising, learning and decision making processes [5]. Moreover, Bower and Cohen have discovered that memory retrieval and learning are mood-congruent [1]. Based on these claims, an Intelligent Tutoring System (ITS) should use emotions to establish good interaction with the user, help the learner for integrating knowledge more easily, monitor and induce the learner's emotions

to an optimal degree in order to keep attention and increase performance. In this study, we are interested in predicting the learner's emotion after the tutor's feedback in a distance learning experience. Feedback is an important component of ITS, as it is an important part of human communication. It helps us to know whether we are doing things well and also what we need to improve or look for.

In this paper, we present a probability-based approach especially the naïve Bayes classifier [14] to predict and model the learner's emotional reaction based on personal traits such as sex and personality as well as the emotional event, such as, the type of tutor's intervention (manner of giving feedback) and the type of feedback itself.

The organization of this paper is as follow:

In the first section, we present the previous work realized in relation to emotion recognition and learning environments. Then, the next section describes our emotion prediction process. The third section shows the results of the experiment. Finally the last section concludes the paper.

## 2. Related work

Several researches have been made by the computer science community in order to let computers recognize, express and have emotions. For example, some research studies use cameras to recognize emotions from facial expressions [15]. In addition, some other researchers use microphones to recognize emotions basing on prosodic and acoustic parameters [8, 3]. Picard [11] and other researchers use physiological sensors to recognize emotions basing on physiological signals such as skin conductance, blood pressure, heart rate, etc. Nevertheless, Picard [11] has noticed that people can feel uncomfortable with video-

cameras or physical sensors and that these devices can interfere with recognition.

This work follows previous work conducted in our lab [4] in which a machine learning technique named the ID3 algorithm [12] was used to predict the learner's emotional reaction towards the expected mark in a quiz. However, in this research work the context is different from the previous one. Here, our aim is to predict the learner's emotional reaction towards the tutor's feedback based on one hand on personal traits like personality, sex, motivation degree, and on the other hand on emotional events such as the tutor's feedback type.

### 3. Our emotion prediction process

After reviewing some previous work in connection with emotion recognition, we present in this section our emotion prediction approach which is summarized in the figure below:

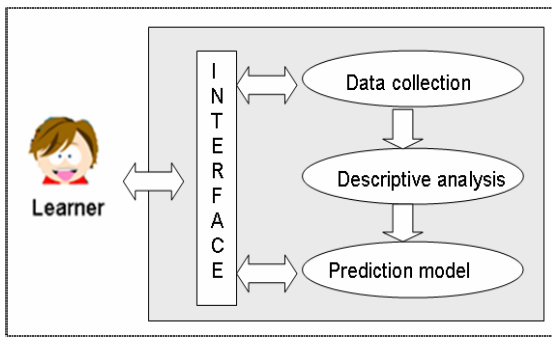


Figure 1. Emotion prediction process

Our emotion prediction process covers mainly three phases:

(1) The data collection phase:

According to the OCC model, emotions result from the cognitive appraisal of situations [9]. The appraisal according to this model is made on the basis of some criteria (goals, standards and attitudes). Although this model was used as a basis for most computational models of emotion, it is too general to use to predict the individual's current emotion. Emotional experience is a complex process which depends on each person and each situation [7]. For this reason, we attempted to be close to the learner by taking into account not only the situation which can start an emotion, but also the learner's personal data (personality, motivation, etc.).

(2) The descriptive analysis phase:

After collecting data, we have to achieve a data descriptive analysis. The descriptive analysis shows the dependencies between the variables. It is important because it helps to find the most relevant attributes for

the outcome variable [6]. There exists several descriptive analysis techniques in particular mutual information which calculates statistical dependencies between categorical variables.

Mutual information is defined as:

$$I(X, Y) = \sum_{y \in Y} \sum_{x \in X} p(x, y) \log \frac{p(x, y)}{p(x)p(y)}. \quad (1)$$

Where  $p(x, y)$  is the joint probability distribution function of  $X$  and  $Y$ , and  $p(x)$  and  $p(y)$  are the marginal probability distribution functions of  $X$  and  $Y$  respectively.

(3) The emotion prediction phase:

In this phase, a supervised machine learning algorithm will be applied on data. The supervised learning tries to learn a function starting from the training data which are in the form of inputs/outputs. In this paper, we have used a Naïve Bayes classifier. The Naïve Bayes classifier is considered to be very efficient in practice and especially in uncertain environments like that of the distance learning. Moreover, it is convenient to small data sets [6].

Suppose that initial emotions are noted by  $e_i$ , personalities are noted by  $p_i$  and tutor's interventions noted by  $t_i$ . We denote attributes set  $A = \{e_i, p_i, t_i\}$ . The naïve Bayes Classifier helps us to find the best emotion class  $c_j$  given to  $A$ , by using the Bayes's theorem:

$$c^* = \text{arg max}_{c_j \in C} P(c_j) * P(A_i / c_j). \quad (2)$$

Where  $P(c_j)$  is the prior probability of  $c_j$  and  $P(A_i / c_j)$  is the conditional probability of  $A_i$  given a class  $c_j$ .

### 4. Experiment and results

In order to predict the learner's emotional reaction, a web-based experiment has been developed to collect useful data (personality, initial emotion, motivation, intervention type and final emotion). Once the data are collected, we carried out data cleaning by deleting the whole tuple if one value of its attributes is missing. As a result, 116 data were used to predict the learner's emotional reaction.

After that, a naïve Bayes model has been constructed based on prior and conditional probabilities. The naïve Bayes model is represented as a Bayesian network with the output variable as the root node and the input variables as leaves (see figure 2).

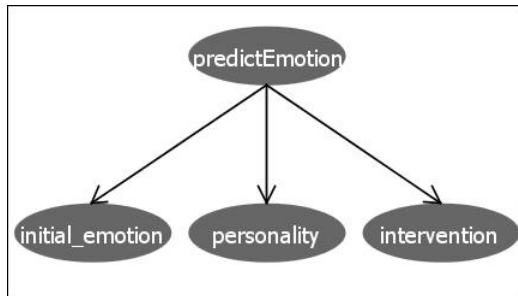


Figure2. Naive Bayes model for predicting the learner's emotion, given the personality, the initial emotion and the tutor's intervention

For the root a prior probably is calculated and for each leaf a Conditional Probability Table (CPT) is built.

Then, as we already said, the predicted emotion is given according to the formula 2.

The naïve Bayes model has been evaluated with 10-fold cross validation. It can predict the learner's emotional reaction with an accuracy rate of 62.93 %.

## 5. Conclusion

The main goal of an Intelligent Tutoring System (ITS) is to increase the student motivation and performance by giving personalized instruction. Buscemi points out that people learn just after comprehension, thus the need for immediate feedback when learning languages is important [2]. This paper proposes a probability-based approach, based on naïve Bayes classifier, to predict the learner's emotional reaction towards the tutor's feedback. So, a naïve Bayes model has been constructed in the form of a two-layer Bayesian network. This model can predict the learner's emotional reaction with 62.93 % accuracy rate.

## 6. Acknowledgements

We address our thanks to the FQRNT (Fonds Québécois de la Recherche sur la Nature et la Technologie) for supporting this project. We acknowledge the support of the FQRSC (Fonds Québécois de la Recherche sur la Société et la Culture).

We also wish to thank Nabil Guerouah for his contribution to the development of this experience.

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