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Predicting Student's Appraisal of Feedback in an ITS Using Previous Affective States and Continuous Affect Labels from EEG Data

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Abstract: Students have different ways of learning and have varied reactions to feedback. Thus, allowing a system to predict how students would appraise certain feedback gives it the capability to adapt to what would help a student learn better. This research focuses on the prediction of a student's appraisal of feedback provided in an intelligent tutoring system (ITS). A regression model for frustration and excitement is created to perform prediction. The frustration model was able to achieve a 0.724 correlation with a 0.164 RMSE and the excitement model was able to achieve 0.6 a correlation with a 0.189 RMSE. These results indicate the potential of using these models for allowing systems to adjust feedback automatically based on student's reactions while using an ITS.

Keywords: intelligent tutoring system, machine learning, brainwave signals, feedback appraisal

Introduction

Intelligent Tutoring Systems (ITS) help students learn by providing assistive feedback. Recent ITS have incorporated affective models motivated by researches that show the importance of emotions in learning [7]. Affective models allow systems to identify the student's emotional state and allow it to provide more appropriate feedback while learning.

The content, timing and presentation of feedback provided are based on an expert's view of what the student needs to progress in learning. However, because of the diversity of students, it is not ensured that the feedback identified by the expert will always work. So not only should a system provide feedback, but also assess its effect on the student so it can adjust the feedback to something more appropriate for the student in the future. This research focuses on automatically assessing the effect of feedback to the student as he uses an ITS in real time.

1. Related Work

Identifying the student's emotion is not a trivial task. Different approaches are taken to identify them like self-reporting, annotation, use of web cameras and physiological sensors [1][3][9]. Manual methods suffer from the amount of work required to identify emotions and noise due to human error, personal biases or fatigue while automated methods suffer from costs and inherent noise picked up by the devices.

In [5], students were asked to report their reactions to test results before and after it was given and their self-assessment about the test. They represented emotions using discrete labels and used ID3 and Naïve Bayes to create a model which got 82.4% and 62.93% accuracy respectively [4][6]. Robison [12] analyzed student's reaction to feedback in a virtual narrative-centered inquiry-based learning environment where they would report their emotions using discrete labels before and after feedback is given. Including personality, goal orientation and empathetic tendency in recent work improved the accuracy of their models where they were able to get 75.2% accuracy using Naïve Bayes, 72.9% using decision trees and 73.11% using support vector machines (SVM) [13].

2. Modeling Student Appraisal of Feedback

Appraisal theory views emotions as the result of evaluations or appraisals of events that are happening or have happened to a person [14]. A particular perspective views it as a continuous interplay between cognition and emotion. Given a stimulus, there is a continuous reassessment of the situation based on the current emotion, past experiences and other relevant factors until it stabilizes [10][15]. Automatically identifying the appraisal of a stimulus, in our case feedback from an ITS, would require emotions to stabilize first. When self-reporting we may consider that a student is able to report his emotion since he has finished appraising the situation. The case will be different however when sensors are used as it will not know when the appraisal process is complete.

In this research students were asked to use an ITS for object oriented programming (OOP). Their appraisal of the system's feedback was collected using the Emotiv EPOC Neuroheadset[1], a commercial electroencephalogram (EEG) based product. The use of brainwave signals minimizes human error seen in self-reporting or annotation and noise as it is not as susceptible to movement compared to other physiological sensors. The device is capable of identifying continuous emotional states instead of discrete emotion labels.

3. POOLE III

The Programmer's Object Oriented Learning Environment III (POOLE III) [2] is an ITS designed to help students learn class design using the Unified Modeling Language (UML). It was modified to incorporate a virtual conversational agent that communicates with the student and gives feedback regarding his work. Haptek People Putty Player[2] was used to render the agent and synthesize speech. Importance was given to the agent's facial expressions and supportive dialogue to provide feedback to the student. Figure 1 shows a screenshot of the system where the agent provides feedback about the student's answer.

The system tracks the student's knowledge using a Bayesian network and is used as basis for feedback. Feedback is categorized into activity transition, solution evaluation and hints. The words and facial expressions of the agent were chosen to appear supportive of the student's activity.

[1] http://www.emotiv.com
[2] http://www.haptek.com

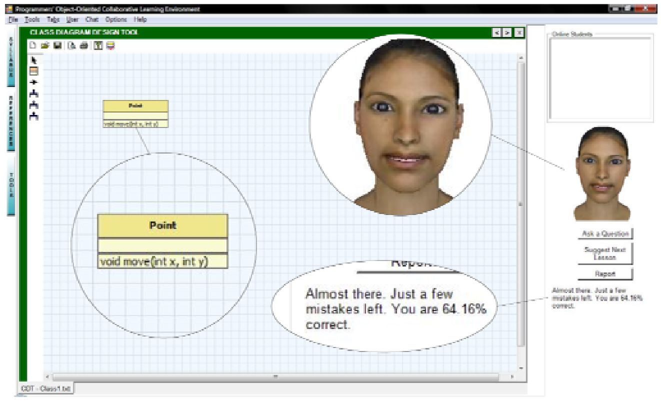

Figure 1: Screenshot of POOLE III's interface

4. Data Collection

Data was gathered from five male and five female first year students taking an introductory course on OOP at De La Salle University. The experiment conductor first gives a tutorial on using POOLE III then the student is asked to wear the Emotiv Epoc while a video of his face was recorded and feedback was logged. Students used the system for 20 minutes. Afterwards they answered a survey to get their profile and the results of their Big Five personality test. Figure 2 shows the experiment setup.

Figure 2: Experiment setup with the student wearing the Emotiv Epoc

5. Data Preparation

Since the focus of the research was to predict appraisal of feedback, only the excitement and frustration values after each feedback was considered. The student's appraisal of feedback was considered complete when there is a change of only 0.08 in both values. This was chosen based on the manual observation of the data. The value for frustration and excitement at this point was considered as the label for the frustration and excitement models that would be created later.

Based on the appraisal theory, previous emotional states affect appraisal. So apart from including the frustration and excitement values when the feedback is given, the average frustration and excitement values from the previous three seconds are also included. Lastly, the feedback given and the student's profile are appended to the data. This gives a total of 14 features namely: (from Emotiv Epoc) frustration, excitement, average frustration, average excitement, (from POOLE III logs) feedback, time elapsed from last feedback, (from survey) age, gender, class standing, extroversion, orderliness, emotional stability, accommodation and inquisitiveness.

6. Modeling Feedback Appraisal

The RapidMiner data mining software [11] was used for selecting the most relevant features from the data through the sequential forward floating selection algorithm [8]. It was used together with linear regression, k-nearest neighbor and support vector machine wrappers. Each wrapper was used for its corresponding machine learning algorithm. Also using RapidMiner, Linear regression, k-nearest neighbor (kNN) and support vector machine (SVM) were used to create the predictive models. The correlation coefficient and root mean squared error (RMSE) of the two models are shown in Figure 3.

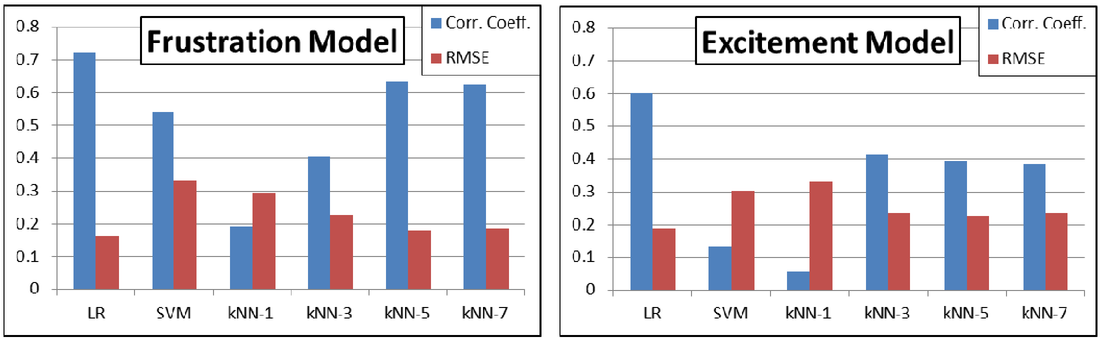

Figure 3. Correlation coefficient and RMSE of the frustration and excitement model

Linear regression gave the best results with a correlation of 0.724 and a RMSE of 0.164 for predicting frustration which is quite promising given that the data was gathered from an actual scenario in real time and that the data from brain waves are quite noisy. The excitement model is less powerful compared to the frustration model, where linear regression also gave the best results but with a correlation of 0.6 and a RMSE of 0.189.

The features commonly selected by the feature selection algorithms for the frustration model were frustration, average frustration, excitement, time elapsed from the previous feedback, extroversion and accommodation. The selection of frustration, average frustration and excitement support the appraisal theory indicating that previous emotions affect appraisal. It was interesting that a relationship was found with the time elapsed from the previous feedback because it was observed in many cases where students continuously ask the system for hints which are behaviors indicative of frustration. Lastly it was also found that certain personality traits have an effect on the student's emotional state supporting the findings of Robison [13]. Similar features were selected in the excitement model except for the replacement of the accommodation personality with orderliness.

7. Conclusions and Future Work

The results gathered are quite promising. The frustration and excitement models are able to predict the student's appraisal of feedback with fairly acceptable correlation and error. Results from feature selection have showed empirically that previous emotional states have a relationship with the appraisal of feedback, supporting appraisal theory. Similarly it was shown that frustration and excitement values do stabilize after feedback is given supporting the recursive view of appraisal. Personality was also seen to have relationships with student's appraisal of feedback supporting previous works on the same domain.

The methodology used gives a good alternative to self-reporting, where student's appraisal of feedback can be identified without interrupting their learning task. The models created are simple and can work in real time allowing it to be incorporated into tutoring systems. The use of continuous affect values in the form of frustration and excitement are capable of capturing more information regarding the student's emotional state unlike discrete emotion labels making it richer and allowing more analysis of the data.

This capability of predicting the student's appraisal of feedback can be used to improve current tutoring systems by identifying what feedback is helpful to the student or not, allowing it to adjust accordingly. This will hopefully improve the support students receive and will allow them to have better learning experiences.

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