Affective Learning with Thought Mining

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Abstract— **Educational technology is defined by the Association for Educational Communications and Technology as "the study and ethical practice of facilitating learning and improving performance by creating, using, and managing appropriate technological processes and resources. Having improved emotional (affective) state may have several benefits on learners, such as promoting higher cognitive flexibility and opens the learner to discovery of new ideas and possibilities. On other side, negative emotional states like boredom and frustration have been linked with less use of self-regulation and cognitive strategies for learning as well as increases in disengaged and disturbing behavior during learning. In the area of computerized learning, several researchers strongly agree that intelligent tutoring systems (ITSs) would significantly improve its performance if it can adapt to the affective state (emotional state) of the learners. Here, a previous method of determining student mood has been refined based on the assumption that the influence on learner mood of questions already answered declines in relation to their distance from the current question. The goal is to demonstrate how the various kinds of evidence could be combined so as to optimize inferences about affective states during a self-assessment test. Here thought mining is also introduced which is very useful for mining student opinions on particular education related topics through their posts or comments so that we can mine actual problems in educational system. Tweet classification is little relevant to our study.**

Index Terms— **Mood recognition, Educational technology, Emotion Sense, thought mining.**

I.INTRODUCTION

Nowadays, the Web can integrate adequate technology and environment, where learners can be uniquely identified, content can be purposely presented, and progress can be individually monitored, supported, and assessed. Recent research in affective neuroscience and psychology have reported that human affect plays a significant and useful role in human earning and decision making, as it influences cognitive processes. However, the extension of cognitive theory to explain and exploit the role of affect in learning is in its infancy. Researchers of artificial intelligence in education have considered the fundamental nature of integrating emotional factors in intelligent tutoring systems. A step towards this direction is to provide computer aided learning systems with an automatic affect recognizer, in order to collect data which identify a student's emotional state. With this information, the computer could respond appropriately to the student's affective state rather than simply respond to student's commands. An appropriate computer response to a student's affective state also requires evolving and integrating new pedagogical models into computerized learning environments, which assess whether or not learning is proceeding at a healthy rate and intervene appropriately. Knowledge relative to how emotions influence learning is a fundamental part of computer-aided affective learning systems.

The recognition of a learner's emotional condition may play a vital role in ameliorating the effectiveness of e-learning. Lack of emotion recognition has been considered to be one of the main limits of traditional tools of e-learning. This is an important issue, since student's performance during a learning session may be seriously hampered due to emotional reasons. When students are facing exams, this effect may be even more intense. Examination conditions require an integration of various skills: Students are expected to read, understand, analyze, apply their knowledge, and then present a structured answer to the questions. However, these activities must be done within a limited time and often under strictly controlled conditions. As a result, students are often emotionally strained. Faced with sadness, worry, shame, frustration, or despair, people lose access to their own memory, reasoning, and the capacity to make mental associations.

The method being presented here could assist in developing a system that would help the student prepare cognitively and affectively before exams through online multiple choice question tests. Sometimes, it may be conducive to the learning experience to be self-assessed with the aid of a tutoring system, rather than with a real teacher. In addition, any learner could benefit from the use of such systems depending on their learning goal, which can range from preparing oneself for a test A flexible e-learning system would take into consideration the student's current knowledge and learning preferences to generate individualized learning paths. In addition, the system would try to introduce students to an emotional state conducive to learning by providing adequate feedback. The tutoring system affective routines will be embedded within learning and the effort to produce an adequate mood and an optimal emotional, motivational state for the current learning task will apply to the entire learning experience. Thus, we are dealing with several different elements which need to be combined effectively to produce a new generation of tutoring systems. Therefore, a way to do this is to formulate and establish every constituent in separation and then try to determine how they can all be combined together to produce optimal results. Here a model is being introduced based on the assumption that student success or failure to the most recent questions influences their mood positively or negatively toward the current question.

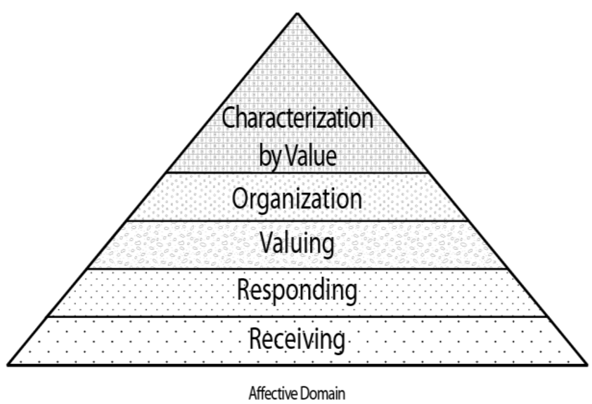

Figure 1.1: affective domain

Traditionally, educational researchers have been using methods such as surveys, interviews, focus groups, and classroom activities to collect data related to students' learning experiences. These methods are usually very time-consuming, thus cannot be duplicated or repeated with high frequency. The scale of such studies is also usually limited. However, to the best of our knowledge, there is no research found to directly mine and analyze student posted content from uncontrolled spaces on the social web with the clear goal of understanding students' learning experiences. The research goal is to explore engineering students' posts and comments in order to understand issues and problems students encounter in their learning experiences.

II.LITERATURE SURVEY

The fundamental nature of affective factors in human cognitive procedures and learning has been acknowledged by numerous researchers [7], [15], [16], [17], [18], [19], [20]. Consequently, during the last few decades, there have been attempts by several educators to develop learning strategies in order to take advantage of these issues [24], [27], [28]. In addition, various researchers have pointed to the need for developing tutoring systems with the ability to recognize a learner's emotional state and activate an appropriately tailored response based on integrated pedagogical models [5], [29], [30]. While some researchers address the issue of motivational skills concerning an intelligent tutoring system [29], [31], others try to develop systems that focus on emotion [33], [34], [35]. However, to the authors' knowledge, there has been no previous effort to develop a tutoring system with mood regulation capacities. Motivation, emotion, and mood overlap, but have distinct characteristics as well. According to Bull et al. [32], there are benefits to extending the scope of student models to include additional information. Therefore, motivation, emotion, and mood could all be essential concerning student modeling. Although even emotions researchers frequently do not agree with each other about the definitions of mood, emotion, and motivation, it would be helpful to provide a brief definition of these concepts before continuing. According to Williams and Burden [36], motivation may be described as a condition of cognitive and emotional arousal, which leads to a conscious choice to take action and initiates a period of continued intellectual and/or physical effort, so as to achieve a previously determined goal. Moreover, mood and emotion have common features, but also have distinctions [38]. Emotion and mood share three basic characteristics:

1) They are subjective experiences,
2) They are expressed through human communicational channels, and
3) They have a physical impact.

On the other hand, emotion and mood are distinct at four basic points:
1. Duration and intensity: Duration is a characteristic of mood, while intensity is a feature of emotion.
2. Timing: It is easier to distinguish between the beginning, climaxing, and end of an emotion than of a mood.

3. Cause-reaction: The cause of an emotion is usually more evident than the cause of a mood. In addition, emotion triggers a target reaction, while mood frequently provokes vague reactions.
4. Information: Emotion carries information concerning the environment, e.g., information about a threat in our environment, while mood carries information concerning our capacity to face the threat of the environment. Similarly, mood informs individuals about their progress toward personal goals [39], [40].

Mood could be useful due to its self-assessment quality. It carries descriptive information concerning a student's self-evaluation toward a learning goal. In addition, duration as a feature of mood could serve long-term learning goals. The student should have a positive attitude toward learning, both during and after interaction with the tutoring system. Positive mood has been indicated to increase human ability to distinguish relevant from irrelevant pieces of information, thus achieving advanced performance concerning cognitive skills [41]. In addition, people in a positive (versus negative) mood are known to perform better on creativity tasks [42], [43]. However, positive mood is not always the optimal state for learning because it widens the thought processes, making it easier to be distracted. When the problem involves focusing, positive affect may interfere with the subject's concentration [44]. In such cases, negative mood could be more helpful. There is conclusive evidence that people in a negative (versus positive) mood tend to further analyze information and perform analytical/systematic information processing prior to making judgments or decisions [44], [45],. Negative mood focuses the mind, reducing distractions. It is when the negative affect is too strong that learning tasks are inhibited [47]. Consequently, the further removed one is from the ideal affective state for the learning task to be accurately carried out, the more definite the impact of non-optimal affect on performance. Thus, people experiencing positive (versus neutral) mood, for example, should be more likely to regulate mood downward when facing an analytical task, since they are further removed from the optimal negative mood [48]. Though Cohen and Andradea [48] have provided evidence that humans indeed try to self-regulate their mood to match the needs of a certain task, there are many students who cannot regulate their mood accordingly. Some children and adults have difficulty managing positive and negative affective states successfully [7]. An online self-assessment test could help students to regulate their mood appropriately during their preparation for exams. Thus, students would not only be cognitively but also psychologically prepared to deal with exams. Hopefully, students could use this mood regulation experience to deal with other challenging issues as well. A first step toward this direction is to provide these systems with affect recognition techniques. Affect recognition has made remarkable progress during the last decade, but has not yet been fully adapted to intelligent tutoring systems. Improving the accuracy of recognizing people's emotions would greatly improve the likelihood of effectively integrating affect recognition methods in intelligent tutoring systems. A survey of audio-video combination efforts and a synopsis of issues in building a multimodal affect recognition system are provided by Pantic and Rothkrantz [49]. Preferably, evidence from many modes of interaction should be combined by a computer system so that it can generate as valid hypotheses as possible about a user's emotions. This view has been supported by several researchers in the field of human-computer interaction (HCI) [49], [50]. Humans recognize emotional states in other people by a number of visible and audible cues. Facial expression is a valuable means of communicating emotion. Moreover, there is evidence of the existence of a number of universally recognized facial expressions of emotion such as happiness, surprise, fear, sadness, anger, and disgust [51]. In addition, the body (gesture and posture) and tone of voice are alternative channels for communicating emotion [52]. There are also a number of psycho physiological correlates of emotion, such as pulse or respiration rate, most of which cannot easily be detected by human observers, but which could be made accessible to computers given appropriate sensing equipment. Through all these channels, researchers of artificial intelligence in education are attempting to infer the student's affective state. Currently, the core affect recognition methods are using personal preference information, facial expressions, physiological data, speech recognition, and questionnaire (either standalone or assisting another affect recognition method).

Questionnaires have also been used as a self-report tool for emotion. However, recently, some innovative technique shave been engaged for obtaining self-reports of emotional experience [53], [54], [55]. These methods indicate that stimulating the student to participate more actively in the process of self-reporting emotional experience could greatly enhance the quality of learning. For instance, Alsmeyer et al. [55] used the concept of color as a means of communicating emotional information. Students reported their emotions to the teacher through the selection of a color, which they had previously associated with one of seven optional emotions. In addition, they suggested that the use of color may be easier for the students to understand than the use of emotional terms themselves. Furthermore, emotional recognition frameworks using personal preference information are based on the assumption that people do not necessarily recognize emotions just by signals seen or heard; they also use a high level of knowledge and reason, to be able to process the goals, situations, and preferences of the user. A person's emotions could be predicted if their goals and perception of relevant events were known [16]. Implemented in a computational model, this can be achieved by using agents, artificial intelligence techniques, reasoning on goals, situations, and preferences. For example, if the system can reason about the reactions of a user from the input that the system receives, (assumption made derived from the time of day, reading speed, personal information provided, etc.) appropriate content could be displayed in a way adapted to the motion or the mood of the user. It has been demonstrated [32] that it is possible to create a tutoring system able to infer a student's motivation judging from the student's interaction with the system based on a set of predefined rules. Emotion recognition systems are generally based on a rule-base system, or on a system that has learnt to solve the problem through extensive training. The richer the information provided by the interaction is, the more parameters can be derived for extracting the interaction environment and for achieving a better emotion recognition performance. This paper suggests combining various evidences in order to optimize inferences about affective states during an online self-assessment test. With regard to learning, there have been very few approaches for the purpose of affect recognition. The adoption of affect recognition methods using personal 52 IEEE transactions on learning technologies, vol. 2, no. 1, january-march 2009 preference information and questionnaires would probably be preferable for certain affective learning systems (e.g. Web-based for distance learning). These methods do not require any special equipment, such as video cameras, microphones, sensors, etc., thus rendering the affective learning system more user-friendly. For that reason, the method developed in this paper is based on personal preference information. Other studies show that there is a lack of awareness about managing online identity among college students [57], and that young people usually regard social media as their personal space to hang out with peers outside the sight of parents and teachers [59]. Students' online conversations reveal aspects of their experiences that are not easily seen in formal classroom settings, thus are usually not documented in educational literature. [60]use emoticons as indicators to provide noisy labels to the tweets thus minimizing human effort needed for labeling. Sentiment analysis is another very popular three-class classification on positive, negative, or neutral emotions/opinions [61].

III. PREVIOUS METHOD

We have 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, if a student knows that they have already failed to reach their goal during the test, because the remaining questions are fewer than the questions they have to answer correctly in order to reach their goal, then it is highly likely that they are in a negative mood. In addition to that, we assumed that student's mood is also influenced by their success or failure in answering the questions just before the current one. For instance, if a student has failed to provide a correct answer to all of the five previous questions, there is a high likelihood that they are emotionally negatively influenced, but if a student has managed to provide a correct answer to all of the five previous questions, they are highly likely to be emotionally positively influenced. In view of confirming these assumptions, we have formulated this model:

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

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.

$$D(q) = I - r(q) \qquad (2)$$

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

$$H(q) = R(q) - D(q) \qquad (3)$$

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

$$M(q) = H(q)^{+rr(q)}{}_{-wr(q)} \qquad (4)$$

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 incorrect 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 incorrect answers in a row just before the current question, we subtract them from H(q).

The above method already indicated that taking into consideration, the recently previous correct or incorrect answers in a row just before the current question increases the method's sensitivity in evaluating student's mood.

What the above model did not take into consideration is that the effect of recently previous correct or incorrect answers in a row just before the current question may diminish as the test proceeds and these answers become less recent. According to this assumption, the recently previous correct or incorrect answers should be weighted proportionately to how recent they are. So, instead of just adding rr(q) (the number of recently previous correct answers in a row just before the current question) or subtracting wr(q) (the number of recently previous incorrect answers in a row just before the current question) from H(q), a new formula is utilized to calculate the number that is going to be added or subtracted from H(q):

$$\left[1 + \sum_{i=1}^{rr(q) \oplus wr(q)} (1/exp(i))\right]$$

Where i is the number of recently previous correct or incorrect answers in a row just before the current question.

Accordingly, if one or more answers just before the current question were correct, we add above formula to H(q). Whereas, if one or more answers just before the current question were incorrect, we subtract above formula from H(q).

The exp() function returns a number specifying e (the base of natural logarithms) raised to a power. That is to say, the natural logarithm of a number is the inverse of the exp() function. The number e is used to express values of such logarithmic quantities as field level, power level, sound pressure level, and logarithmic decrement . Affective issues concerning humans could be defined as logarithmic quantities as well. We suggest that human cognitive and affective reactions are not linear to the stimulus causing these reactions, but rather exponential. Hence, in order to express the logarithmic decrement of the influence of its recently previous answer proportionately to how recent this answer is, we use the exp() function.

IV. PROBLEM ANALYSIS

One of the major problems in the online learning is the lack of methods to recognize learner behavior during learning. Therefore, the current model addresses the problem of recognizing e learner's emotional state during learning. Although, most of the researchers studied about online learning concepts, there is a lack of a study on how learning performance reflect the emotional status of e-learners of online learning in higher education. As per literature review following problems are analyzed.

1. Difficult to recognize the running affective state of the student.
2. Problem may occur in order to recognize when to intervene in order to influence the student's affective state.
3. Difficult to produce the most optimal affective state for learning.
4. Previous mood recognition models have no feedback reminder for the students to improve their affective state.
5. There is no way to inform the particular instructor about the student's current affective state (positive or negative mood).
6. Difficult to analyze the problems that students' face in their learning.
7. Lack of thought mining module to improve learning environment.

V. PROPOSED WORK AND SYSTEM ARCHITECTURE

The combination of technology enhanced learning and affective computing can be applied to the online learning community. This paper focuses on building the relationships among affective computing concepts and methodologies in line with e-learning.

The main aim of this is to develop an affective learning model with thought mining to recognize learner emotions in an online learning environment. Additionally system should be able to mine the problems in learning with the help of feedback analysis.

The system architecture will help to identify e-learner's emotional state with respect to their level of learning.

The basic architecture of the system consists of different modules. The mood recognition module described in the system architecture elaborated on how the existing learner interact with the system and how his/her mood can be recognized with the help of test in the online learning environment. The thought mining module described in the system architecture elaborated on how the problem can be analyzed using feedback given by learners.

In the following System Architecture, there are five main modules-

1. User
2. Database
3. Mood Recognition Module
4. Thought Mining Module and
5. Instructor

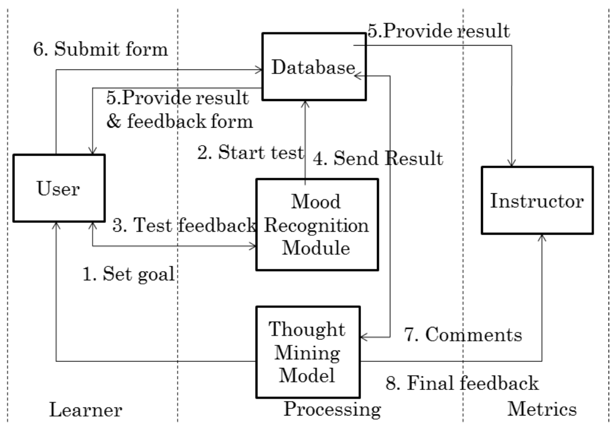

Figure 5.1: Proposed System Architecture

Working is as follow-

When the application is opened, the index page will appear. There will be a link for registration (first time user) and for login. When the user will login, a selection form will appear where user can set their goal. After submitting a Selection form Database will provide the test to the user. During test mood recognition module will provide user with intermediate result in order to make the user known about their performance and the running affective state. After the test is completed database will provide the result to the user. All user information for example user's results login details and feedback analysis can be viewed by instructor . There will be a feedback form for the user. Database will send all the selected option information (from feedback form) to the Thought Mining Module in order to perform feedback analysis.

Two proposed algorithms are:

- Algorithm for mood recognition.
- Algorithm for feedback analysis.

ALGORITHM FOR MOOD RECOGNITION

1. Correct Answer(Ans) ← Return total number of correct answers present in answer sequence.
2. Incorrect Answer(Ans) ← Return total number of incorrect answers present in answer sequence.
3. Not Attempted Answer(Ans) ← Return total number of not attempted answers present in answer sequence.
4. Length(Ans) ← Return length of answer sequence.
5. Difference(x, y) ← Return difference of x and y.

```
Start

Ans ← read answer sequence( )

Mood := NULL
CorrAns :=   CorrectAnswer (Ans)
IncorrAns :=   IncorrectAnswer (Ans)
NotAttempAns :=   NotAttemptedAnswer
(Ans)

If  (CorrAns > (IncorrAns+NotAttempAns))
   Then
   Mood :=  Good

Else if
(CorrAns=(IncorrAns+NotAttempAns))
   Then
        Mood :=  Neutral
Else
Start Repeat
      (repeat for i where i >(length(Ans)/2))
         If (Ans[i] not contain CorrAns)
          Then
               Mood:= Bad
      End Repeat

      If (Mood=NULL)

  Start Repeat
(repear for j where j > ( length(Ans)/2))

     LastCorrAns  ← CorrectAnswer (j)
LastIncorrAns  ← IncorrectAnswer (j)
```

LastNotAttemptAns ←NotAttemptedAnswer (j)

End Repeat

If (Difference(LastCorrAns , LastIncorrAns+ LastNotAttemptAns)=1)

Then

Mood:= Neutral

If (Difference(LastCorrAns , LastIncorrAns+ LastNotAttemptAns)>=2)

Then

Mood:= Good

If (Difference(LastCorrAns , LastIncorrAns+ LastNotAttemptAns)>= -2)

Then

Mood:= Bad

Return Mood

End.

ALGORITHM FOR FEEDBACK ANALYSIS

1. GoodSubmittedFeedback(i) → Count total ‘good’ submitted feedback for Question number i
2. OkSubmittedFeedback(i) → Count total ‘ok’ submitted feedback for Question number i
3. BadSubmittedFeedback(i) → Count total ‘bad’ submitted feedback for Question number i
4. plotGraph (v1, v2, v3, i) → Plot graph for question i with v1, v2 and v3 magnitude

Start

Start Repeat (repeat for i for all questions)

CountGood ← GoodSubmittedFeedback(i)

CountOk ← OkSubmittedFeedback(i)

CountBad ← BadSubmittedFeedback(i)

End Repeat

Start Repeat (repeat for j for all questions)

PlotGraph(CountGood, CountOk, CountBad, j)

End Repeat

End

VI. COMPARISON WITH PREVIOUS SYSTEM

Based on the previous method, mood of the student would varies very largely just because he/she answered only one question of the test correctly or incorrectly. This is a very unrealistic prediction. Predicting mood with the new method leads to the solution of this problem as proposed method predicts mood of the student based on:

1. Correct answers, incorrect answers and unanswered questions
2. last 50% of the attempted questions up to the current point.

Therefore, the new method provides a much more realistic prediction. The new method agrees with the previous on the fact that the student’s success or failure to the previous questions does have an influence on student’s mood. Nevertheless, the new method weights this influence differently.

Following graph shows how new method is differ from previous method (figure 6.1). In the graph, according to previous method, mood of the student varies largely with number of question attempted whereas according to new method mood varies based on two parameters described earlier.

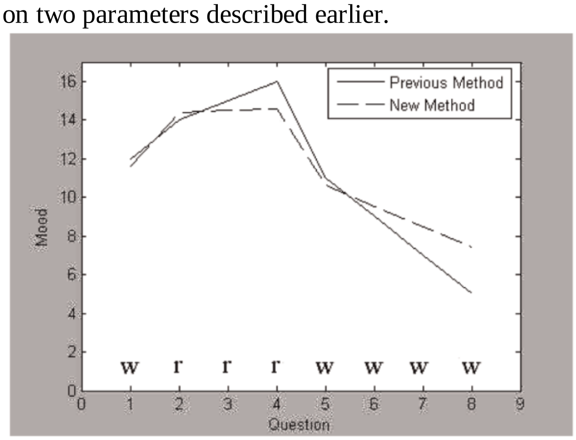

Figure 6.1: graph showing comparison between proposed method and new method.

VII. CONCLUSIONS

This paper has presented formulas for recognition of student mood during an online self-assessment test. Additionally, it has argued that the assumptions underlying the formulas may prove useful for future research.

The presented work aims to provide tutoring systems with mood recognition methods for use during an online self-assessment test. The proposed methods are easy to implement in a system. So far, there has been no applicable computational model for affect recognition during an online test. The two methods are examined for their reliability.

Simultaneously this paper shows that thought mining can be more useful to improve education system performance.

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