An Ontology for Predicting Students’ Emotions During a Quiz.  
Comparison with Self-reported Emotions

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Abstract— Recent research suggests that predicting students’ emotions during e-learning is quite relevant but should be situated in the learning context and consider the individual profile of users. More knowledge is required for assessing the possible contributions of multiple sources of information for predicting students’ emotions. In this paper we describe an ontology that we have implemented for predicting students’ emotions when interacting with a quiz about Java programming. An experimental study with 17 computer science students compares the automatic predictions made by the ontology with the emotions self-reported by students.

Keywords - Emotion; personalized e-learning system; intelligent tutoring systems; ontology; affective computing.

I. INTRODUCTION

Students display individual differences in the way they react emotionally to lectures, hands-on sessions or examinations. Some students might be interested in a lecture on Computer Graphics while others will get bored from the very beginning of the lecture. Some others get easily and intensely stressed during examinations. Our research targets two related issues of affect-sensitive e-learning systems. First, these systems need to consider individual differences between students in terms of emotions and their expressions. Second, these emotions and their expressions need to be observed using a situated learning approach as much as possible. One example of this would involve observing students in their regular learning activities, such as testing their Java programming language during a semester of Java programming lectures. In order to tackle these issues, we extend our previous work on personalized interface agents and propose an ontological model to predict students’ emotions. We apply the model to a test of Java programming language skills and define an experimental protocol for assessing this model.

E-learning systems are used by a wide variety of students with different skills, backgrounds, preferences, and learning styles. Therefore, a desired characteristic of these systems is that of being personalized [1]. One way to personalize an e-learning system is to design interface agents [2]. Interface agents collaborate with students in the use of an e-learning system. To help a student, an interface agent needs to understand who, what, where, when and why the student is learning. The answers to these questions are the learning context [3]. Emotions are considered to be a key issue in such learning tasks [4], [1]. Cognitive evaluation theories suggest that emotions result from a cognitive appraisal of the current situation by the individual [5]. Several studies about affect-sensitive intelligent tutoring systems consider other affects than the basic emotions [6]. They consider for instance boredom, frustration, confusion, engaged concentration and delight [7]. The whole learning process is strongly influenced by student’s affects [8], [1], [9]. Positive emotions ensure cognitive engagement and improve creativity and flexibility in problem solving [4]. Negative emotions can block thought processes [8]. Negative emotions are experienced when expectations are not met, failure is imminent, or important goals are blocked [10]. Kaiser et al. [11] argue that two negative regions of emotions should be avoided for e-learning. The first region includes emotions such as frustration and anger. The second region features emotions such as boredom and sleepiness. An e-learning system should stimulate positive emotions while diminishing negative ones. One way to reduce negative emotions is to increase student’s motivation. Motivation is well known for its importance in learning and its influence on cognitive processes [12]. An affect-sensitive e-learning system should incorporate assessments of the students’ cognitive, affective, and motivational states into its pedagogical strategies to keep students engaged, boost self-confidence, heighten interest, and maximize learning [10].

In recent years there has been an increase in interdisciplinary research on computational models of emotions [17]. The OCC model is a psychological model based on the cognitive approach of emotions that explains the origins of emotions by describing the cognitive processes that elicit them. In particular, several research teams have defined or applied a computational model of emotion to e-learning [8]. Some studies focus on the six basic emotions applied to peer-to-peer interaction [9]. Cocea et al. present a model of learners’ motivation that is estimated from the analysis of log files [12]. They use several data mining techniques in order to find the best method and indicators for predicting disengagement. They define a conceptual model based on Case-Based Reasoning (CBR) and Multicriteria Decision Making (MDM) components for learner modeling and feedback generation. Kay explores the relations between the acquisition of computer related skills and four emotions: anger, anxiety, happiness, and sadness [15]. The
influence the emotion process at three stages: i) the perception of the situation, ii) the appraisal process and iii) the emotion display. Most studies consider only a limited quantity of contextual information for emotion recognition. They do not always rely on computational models of emotions such as the OCC model [23]. Emotional models represent the emotions and reactions of users in different scenarios such as the occurrence of an unexpected event [8].

In summary, previous research suggests that predicting students’ emotions during e-learning is quite relevant but should be situated in the learning context and consider the individual profile of users. More knowledge is also required for assessing the possible contribution of multiple sources for predicting students’ emotions.

We propose improving the current models of e-learning systems with better contextual and emotional capabilities in order to personalize the assistance given to students. Our goal is to collect a video corpus that includes spontaneous facial expressions of complex affective states expressed by students answering exercises that match the series of lectures that they are currently attending. By enhancing an e-learning system with emotional and context-aware features, we aim at encouraging and facilitating students’ learning process. Researching the usefulness of affective computing in e-learning requires the definition of adequate protocols for collecting and analyzing the emotions expressed by students. In this paper we describe an ontology that we have implemented for predicting students’ emotion when interacting with a quiz about Java programming. An experimental study with 17 students compares the automatic predictions made by our ontology with the emotions self-reported by students.

II. **OLA: AN ONTOLOGY FOR PREDICTING LEARNERS’ AFFECT**

Predicting emotions is a difficult task, in which multiple sources of knowledge need to be evaluated and integrated to validate the recognized emotions. In this section, we present how we estimate student’s emotions from log files using ontological inference. We designed an interactive application for assessing the students’ skills in the Java programming language. We start by analyzing the student’s actions when interacting with the quiz about Java programming. Then we use an ontological inference approach for predicting the student’s emotion. Potential future applications include identifying the negative emotions that hinder learning and trying to overcome them by taking the corresponding pedagogical incentive.

The interaction log files are used as input for our ontology-based emotion learning module. This emotion learning process is based on the OCC model of emotions [23]. The OCC model is appropriate as a first approach because it is based on the cognitive theory of emotions and it is easy to implement computationally. Following the classification of emotions defined in this model, we have built an emotional ontology adapted to our quiz. Our ontology-based learning process of emotions involves two steps: 1) computing the values of the OCC variables, and 2) predicting the OCC emotions.
In the first step, we analyze the data logged by the system in the interaction log files in order to extract the values of variables defined by the OCC model. For example when the student does not answer a question correctly, the variable status_of_event is set to confirmed and the variable appreciation is set to disliking. In the second step, we use the values of these variables for predicting the student’s emotion using ontological inference. For example, we infer that the student feels Fear when cause=cause=consequence_of_event, occurrence=prospective, and appraisal_of_event=undesirable. In the following sections we explain the two steps in detail.

A. Java skills evaluation application

Our interactive application for assessing skills in the Java programming language contains twelve exercises (Figure 1). Each exercise is scripted so as to elicit a priori one or several tentative emotions. For example, an exercise with an unexpected personal question is expected to elicit Surprise. In contrast, an exercise with a limited time to answer is expected to elicit Stress. Our purpose was to ensure rich enough students’ expressions. Table I summarizes the expected emotions for each exercise.

B. Computing the values of OCC variables

In this section we explain how we compute the OCC variables from the interaction log files. A student might feel and express different emotions at different stages of a single exercise. For example, at the beginning, when the question is displayed, the student might be nervous or stressed. He or she could feel satisfaction or relief at the end of the exercise if the answer is correct. Hence, we decided to study the student’s emotions for each exercise at three different steps: i) at the beginning, when the exercise is presented, ii) in the middle of the exercise, when the student selects an answer, and iii) at the end of the exercise, when the correct answer is displayed.

<table>
<thead>
<tr>
<th>TABLE I. ILLUSTRATION OF EXPECTED EMOTIONS FOR EACH EXERCISE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description of the exercises</strong></td>
</tr>
<tr>
<td>Exercises 1 and 2</td>
</tr>
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<td>Exercises 3 and 4</td>
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<td>Exercises 5 and 6</td>
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<td>Exercise 8</td>
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<td>Exercise 9</td>
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<td>Exercise 10</td>
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<td>Exercise 11</td>
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<tr>
<td>Exercise 12</td>
</tr>
<tr>
<td>Test end.</td>
</tr>
</tbody>
</table>
For each exercise we obtain the following events and logged data, hereafter called “learning events”:

1. the student’s answer (correct or incorrect)
2. the time that the student spent answering the question (and how it compares to the average time taken by all the students)
3. the time the student spent reading the correct answer
4. the exercise’s difficulty
5. the student’s knowledge level (low or high)
6. the event’s elicitation time (i.e. the three steps described previously: exercise presentation, student’s answer, or feedback from the system)
7. the number of times that the student chose a different answer
8. the number of incorrectly answered exercises thus far

We considered the following six OCC variables since they are relevant for processing the learning events:

- Occurrence = {actual, prospective}
- Status of event = {confirmed, disconfirmed}
- Appraisal of event = {desirable, undesirable}
- Appreciation = {liking, disliking}
- Cause = {consequence of event, action of agent, aspect of object (attraction)}
- Subject of emotion = {me, others}

We analyze the learning events extracted from the data logged by the system in order to estimate the values of these OCC variables. Then we compute the correlation between the learning events and these OCC variables. For example, when the student answered a question correctly, we assign the value desirable to the variable Appreciation. When the application displays the correct answer after the student answered the exercise, the variable status_of_event is set to confirmed. Since the student interacts alone with the Java application and we recognize emotions at specific moments, the variable cause is always set to me and the variable subject_of_emotions is set to consequence_of_event. The mapping between OCC variables and emotions is displayed in Table II. To compute this correlation, we generate a decision tree for each of the learning events using the WEKA toolkit [25]. We used the J48 algorithm that is an implementation of the C4.5 decision tree learner. This implementation produces decision trees. The decision trees are built by analyzing data in the interaction log files and are used for emotion classification.

C. Computing OCC Emotions

The goal of our OLA (Ontology for predicting Learners’ Affect) ontology is to infer the student’s emotions based on the values of the OCC variables. In this current stage, our ontology is used as a set of rules (axioms). We explain in the future directions section the advantages of using this representation and how we plan to improve it.

<table>
<thead>
<tr>
<th>OCC Emotions</th>
<th>Cause</th>
<th>Subject</th>
<th>Occurrence</th>
<th>Appraisal</th>
<th>Status</th>
<th>Appreciation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfaction</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Desirable</td>
<td>Confirmed</td>
<td></td>
</tr>
<tr>
<td>Disappointment</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Desirable</td>
<td>Disconfirmed</td>
<td></td>
</tr>
<tr>
<td>Joy</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Desirable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distress</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Undesirable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fears-confirmed</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Undesirable</td>
<td>Confirmed</td>
<td></td>
</tr>
<tr>
<td>Relief</td>
<td>Event</td>
<td>Me</td>
<td>Actual</td>
<td>Undesirable</td>
<td>Disconfirmed</td>
<td></td>
</tr>
<tr>
<td>Hope</td>
<td>Event</td>
<td>Me</td>
<td>Prospective</td>
<td>Desirable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fear</td>
<td>Event</td>
<td>Me</td>
<td>Prospective</td>
<td>Undesirable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hate</td>
<td>Attraction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Disliking</td>
</tr>
<tr>
<td>Love</td>
<td>Attraction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Liking</td>
</tr>
</tbody>
</table>
We represent emotions as combinations of OCC variables. These combinations were mapped as axioms in the ontology in order to enable ontological inferences. As we define the OCC variables with ontological concepts, we predict the corresponding emotion by applying ontological inference. We define an axiom for each emotion. An axiom specifies the restrictions that an emotion should satisfy to be classified as a certain type, such as Disappointment.

Since our students interact alone with our java application, we do not consider the OCC emotion “Fortunes of others”. Our ontology has seventeen concepts (see Figure 2) and six concepts representing the OCC variables mentioned above (Occurrence, StatusOfEvent, AppraisalOfEvent, Appreciation, SubjectOfEmotion and Cause). The ontology consists of the central concept Emotion with relations that contribute to its characterization and recognition. The concept Cause splits the whole classification of emotions in three groups: ConsequenceOfEvent, ActionOfAgent, AspectOfObject. The cause of an emotion is modeled by the existence of one instance of the relation hasCause connecting the emotion with the cause. Occurrence expresses whether the student perceives the consequence of the emotion’s cause as either prospective or actual (both values are represented by the concepts Prospective and Actual respectively). The concept AppraisalOfEvent defines the student’s desirability on the consequence of an event. This OCC variable can take two values: Desirable or Undesirable. Another characteristic of an emotion is the subject of the emotion (defined in the ontology by the concept SubjectOfEmotion). Finally, the concept StatusOfEvent is used to indicate if the status of the event that causes the emotion is confirmed or not.

Inferences are possible thanks to axioms defined in the ontology. Suppose that e: is an Emotion, c: one instance of the concept ConsequenceOfEvent, m: one instance of Me, a: one Actual instance, and d: a Desirable instance. The axiom for Satisfaction is defined as follows:
∀e ( \langle e, c \rangle \in \text{hasCause} \land \langle e, m \rangle \in \text{hasSubjectOfEmotion} \land \langle e, a \rangle \in \text{hasOccurrence} \land \langle e, d \rangle \in \text{hasAppraisal} ) \rightarrow e \text{ is a Satisfaction}

This axiom states that an emotion whose Cause is ConsequenceOfEvent, the Subject is Me, the Occurrence is Actual and the Appraisal is Desirable, this emotion is inferred as Satisfaction.

III. EXPERIMENT

In order to test our approach for inferring student's emotions, we conducted an experiment with 17 students. A preliminary analysis of our video corpus reveals that it contains subtle facial expressions of complex affective states, rather than prototypical expressions of full-blown basic emotions (Figure 3).

We used the same set of exercises for all the students, but we analyzed student's actions considering the student's level of expertise. While a difficult question might be stressful for a beginner programmer, the same question could be easy for an expert. At the end of each exercise, the students were asked to answer a questionnaire about that exercise, reporting the perceived difficulty of the exercise and the emotions they felt while doing it. Students were asked to select one or several labels from the list: Satisfaction, Disappointment, Joy, Distress, Fears-Confirmed, Relief, Boredom, Surprise, Stress. They could also select “Neutral” and “I do not know”. We selected this list so as to enhance the OCC emotions' classification with some other emotions that are frequently observed in the e-learning domain, such as Boredom or Surprise [10].

![Images of students' facial expressions](image1)

Figure 3. Pictures showing students’ facial expressions

The actions and emotions reported by the 17 students were recorded with a total of 204 self-reports. Some students occasionally reported several emotions at a time: three emotions were selected 6 times, all of them by the same user; whereas five students selected two emotions for a total of 13 times. The rest of the students selected a single emotion at a time. The very emotion label predicted by the ontology was self-reported by the student in 77 cases out of the 204 cases (37%). When we grouped emotions according to the PAD quarter as in Russell & Mehrabian’s studies [27], the agreement between the emotion inferred by the ontology and the emotion reported by the student amounts to 96 / 204 = 47%.

We assessed how much the emotions predicted by the ontology matched the self-reported emotions using f-measure, precision and recall measures (Figure 4). F-measure’s results were not perfect due to corpus’ size (the best value is 0.69 for “Satisfaction”). The corpus was not large enough for ontology training. In terms of precision, the best emotion inferred was “Disappointment” (80%) and the worst one was “Distress” (43%). Therefore, we can conclude that the system mistook some emotions and not only inferred the correct ones. However, the ontology had better results in terms of recall. Considering recall, the worst inferred emotion was also “Distress” (33%) due to the small quantity of evidence on that emotion. Distress was reported only seven times by the students.

![Graph showing precision, recall, and F-measure](image2)

Figure 4. Precision, Recall and F-measure

Figure 5 presents a comparison between the ontologically inferred emotions vs. the self-reported ones. On the one hand, black bars display the percentage of emotions inferred by the ontology. In the current version of our ontology, only the first six emotions of the previous list can be inferred. Therefore, there are three emotions (Stress, Boredom, and Surprise) with zero percentage of ontological inference. The most frequently inferred emotions are Joy, Satisfaction, and Disappointment. On the other hand, white bars present the percentage of emotions reported by the students: Disappointment (24%), Neutral (20%), and Joy (18%), Satisfaction (11%), Surprise (11%), Relief (7%), Stress (3%), Distress (4%) and Fears-Confirmed (0%). Disappointment, Neutral, and Joy are frequently reported emotions. Disappointment was observed mostly with students with advanced knowledge of java and wrong answers. Only a small number of students selected the “I do not know” for reporting the emotions (1.7% of the answers).
We believe in the importance of studying emotions in the modality. Express subtle and few signs of emotions in the face that, even collected with data on emotional expression. Combining our previous work on the occ

[10]

We are willing to investigate if the appraisal process of the observed emotions intended by the exercises and the list of emotions, as well as the emotion’s intensity, will be reported in the self-report. We plan to make several experiments with more students.

Figure 5. Comparison between ontological inferred emotions vs. self-reported emotions.

IV. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper we introduced our OLA ontology based on the OCC model [23] applied to a programming quiz. We described an experiment that we conducted with 17 students in order to evaluate the predictions made by the ontology.

We plan to augment/enhance the ontology so as to improve the inference results and enable the prediction of all the emotions intended by the exercises and the list of emotions observed in the self-report, as well as the emotion’s intensity. We are willing to investigate if the appraisal process of the actual learning emotion can be influenced by previous events [10]. We will thus consider the sequence of learning events occurring from the beginning of the session. We also aim at combining our previous work on the student’s learning style with data on emotional expression. We will annotate the videos that we collected. A preliminary analysis of the videos revealed that, even with our script cued to elicit emotions, students express subtle and few signs of emotions in the face modality. The video corpus will be exploited to confirm this observation. We plan to make several experiments with more students who are attending a curriculum on the JAVA language.

We believe in the importance of studying emotions in the context of educational material that corresponds to student’s long-term motivation.

V. REFERENCES


