

Modeling Student's Mood during an Online Self-assessment Test

C.N. Moridis and A.A. Economides

Information Systems Department University of Macedonia, 156 Egnatia Avenue
Thessaloniki, 54006 Greece
papaphilips@gmail.com, economid@uom.gr

Abstract. Student's emotional state is crucial during learning. When a student is in a very negative mood, learning is unlikely to occur. On the other hand too positive mood can also impair learning. Thus a key issue for instructional technology is to recognize student's mood, so as to be able to provide appropriate feedback. This paper introduces a model of student's mood during an online self-assessment test. The model was evaluated using data emanated from experiments with 153 high school students from 3 different regions of Greece. The results confirm the model's ability to estimate a student's mood.

Keywords: computerized testing; computer based assessment; affective computing; affective learning; modeling mood; mood recognition.

1 Introduction

Educational learning and success are among the most significant topics across the life span in knowledge society, particularly since educational and professional careers, social relations, and the distribution of many kinds of resources are largely dependent on individual achievement. This indicates that learning and achievement are exceptionally essential and therefore key sources of human emotions nowadays, instigating a variety of self-referenced, task-related, and social emotions [1]. As a result, students receive emotional pressure from many different sources (teachers, schoolmates, parents, themselves etc.) to perform well in a learning task. Consequently, student's failure to accomplish a learning task may be due to emotional pressure. Faced with frustration, despair, worry, sadness, or shame, people lose access to their own memory, reasoning, and the capacity to make connections [2].

Research community is increasingly acknowledging that emotions play a crucial role in human learning procedures. During the last decade, artificial intelligence in education is trying to integrate emotional factors into computerized learning systems. If the system can reason about the emotional state of a user from the input that the system receives, appropriate feedback could be displayed in a way adapted to the emotion or the mood of the user. Besides, the learning flow corresponds to the archetype of human behavior that action and feedback promote understanding and adoption to the environment [3].

A person's emotions could be predictable if their goals and perception of relevant events were known [4]. Implemented in a computational model this can be achieved by using agents, artificial intelligence techniques, reasoning on goals, situations, and preferences [5]. The student's recognized emotional state would be properly managed from the computer-aided affective learning system, based on pedagogical models, which integrate our knowledge about emotions and learning. The system would assess whether the learning process is developing at a healthy rate. If there is a positive development, the system should help the learner maintain this emotional state. If not, the system should induce the learner to an emotional state beneficial to learning.

Students' detrimental to learning emotional states could be healed through a self-assessment system. Our aim is to develop an online multiple choice questions platform that would help students to identify and improve their weaknesses. A flexible e-learning system would take into consideration the student's knowledge state and learning preferences [6] to generate individualized learning paths [7]. In addition, the system would try to introduce students to an emotional state beneficial to learning, providing adequate feedback [8]. The emotional feedback can occur before and after the test, during the test, and before and after a student's answer to a question. In all these cases emotional feedback can be provided either automatically according to the student's emotional state, either by the student's or the teacher's request. Emotional feedback can be implemented by using beneficially positive emotions, while preventing, controlling and managing negative emotions. Moreover, the emotional feedback can also be implemented using negative emotions in order to increase the student's devotion and engagement. These "strategies" can be applied using humor and jokes, amusing games, expressions of sympathy, reward, pleasant surprises, encouragement, acceptance, praises but also through criticism and punishment [9]. Thus, students would receive psychological and cognitive assistance through their preparation for the exams.

For this purpose we need a method in order to provide a measurement for the evaluation of student's mood with respect to each question the student is about to answer, and determine the system's feedback to the student. Modeling multiple variables is important as students have complex characteristics that ultimately affect their performance. However, adding additional variables will not always increase the accuracy of the student model [10]. After several assumptions, we developed and evaluated a model in order to provide a measurement for the estimation of student's mood while undertaking a self-assessment multiple choice questions test. To evaluate the model, we created a suitable online test of multiple-choice questions about basic computer knowledge and experimented with 153 high school students from 3 different regions of Greece. The results verified our assumptions and proved the model's ability to approximate students' mood at a satisfactory level.

2 Our Approach

We explored several research questions in the context of an online multiple choice questions self-assessment test, providing a measurement for evaluating students' mood during the test. One assumption was that students' goal does influence students' mood during the test in relation to the remaining questions and their record. That is to

say, that if a student knows that he has already failed to reach his goal during the test, because the remaining questions are less than the questions he has to answer correctly in order to reach his goal, then there is a high possibility to be in a negative mood. In addition to that we assumed that student's mood is also influenced by his success or failure to answer the questions just before the current one. For instance, if a student has failed to provide a correct answer to all of the 5 previous questions, there is a high possibility to be emotionally negatively influenced, but if a student has managed to provide a correct answer to all of the 5 previous questions, there is a high possibility to be emotionally positively influenced. With the purpose of checking these assumptions we formulated this model:

$$R(q) = N - q, R(q) \in (0, N) \quad (1)$$

where R is the number of questions remaining before the end of the test, N is the total number of questions, and q is the number of the current question.

$$D(q) = I - r(q), \quad (2)$$

where $D(q)$ is the number of questions that the student still needs to answer in order to reach his goal, I is the student's goal, and $r(q)$ is the number of student's correct answers up to the current point.

$$H(q) = R(q) - D(q), \quad (3)$$

where $H(q)$ is a number that shows whether the remaining questions are enough for the student to reach his goal. For example, $H(q) = -4$ would mean that the student has already failed to reach his goal for 4 questions.

$$M(q) = H(q) \begin{matrix} +rr(q) \\ -wr(q) \end{matrix} \quad (4)$$

where $M(q)$ is the student's mood, $rr(q)$ is the number of correct answers in a row just before the current question, and $wr(q)$ is the number of wrong answers in a row just before the current question. So, if there are one or more correct answers in a row just before the current question, we add them to $H(q)$, while if there are one or more wrong answers in a row just before the current question, we subtract them from $H(q)$. The model also provides minimum and maximum values for M , which are given from the formulas shown below:

$$\max M = 2N, \quad (5)$$

$$\min M = -2N \quad (6)$$

2.1 Calculating the Agents Feedback to Student's Mood

Since, according to (5) and (6) we know the maximum and minimum values that M can take into the system, we can use a set of discrete values in order to approximate the real value of M . In this way, each discrete value of input M is mapped to a discrete output value which corresponds to a set of certain actions the agent will perform as a

feedback to the student. Thus, we can calculate the agent's feedback to the student using the formula shown below:

$$\text{feedback}(M, L) = A, \quad (7)$$

where L is the discrete level to which M is assigned, and A is a set of actions that can be triggered from the M, L pair. In order to provide the agent with a much richer and varying behaviour, we can attach more than one possible action to each M, L pair. These actions could be triggered randomly or based on the frequency of their appearance. It would be preferable, if the agent wouldn't repeat the same action for the same M, L pair.

3 Experiment Method

3.1 System Architecture

We build the online multiple choice questions test in a Windows XP machine using JavaScript with Perl CGI on Apache web server with MySQL. Common Gateway Interface (CGI) is used to provide dynamic web pages to students and the Perl programming language is a common choice for various reasons including simple and powerful string manipulation, Web server integration (i.e., Apache web server), and data manipulation [11]. Many students took the online test simultaneously, thus MySQL which is designed for multiple users accessing the files through a single server process was a very convenient choice for this kind of work [12].

The student's terminal sent a standard HTTP request encoded with special variables (commonly called CGI variables) and their values. The apache web server received the HTTP request and determined that the request was destined for a CGI program and not for a HTML file. The perl interpreter accepted the input from the server, parsed the variables, contacted the MySQL database for reading and recording data, applied some programming logic to the data, and returned a document back to the web server.

3.2 Participants

High schools students ($N = 153$) were recruited from 3 different regions of Greece (60 students from Athens, 50 students from Thessaloniki, and 43 students from Mitilini). Respondents consisted of 56% females and 44% males. The average age of participants was 16.8 ($SD = 1.98$) with 90% of the sample ranging from 15 to 19 years.

3.3 Materials

The multiple choice questions were focused on basic computer knowledge and skills, based on material taught in lectures. The context of questions was pre-specified by the teachers prior to the study. The test was constituted from 45 questions. The order of questions presented was randomly altered among students.

3.4 Procedure and Data Collection Methodology

The duration of the experiment was approximately 45 minutes and took place during the regular schedule of laboratorial courses. Students were told that this is a general education test concerning computer knowledge that would help them assess their knowledge about computers. At the beginning of the test, the system asked students how many correct answers would make them feel satisfied considering the level of their knowledge, making them set their personal goal. Throughout the test, a student choused his answer among 4 possible answers and confirmed his choice by clicking the “submit” button. After each question the system informed the student whether his answer was right or wrong and presented his score. Then the student could proceed to the next question by clicking the “next” button. During these 45 questions a slide bar appeared asking the student to move it according to his mood concerning the test, from -100(extremely negative mood) to +100(extremely positive mood).

The slide bar appeared 5 times during the test at a different instant for each student, as shown in Table 1. Accordingly, every 9 students we had checked once students’ mood after every question of the test, so that the 153 participants gave us the chance to check students’ mood after every question 17 times. Thus, the data set consisted of 765 instances (5 instances of each student).

Table 1. The slide bar sequence which was repeated every 9 students

Student	Question after which the slide bar appeared				
1 st student	1 st	9 th	18 th	27 th	36 th
2 nd student	2 nd	11 th	20 th	29 th	38 th
3 rd student	3 rd	12 th	21 st	30 th	39 th
4 th student	4 th	13 th	22 nd	31 st	40 th
5 th student	5 th	14 th	23 rd	32 nd	41 st
6 th student	6 th	15 th	24 th	33 rd	42 nd
7 th student	7 th	16 th	25 th	34 th	43 rd
8 th student	8 th	17 th	26 th	35 th	44 th
9 th student	10 th	19 th	28 th	37 th	45 th

Following each completed interaction, 10 parameters were calculated and recorded: (1) The number of the current question, (2) the number of questions remaining before the end of the test, (3) the number of questions that the student still needs to answer in order to reach his goal, (4) the number that shows whether the remaining questions are more or less than the number of questions that the student has to answer so as to reach his goal, i.e., student’s hope to reach his goal, (5) the number of correct answers in a row just before the current question, (6) the number of wrong answers in a row just before the current question, (7) the number of correct answers up to the current question, (8) the number of wrong answers up to the current question, (9) the score, and (10) the mood that the student indicated by moving the slide bar.

4 Results

Initially we evaluated the model based on its divergence from the mood that students pointed out on the slide bar. The mean error was normalized from 0 to 1. Nevertheless, this is a quantitative way of evaluation, while it is difficult to be highly accurate in predicting students' mood, which is an extremely sensitive variable.

Though in a quantitative evaluation, the linear correlation coefficient between the user declared mood and the mood estimated by the model, is strong ($r = 0.71$). Experiments in Human Computer Interaction (HCI) involve people, who would be unpredictable. Thus, we consider that a mean error of 0.1 with a standard deviation of 0.1 and having a normal error distribution is a pretty fine performance in predicting a student's mood. A confidence level of 90%, gives us a confidence interval of 0.01, which means that the range for true population mean error is 0.09 to 0.11.

It is obvious that the more close to his goal the student is throughout the test, the more positive his mood becomes. On the contrary, as long as the student's distant from his goal gets bigger as he proceeds into the test, the more negative his mood becomes.

Another important issue is that adding or subtracting the number of correct or wrong answers in a row just before the current question increases the model's efficacy (Table 2). We compared $H(q)$ alone with the entire model, which is $H(q)$ plus $rr(q)$ (the number of correct answers in a row just before the current question) or minus $wr(q)$ (the number of wrong answers in a row just before the current question). This shows that student's success or failure to recently previous questions influences his mood positively or negatively towards the current question.

Table 2. Comparing $H(q)$ with the entire Model shows that taking into account the number of correct or wrong answers in line just before the current question increases the model's efficacy

Models	R	Mean error	SD	Mean success recognizing whether student is in a positive or negative mood	Mean success recognizing whether student is in a positive mood	Mean success recognizing whether student is in a negative mood
$H(q)$ alone	0.64	0.11	0.1	77%	79%	80%
$M(q)$	0.71	0.1	0.1	82%	85%	82%

Trying to determine the exact percentage of student's positive or negative mood is a difficult task. However, if we try to determine just whether a student is in a positive mood or in a negative mood, things are getting much easier. So, in a qualitative evaluation, we would judge the model by its success in predicting whether a student is in

positive or negative mood, no matter how positive or how negative this mood is. Using this model we can have a safe prediction of student's mood in terms of whether this mood is positive or negative (Table 2). A problem that is difficult to be solved from a quantitative point view, becomes more approachable from a qualitative point of view.

5 Conclusions

We have presented a model for recognition of student's mood during a computer based self-assessment test, with respect to each question the student is about to answer. We showed that this model is accurate enough and easy to implement. A relatively large number of students took an online test. The system informed the student after each question, whether he had provided a correct or a wrong answer and presented his score. The recorded data was used as input to the model. The system also presented a slide bar 5 times during the test at a different sequence for each student, asking the student to declare his current mood concerning the test. The evaluation of the model was based on students' feedback concerning their mood during the test. The present study is unique for a number of reasons. First, it demonstrated the ability to find good statistical fits on the model to predict the students' mood based on students' goal and record during the test. Second, it made obvious that student's verification or rebuttal of hope to reach his goal configures his mood during a test. Third, it demonstrated that student's success or failure to recently previous questions influences his mood positively or negatively towards the current question. Fourth, it showed that it may be helpful to see HCI problems from a qualitative point of view rather than from a quantitative point view.

In the future, we plan to use our mood-recognizer models for providing feedback to students' mood while taking a self-assessment test, so as to help the students improve their knowledge and acquire a positive attitude towards learning.

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