

# Predicting the Emotional Reaction of the Learner with a Machine Learning Technique

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**Abstract.** Emotions play an important role in cognitive processes and specially in learning tasks. Online learning is no exception. Detecting a learner's emotional reaction for a given situation is an essential element for every Distant Learning Environment. Nevertheless, inferring a learner's emotional reaction in those environments is not a trivial task. In this paper, we present an agent capable of predicting a learner's emotional reaction in a distant learning environment based on the learner's personal and non-personal traits using a machine learning technique, namely the ID3 algorithm. We then describe the agent's method for predicting the learner's emotional reaction and discuss the obtained results.

## 1 Introduction

Learning theories have largely treated emotion and cognition as occupying separate realms where cognitive process rules as master in the educational field (Ferro, T. 2005; Martinez, M. 2001). Nevertheless, new researches in neurosciences and psychology have proved that emotions are widely related to diverse cognitive processes, such as attention, problem solving, decision-making, etc. (Isen, A.M. 1999; Damasio, A. 1994). There is ample empirical data in the psychological literature which shows that emotions are systematically affected by the knowledge and goals of the learner, as well as vice versa (Mandler, G. 1999; Mandler, G. 1976). In fact, online teaching and learning have emerged as a new environment in which the importance of the emotional factor should not be minimized (O'Reagan, K. 2003).

Inferring the emotional reaction of a learner in a distant learning environment is not a trivial task. The changing of the emotional state in a learning experience depends on individual differences and the events that have been occurred (Hess, U. 2001). So, we address here the following two challenging questions: Can an emotional reaction be predicted in an online learning environment? How is this emotional reaction related to the learner's attributes? To this end, we propose an agent capable of predicting the emotional reaction of the learner in an online environment based on the appraisal model of emotion proposed by Ortony, Clore and Collins (OCC) (Ortony, A., Clore, G.L., and Collins, A. 1988), a widely known and accepted model (Seif El Nasr, M., Yen, J., and Ioerger, T. 2000; Conati, C. 2002), using a machine

learning technique, namely the ID3 algorithm. Our agent's prediction applies a machine learning technique on the learner's personal attributes such as his sex and personality as well as on the non-personal attributes such as the passing score, the expected score and the obtained score in order to find his corresponding emotional reaction class.

The organization of this paper is as follow: In the first section, we present the previous work realized related to emotion and e-learning environments. Then, the next section presents the architecture of the Emotional Response Predictor Agent (ERPA) and describes in detail each component. The third section describes the experiment as well as the algorithm used to infer the emotional reaction of the learner. After that, the Results section presents the fruit of the experiment and finally the last section concludes and discusses our future work.

## 2 Previous work

We demonstrated in the previous section that emotion and cognition are widely inter-related. Indeed, emotion is very important for cognition, decision making and social behaviors. For this reason, in the purpose to create intelligent machine, a variety of work has been realized by the computer science community in order to recognize, express or manage emotions. A large amount of these realizations are based on the model developed by Ortony, Clore and Collins (OCC). For instance, Seif El-Nasr and colleagues have created a computational model of emotion that can be integrated into intelligent agents. It is called FLAME (**F**uzzy **L**ogic **A**daptive **M**odel of **E**motions) and is based on various previous models, mainly the OCC model and the Roseman et al's model (Roseman, I.J., Jose, P.E. and Spingel, M.S. 1990). FLAME uses fuzzy logic to represent emotions, events and emotional observations. It uses also a machine learning technique to learn patterns of events, associations between objects and expectations about the user (Seif El-Nasr, Yen and Ioerger 2000). Moreover, Gratch and Marsella have developed the EMA (**E**motion and **A**daptation), a computational model of emotion. This model is incorporated into virtual characters aiming to aid decision making and behavioral reaction, in particular coping reactions in the Mission Rehearsal Exercise training system (Gratch, J. and Marsella, S. 2004).

In the purpose to motivate the student, researchers have improved tutoring systems with the ability to recognize, express, and induce emotions. Lester, Towns and Fitzgerald, for example created COSMO, a pedagogical agent which expresses emotions to motivate the student in a tutoring system and especially to support learners in problem-solving activities (Lester, J., Towns, S. and Fitzgerald, P. 1999).

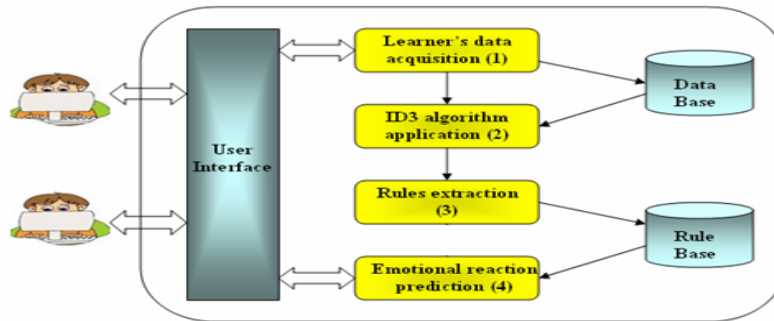
All the previously cited work are concerned with modeling emotions in agent. We use a probabilistic representation of the OCC model to predict a variety of emotional reactions that a learner can express in the specific context of online evaluation.

Besides, Conati used educational games and a probabilistic model based on Dynamic Decision Networks to recognize the emotional state of the user (Conati, C. 2002). In contrast to Conati's work, our agent's goal is to predict the emotional reaction that occurs in a distant and relatively constraint learning environment such as online evaluations for example.

In this research work, our goal is to predict the emotional reaction of the learner in a distant learning environment and especially in an online exam, based on the appraisal model of emotion proposed by Ortony, Clore and Collins (OCC) by using the ID3 algorithm.

### 3 ERPA architecture

To predict the emotional reaction of the learner, we define the Emotional Response Predictor Agent (ERPA). This agent is designed to infer the learner’s emotional reaction after having obtained his score in an exam. Thus, the ERPA architecture is conceived as bellow:



**Fig. 1.** The ERPA architecture.

As shown in the figure above, the ERPA architecture is composed of four main components which intervene according to the following sequence:

(1) The learner’s data acquisition component is responsible for collecting and storing in a Data Base the learner’s personal and non-personal data through a user interface. Personal data includes age, sex, country and personality. Non-personal data are collected through different steps of the experiment and include the chosen category for the quiz, the obtained score, the expected score, the passing score, the quiz start time, etc.

(2) After collecting the learner’s data, the ID3 algorithm application component is triggered by the system and consists in applying the ID3 algorithm to the data stored in the Data Base and in producing a decision tree. To construct the tree, the ID3 algorithm needs to calculate the information gain for each attribute and to select the one with the highest value of the information gain. Before calculating the information gain, we first determined the entropy to measure how informative is an attribute for the classification. The decision tree produced by the ID3 algorithm application component will be used by the rules extraction component.

(3) After the ID3 algorithm application having finished its work, the rules extraction component will be launched automatically to extract rules from the decision tree produced by the ID3 algorithm application component and to store them into the Rule Base.

(4) When the new rules are stored in the Rule Base, the emotional reaction prediction component will be triggered to predict the learner's emotional reaction by using these rules from the Rule Base.

In the next section, we describe in detail the experiment used to fill the Data Base with the initial set of training data used by the ID3 algorithm application.

## 4 Experiment

The goal of this experiment is to predict the emotional reaction in a distant learning environment based on attributes of the learner. These attributes are sex and personality. The data collected will serve to train our agent who will ultimately be able to predict the emotional reaction of the learner using machine learning techniques. The experiment is web-based (Chalfoun, P., Chaffar, S., and Frasson, C. 2005) and available both in English and French.

### 4.1 Design of the experiment

The experiment is divided in four parts : Identification, Personality test, Quiz and Emotional reaction. In the first part (Identification), the learner is invited to identify himself by providing personal attributes, namely his age, sex, country and nickname. The nickname's purpose is to act as a unique identifier for each learner taking part in this experiment.

The second part (Personality test), presents the learner with the abbreviated form of the Revised Eysenck Personality Questionnaire (EPQR-A) (Francis, L.J., Brown, L.B. and Philipchalk, R. 1992) measuring four personality traits. These are extraversion, psychoticism, neuroticism and "lie scale". The "lie scale" is a trait representing the measure of socially desirable responding in both men and women. The highest value of the four measured traits will be considered as the learner's predominant personality trait. The EPQR-A set of twenty four questions are presented on a single web-page.

The third part of the experiment (Quiz) is a quiz consisting of ten multiple-choice questions in six diverse categories such as Emotional Intelligence and Sports. The learner is invited to choose the desired category to be quizzed on. The questions are presented one at a time and an answer must be given to each question before going on to the next one. Each correct answer is worth one point and each incorrect answer is worth 0 points. At the end of the quiz, the learner is prompted to input his expected score on a scale of zero to ten. This part of the experiment places the learner in a state of belief.

In the fourth part of the experiment (Emotional reaction), the learner is presented with the expected score as well as the obtained one. Furthermore, the learner's personality trait resulting from the EPQR-A test is presented along with a succinct explanation. The goal of this part is to get the emotional reaction from the learner regarding his results. The (OCC) model is used in this experiment to select a relevant

and specific set of emotional reactions a learner might experience in this given situation. Thus, we determined that the learner may either express disappointment, distress, joy, relief, satisfaction or fear-confirmed.

Furthermore, the passing score in this experiment has been set to 5 on 10. A score above or equal the passing score is considered as a success while a score lower than 5 is considered as a failure.

## 4.2 Learners tested

The experiment is web-based and thus learners tested originate from all over the world. Invitations to participate have been sent to different forums and news groups with respect to forum and news group rules and regulations. Table 1 presents the description of the participants sorted by personality.

**Table 1.** Participant's description.

<b>Personality</b>	<b>F</b>	<b>M</b>	<b>Total</b>
Extraversion	30	29	59
Lie Scale	24	14	38
Neuroticism	18	12	30
Psychoticism	0	12	12
<b>Total</b>	<b>72</b>	<b>67</b>	<b>139</b>

## 5 Results

The main goal from developing the experiment described above is to predict the learner's emotional reaction using a machine learning technique. The machine learning method used is the ID3 algorithm developed by Quinlan in the purpose to produce, from data, classification models or decision trees (Quinlan, J.R. 1983). The data used to produce the decision tree includes four attributes: The learner's sex, the learner's personality, a first Boolean attribute (learner's obtained score > than his expected score) and a second Boolean attribute (learner's obtained score > than the passing score).

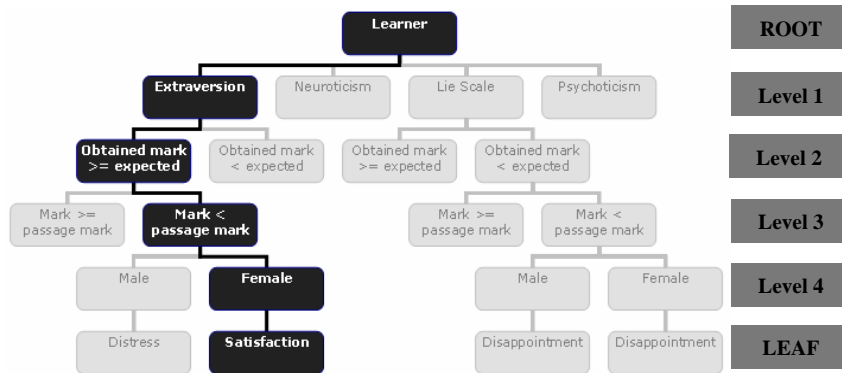
The first two attributes are directly related to the learner. The last two boolean attributes are related to his performance on the quiz. The data for the two boolean attributes is shown in Tables 2 and 3 grouped by personality. The ID3 algorithm was ran with ten fold cross-validation to build a decision tree by calculating the information gained for each attribute and selecting the greatest one. ERPA's rule extraction module analyzes the ID3's tree structure and adjusts the leaves values in our uniform tree in order to extract the required rules and properly train our ERPA. Figure 2 shows an example of such a uniform tree.

**Table 2.** Personality and passing score.

Learner's personality	Learner succeeded the quiz	
	Yes	No
Extraversion	52	7
Lie Scale	30	8
Neuroticism	23	7
Psychoticism	7	5
<b>Total</b>	<b>112</b>	<b>27</b>

**Table 3.** Personality and expected score.

Learner's personality	Learner's score $\geq$ his expected score	
	Yes	No
Extraversion	37	22
Lie Scale	16	22
Neuroticism	20	10
Psychoticism	5	7
<b>Total</b>	<b>78</b>	<b>61</b>



**Fig. 2.** Example of a followed path in the decision tree

Indeed, each level between the root and the leaf represents one of the four mentioned attributes for the learner. The root represents the learner as a starting point to predict his or her emotional reaction. The first level represents the four possible personalities: extraversion, neuroticism, lie scale and psychoticism. The second and third levels represent boolean attributes, and thus two possible outcomes. In the second level, the learner can either obtain a score higher or equal to his expected score or lower. In the third level, the learner can either fail or pass the quiz. The fourth level represents the learner's sex and the leaves contain the predicted emotional reaction. The path varies according to the values taken by the four attributes. Figure 2 illustrates the case of a female learner with an extraversion personality expecting a score of 3 on 10 and ending up obtaining a score of 4 on 10. The predicted emotional response by the ERPA would be Satisfaction.

The ERPA was then implemented, put online and tested by thirty four volunteers. The results are shown in Table 4. The percentage of success of the ERPA prediction technique is 82.4%.

**Table 4.** Results from the implementation of the ERPA

Personality	ERPA correctly predicted the emotional reaction	
	Yes	No
Extraversion	14	2
Lie Scale	8	1
Neuroticism	2	2
Psychoticism	4	1
<b>Total</b>	<b>28</b>	<b>6</b>

## 6 Conclusion and future research

In this paper, we have presented an agent capable of predicting the emotional reaction of the learner in an online learning environment. The agent predicts the emotional reaction based on the appraisal model of emotion proposed by Ortony, Clore and Collins (OCC) by taking into account personal attributes such as sex and personality as well as non-personal one such as the obtained score, the passing score and the expected score. Thus, the machine learning technique used, the ID3 algorithm, builds a decision tree to predict the learner's emotion reaction in a given situation. We also presented the ERPA architecture, the originality of this architecture resides in predicting a variety of specific emotional reactions using a machine learning technique in online and distant learning environments by using a probabilistic representation of the OCC cognitive theory of emotions. Moreover, the presented ERPA defines a relationship between personal and non-personal attributes. Finally, the architecture introduces flexibility throughout the learning session since the predicted emotional reaction can vary depending on the performance of the learner. We also presented the online experiment, in four parts, aiming at collecting the required data to efficiently train our agent by placing the learner in a state of belief between part three and four of the experiment. The learner is prompted to provide his emotional reaction to the obtained results, data which will be stored in the ERPA's Data Base. The resulting decision tree for all the participants taking part of the experiment has been presented in the Results section with a brief but clear example.

We have implemented our ERPA's decision tree in order to validate the quality and exactitude of its prediction. We plan for future research to keep running the experiment in order to obtain a better and more precise classification results.

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