An Approach for Identifying Affective States through Behavioral Patterns in Web-based Learning Management Systems

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ABSTRACT

In a learning environment, the students experience different affective states. Learning environments that takes into account the students' affective state enhance the students' learning, gain and experience. Therefore, it is crucial to provide students with different learning material and activities according to different affective states. To provide learning that considers students' affective states, the primary step is the detection of affective states of a student. In this paper, we present an approach for the detection of affective states from the patterns of students' behavior observed during an online course. By calculating the affective states and then filling that affective state data into the student model of a learning management system a basis for adaptivity is provided.

Categories and Subject Descriptors

H.3.5 [**Online Information Services**]: *Web-based services.*

General Terms

Human Factors

Keywords

Human Computer Interaction, Affective States, Adaptive Learning Systems, Confidence, Confusion, Effort, Independence.

1. INTRODUCTION

Education is no long restricted to a certain time or a designated place due to using internet technology [1]. Picard et al. [2] indicated that such benefits have been bought at the cost of bias towards the cognitive and relative neglect of the affective state of the student.

Learning management systems (LMSs) such as Moodle and Blackboard, are very successful in e-education but the facility they lack is providing full fledged adaptivity [3] and particularly they do not accommodate current adaptivity approaches such as adaptivity based on affective states. Learning environments that respond to differences in students' affective states boost up students' learning gains as well as enhance their overall learning experience [4]. In recent years, researchers of intelligent tutoring systems and interactive learning environments have investigated ways in which such systems can be made adaptive according to students' affective states. To provide affective adaptive learning environments, the primary step is the recognition of the affective state. Currently, there are different approaches used for obtaining information about the students' affective states such as a verbal and nonverbal approach and an intrusive and non-intrusive approach [5]. In a verbal (also called self report) instrument (i.e. questionnaire) students provide explicit information about themselves or in other words about their state. On the other hand, a nonverbal, also called physiological, instrument measures physical states, for example stress through Skin Conductance (SC), Galvanic Skin Response (GSR) etc. The intrusive instrument measures the physical appearances through observational cues such as gesture, posture, conversation etc., whereas the non-intrusive instrument measures the behaviors while interaction between students and the system takes place.

According to Zhang et al. [1], students consider answering a questionnaire (verbal instrument) a big burden in the learning process. So, in order to arrive at the contents quickly, they might provide invalid data. Moreover, the students can provide invalid data due to privacy concerns or having a lack of knowledge about their own characteristics [6]. Physiological instruments provide information related to the physical state of the students wearing that instruments like GSR, measure the skin's conductance between two electrodes and blood volume pulse sensor to detect the blood pressure in the extremities. These kinds of instruments are usually applied in controlled environments not in real time environments. Picard et al. [2] described that conducting controlled experiments dealing with affective states has been a challenge. Moreover, students can show a negative reaction to the use of body sensors. Due to user's reaction this kind of instrument could be limited to a certain type of application [7].

Picard and Bryant Daily[8] and Khan et al. [9] indicated that intrusive instrument has influence upon the normal affective state of the student and may lead to misinformation. This feeling of misinformation may arise from a student feeling of being monitored. Kapoor, Picard and Ivanov [10] addressed the affective state of children interested in solving a puzzle by introducing multi modalities. The scenario is presented as child solving a puzzle and machine trying to infer the affective state using the information from the puzzle, face and the postures. Processing these kinds of observational cues e.g. conversational cues, gesture, posture etc. is difficult for adaptive systems and recent research trends are shifting towards systems that process emotion (non-intrusive) cues e.g. student's interactions with system, time spent on a task etc. automatically, as a means to assess affective states [11].

Recent research has given indication about the student as a source of information for his/her affective state and trying to infer his/her affective state from the interactions with the system, rather than directly involving the student. Information obtained in this way about the affective state of the student would enable the adaptive systems to tailor contents and interventions to the individual student [12].

In this paper, we propose a method that investigates patterns of behavior in LMSs that correspond to the students' different affective states, in order to provide the students with a personalized support.

This paper is organized as follows. In Section 2, we introduce affective states important for learning. In Section 3, the concept for identifying affective states is introduced. Section 4 concludes the paper.

2. AFFECTIVE STATES IMPORTANT FOR LEARNING

The affective states range from traditional affective states such as anger, fear, joy, surprise and disgust identified by Ekman and Friesen [13] as well as other states such as confidence, confusion, and effort. A study conducted by Craig, et al. [14], explored that traditional affective states do not play a significant role in learning.

There are many parameters that can be used to describe the students' affective state e.g. motivation, interest and proclivity. Motivation is considered to be the most important factor in learning, as it reflects the learning process [1]. Psychologists have presented different motivation theories and models, for example, Social cognitive learning theory(SCT) [15], Keller's ARCS model [16], Motivational planner [17], Attribution theory [18] etc.

E-learning research based on SCT highlights the importance of self-efficacy and self-regulation. Keller's ARCS model has been used effectively as basis for e-learning course design. The Motivational planner contains practical approaches depending on the students' motivational state, and it uses three parameters to infer motivation: confidence, effort and independence. Attribution theory highlights four factors that influence motivation in education such as ability, task difficulty, luck and effort. Qu, Wang and Johnson[19] following the human tutoring studies related to coaching students in on-line tasks found confidence, confusion, and effort amongst the several factors that influence the students' motivation most. De Vicente and Pain [20] presented a student motivational model consisting of trait and state variables. The trait variables include control, challenge, fantasy and independence, and state variables include confidence, sensory interest, cognitive interest, effort and satisfaction.

3. A CONCEPT FOR IDENTIFYING AFFECTIVE STATES

In this study, we consider four affective states. The selected affective states include: confidence, effort, independence and confusion. These were selected because they are prevalent in student learning interactions in learning management system.

In the following subsections, the patterns of behavior suitable to each selected affective state as well as the concept for calculating affective states from these patterns is presented.

3.1 Affective States and Relevant Patterns of Behavior

Commonly used features in LMSs were selected to be the basis for patterns, in order to make our approach applicable for LMSs in general. Our approach is based on the work by Qu, Wang and Johnson [19] as well as De Vicente and Pain [20], and is composed on a number of affective states including academic confidence, effort, independence and confusion. These selected affective states represent characteristics of the students that relate to commonly used features like content objects, outlines, exercises, self assessment tests, examples, discussion forum for assignment related queries, discussion /peer rating forum related to the content objects, and assignments. In addition, the navigation behavior of the students within the course is also considered. Considering information from all these features provides us with relevant data for identifying students' affective states.

In the next subsections, the characteristics of each affective state with respect to relevant models from literature are described and the relevant patterns for identifying each affective state are presented, using the models from literature as basis.

3.1.1 Confidence

Sander and Sanders [21] indicated that students have different levels of confidence in different situations and also confidence differs between students in same situation. A new mediating term was introduced in this context, known as academic confidence. Besterfield-Sacre et al. [22] indicated that academic confidence influences student performance, motivation, and retention in future academic studies. A study for measuring academic confidence was conducted by Sander and Sanders [21]. Results of the academic confidence measurement study yielded factors of studying, understanding, verbalizing, clarifying, attendance and grades. On the other hand, Qu, Wang and Johnson [19] defined the confidence of students in a learning environment through solving problems.

In our approach, we consider the factors of academic confidence identified by Sander and Sanders [21] except a single factor i.e. grades as the remaining five factors co-relate with the learning behavior of the student. We can therefore assume that the following behavior provides us with information related to the student's academic confidence. Visiting content objects, outlines and examples gives us an indication about student's behavior of *studying*. Attempting exercises and self assessment tests gives us an indication about student's behavior of *understanding*. Forwarding a new post by students as well as commenting each new posting forwarded by other students related to the content objects over the discussion/peer rating forum gives us an indication about *verbalize* behavior of students with respect to verbalizing. Visiting assignment related queries forum, queries and visiting new postings related to the content objects over the discussion/peer rating forum give us an indication of student's behavior of *clarifying*. Counting student's postings over the discussion/peer rating forum related to content objects, commenting/peer rating of each new posting and replying to queries posted over the assignment related queries forum give us an indication about student's behavior of *attendance*.

The above mentioned patterns help in identifying students' academic confidence. We can assume that students, having high values for the mentioned patterns have a high level of academic confidence and students having low values for the above patterns have a low level of academic confidence.

3.1.2 Effort

According to attribution theory [18] effort is an unstable factor but the student has great deal of control over it. For example, we can control our effort by trying harder or a student often failing a difficult course could succeed by taking an easier one. Weiner et al. [23] concluded that a student attribution of failure to unstable factors like luck or effort facilitates continued expectations and performance for future success. For example, if a student believes that failure is due to low effort, he/she can try harder in the future and experience greater success but if a student believes that failure is due to low ability, he/she will expect to fail in future because there is no way he/she can alter his/her ability. Weiner [24] reported that attribution of nonattainment of a goal to low ability results in giving up and the termination of goal-oriented behavior. Motivation theory conception given by Pintrich and DeGroot [25] in which an individual willingness to display learning or put forth the effort to learn not only depends upon the individual's interest or the importance of the task, but also on the student's disposition to put forth the necessary work to complete the task.

Qu, Wang and Johnson [19] derived the student's effort from the amount of time the student spends on performing tasks. Wise and Kong [26] argued that in low-stakes situations (absence of personal consequences associated with student test performance), rapid guesses represent non-effortful behaviors by unmotivated students. De Vicente [27] questioned experts about students' interactions and the analysis of their responses elicited some motivational rules related to effort, confidence, satisfaction and interest. After that an empirical study was conducted to validate those rules and found five rules valid related to effort out of seven formulated rules. Validated rules include, for example, that if the quality of attempting an exercise (correctness of the answers provided to the exercise) is very high, the student's effort was considered to be high etc.

Following the motivational theory conception [25], Qu, Wang and Johnson's model [19] and De Vicente's validated rules related to effort [27] , we can therefore assume that the following behavior provides us with information related to the student's effort. Attempting a high number of self-assessment tests and exercises with a high number of correct answers in first attempt gives us an indication about student's behavior of exerting high effort. Similarly visiting a high number of postings related to the content objects and consequently forwarding a high number of peer rating of visited postings related to the content objects over the discussion/peer rating forum predicts a great deal of effort from the student in such activities. Submission of assignments before the deadline as well as revising and resubmitting the corrected assignment before the deadline in case of not getting positive feedback at the first attempt gives an indication of students' behavior of exerting high effort.

We can assume that students, having high values for the above mentioned patterns have exerted a high level of effort and students having low values for the above mentioned patterns have exerted a low level of effort. The above mentioned patterns not only indicate the student interest and commitment while performing tasks but also give indications about how such tasks were considered to be important by the student.

3.1.3 Independence

Student's independence (autonomy) is the characteristic of the student, in which he/she independently exhibit agency (intentional behavior) in learning activities. To describe 'independent learning' academic discourse abounds with synonyms like 'autonomous learning, self directed learning, independent study, student initiated learning and lifelong learning' [28]. Singh and Embi [29] highlighted the importance of four factors to look into student autonomy abilities i.e. planning, organizing, monitoring and evaluating their learning tasks. Planning and organizing deals with student ability to formulate learning aims and to decide upon time, materials and techniques to accomplish learning tasks; monitoring deals with the student ability to check, verify and correct themselves during learning tasks; evaluating deals with student ability to judge, evaluate and make decisions on performance in achieving the learning tasks.

According to Singh and Embi [29], we can therefore assume that visiting content objects, outlines, examples, and forwarding and visiting postings over the discussion/peer rating forum related to content objects give us an indication of student's behavior of planning; peer rating of postings, submission of correct assignment although in several attempts give us an indication of students' behavior of monitoring; attempting and repeating self assessment tests again and again, and solving exercises give us an indication of students' behavior of evaluating.

The above mentioned patterns help in identifying students' level of independence. We can assume that students, having high values for the above patterns have a high level of independence and students having low values for the above patterns have a low level of independence.

3.1.4 Confusion

Recent research has indicated confusion as an important affective state for scientific studying [30]. Rozin and Cohen [31] indicated that confusion often go along with cognitive disequilibrium and in states of perturbation and uncertainty there is need for clarification or more information. Graesser and Olde [32] highlighted the importance of cognitive disequilibrium in comprehension and learning processes. Deep comprehension occurs when students confront challenges, incongruities, barriers to goals or experiences that fail to match expectations. When students are in a state of cognitive disequilibrium there is a chance of activating conscious, questions and inquiry, and effortful cognitive deliberation that aims to restore cognitive equilibrium. Baker et al. [33] concluded that confused students are likely to game the system. Qu, Wang and Johnson [19] mentioned that a student in highly confused state is most likely to be stuck or frustrated.

According to Baker et al. [33] and Qu, Wang and Johnson [19], we can therefore assume that students with state of confusion can be divided at least into two types 1) Gamer and 2) Stuck.

Gamer students are supposed to be those who involve in gaming activities while attempting the self assessment tests such as inputting answers systematically and quickly, for example 1,2,3,4 in case of filling the blanks. Stuck students are supposed to be those who solve low number of self-assessment tests and exercises. They tend to leave high number of questions un-attempted in self assessment tests and exercises, and answer the same question twice or more often wrong in the self-assessment tests. Moreover, they are supposed to visit a high number of examples and also spend more time on examples. In case of submission of assignments stuck students are supposed to forward quick and repeated inquiry messages over the forum related to assignment. Stuck students are supposed to have a high number of sessions to resubmit the corrected assignment after getting not a positive feedback on their first submission. They are supposed to spend much time on content objects. Moreover, they tend to visit a high number of postings related to content objects but unlike that they are supposed to forward a low number of peer rating related to posted content objects.

The above mentioned patterns of gamer and stuck students help in identifying students' level of confusion. We can assume that students having high values for the above patterns related to gamer and stuck students have a high level of confusion and students having low values for the above patterns have a low level of confusion.

3.2 From Behavior to Affective States

The patterns described in Section 3.1 are incorporated for each affective state and a high or low occurrence indicates a specific affective state level. Based on this information, data about students' behavior can be used to calculate hints for specific affective state levels. The approach for calculating hints for specific affective state levels is based on the approach proposed by Graf, Kinshuk and Liu [34] for calculation of learning styles from the patterns of behavior. Hints are described by four values i.e. 0-3, where 3 indicate that the student's behavior gives a strong indication for the respective affective state, 2 indicates the student's behavior is average and therefore does not provide a specific hint, 1 indicates that the student's behavior is in disagreement with the respective affective state, and 0 indicates that no information about the student's behavior is available. In order to classify the behavior of students into these four values, thresholds from the literature [34-36] are used as basis, considering additionally the characteristics of the respective course.

By summing up all hints and dividing them by the number of patterns that include available information, a measure for the respective affective state is calculated. This measure is then normalized on a range from 0 to 1, where 1 represents a strong positive level and 0 represents a strong negative level for the respective affective state. If no pattern contains available information, no conclusion can be drawn.

4. CONCLUSION AND FUTURE WORK

In this paper, we presented an automatic student modeling approach for identifying affective states in LMSs. The proposed approach uses the behavior of students' while they are learning in order to gather hints about their affective states. Based on the gathered indications of behavior, affective states are calculated using a simple rule-based mechanism. The information about the students' behavior can be used as basis for providing course material that fits to students' affective states. The approach is proposed for LMSs in general rather than for one specific system.

Future work deals with further verifying our approach. For this we plan additionally to conduct an experiment and then to compare the results derived from patterns with the results obtained from questionnaires used for the respective affective state.

To ensure the privacy of data related to students' profiles, there are different paths that we could follow. For instance, role-based access control [37] would offer a fine-grained access control model and also existing security mechanisms could be adapted easily to ensure who accesses sensitive information.

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