Smart Classroom

Affective Computing in Today's Classroom

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Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects, i.e. the experience of feelings or emotions. Over the past decade, research has shown the impact of affective states on work performance and on team collaboration. This also applies for software engineering that involves people in a broad range of activities, where personality, moods, and emotions play a crucial role.

I believe that affect can significantly influence education/learning. Thus, understanding a learner's affect throughout the learning process is crucial for understanding motivation. In conventional education/learning research, learner motivation can be known through postevent self-reported questionnaires. With the advance of affective computing technology, we are able to objectively identify and measure a learner's affective status during the entire learning process in a real-time manner, which enables us to understand the interrelationship between emotion, motivation and learning performance.

Analyzing today's world, we can clearly see that the act of class teaching is starting to be slowly replaced by the internet. Having such a huge mass of information online or the fact the Internet enables so many passionate individuals to help or teach others online has changed the way students see the classic classroom teaching. I believe something needs to be changed as soon as possible, and a good way to start would be to monitor and analyze students' behavior during a normal lab/class to see how we can modify the way we are teaching today or the structure of the information delivery so that we have and keep our students engaged.

I will present a theoretical and practical framework for the creation of a smart classroom that incorporates affective and cognitive state of students based on inputs from low cost, non intrusive sensors. This framework has theoretical foundations in learning science and physiological measurement and could drastically increase the diagnostic capability of current intelligent training systems. Implementation of this framework could transform adaptive training based on cognitive/affective states from a cost prohibitive endeavor to a goal well within reach. The raw estimated cost of all the elements embedded for one user system is around $80-90.

Emotions and Learning

Learning Design is described as a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies.

Many educational institutions across the globe have high expectations of learning analytics to make their organizations more innovative, flexible and fit-for-purpose. Learning analytics applications are expected to provide educational institutions with opportunities to monitor, support and engage learners' attitudes (e.g., emotions, motivation, engagement), behavior (e.g., contributions to discussion forums, clicks, likes) and cognition. These applications will, one day, enable personalized, rich learning on a large scale (Bienkowski et al. 2012; Hickey et al. 2014; Rienties et al. 2015; Tobarra et al. 2014)

Historically in Western thinking, emotions and human feeling were considered outside the sphere of rational thought. More recently, there has been a reconceptualization of emotions as being inextricably linked to cognition and learning, and therefore of interest to educational researchers (Artino 2012). Emotions play a critical role in the teaching and learning process (Schutz and DeCuir 2002) because learners' feelings affect motivation, self-regulation and academic achievement (Chew et al. 2013; Kim et al. 2014; Mega et al. 2014). Research suggests that learners' emotions can influence their choice of study mode (Abdous and Yen 2010) and can inform instructional design (Gläser-Zikuda et al. 2005; Meyer and Turner 2002).

The complex relationship between emotions and learning can be characterized by the effect emotions have on the learning process (e.g., attention, encoding, recall). For example, boredom leads to lower retention and less ability to apply information (Small, Dodge and Jiang, 1996) and is negatively correlated with learning gains (D'Mello, Graesser, and Taylor, 2007). On the other hand, joy leads to significant increases in intellectual gains and performance. Impacts on learning were found for a variety of emotions including anger and anxiety (Woolf et al., 2009; Burleson and Picard, 2004), frustration (McQuiggan et al., 2007), shame (Ingleton, 2000) and surprise (Holland and Gallagher, 2006). Additionally, when the trainee lacks motivation, it hinders creativity and flexibility in problem solving, as well as leading to withdrawal from learning (Woolf et al., 2009).

A list of affective states that have been found to impact learning was summarized into the following: Anger/Frustration, Boredom, Confidence, Confusion, Fear/Anxiety, Joy, Motivation, Sadness, Shame, Surprise, Wonderment/Awe. In order to provide a more standardized set of affective states, non-orthogonal states that are actually different intensity levels within the same emotional category were consolidated into one emotion. These consolidations included both anger and frustration as well as fear and anxiety

(Scherer, 2005). Unfortunately, only a few of these states can be identified using the proposed system, given our non intrusive means.

McQuiggan, Lee, and Lester (2007) found that anxiety and frustration divert attention from the task at hand, impeding learning. Furthermore, students who are anxious or angry do not learn as well because they do not take in information efficiently (Woolf et al., 2009; Burleson and Picard, 2004). Alternatively, motivation is positively correlated with learning. If student motivation is sustained throughout periods of disengagement, students can persevere through frustration to a greater extent (Woolf et al., 2009; Burleson and Picard, 2004). Similarly, confusion was found to be significantly positively correlated with learning gains. In fact, Craig et al. (2004) found an effect size on learning, observed when confusion was present versus absent, suggesting that some level of confusion is critical for optimal learning. D'Mello, Taylor, and Graesser (2007) found that when learners are confused, they are less likely to become disengaged and transition into boredom, which is significantly negatively correlated with learning (Craig et al., 2004). Boredom leads to lower retention and less ability to apply information.

However, in determining the types of physiological data indicative of these states, only three of these states have shown correlation with data from physiological sensors. For example, Lisetti and Nasoz (2004) found that heart rate values for a fearful participant increased, whereas heart rates decreased when the participant was angry. Heart rate has also been shown to be correlated with boredom (Merrifield, 2010). According to Woolf et al. (2009), facial expressions can be used to detect fear and anger. Additionally, posture has been used to detect frustration (Kapoor et al., 2007) and boredom (D'Mello, Chipman and Graesser, 2007). It should be noted that some states were excluded due to lack of validated methods to induce the state, and hence inability to validate measurement effectiveness.

Setup

The proposed framework (Figure 1) is planned to be used inside any classroom that has its students in front of computers. In case the room has a whiteboard, the room setup needs to have the students also facing the computers. The idea is to augment and enhance the professor's teaching abilities during the whole duration of class/lab, whether he/she is presenting something on a board or gives certain tasks to the students.

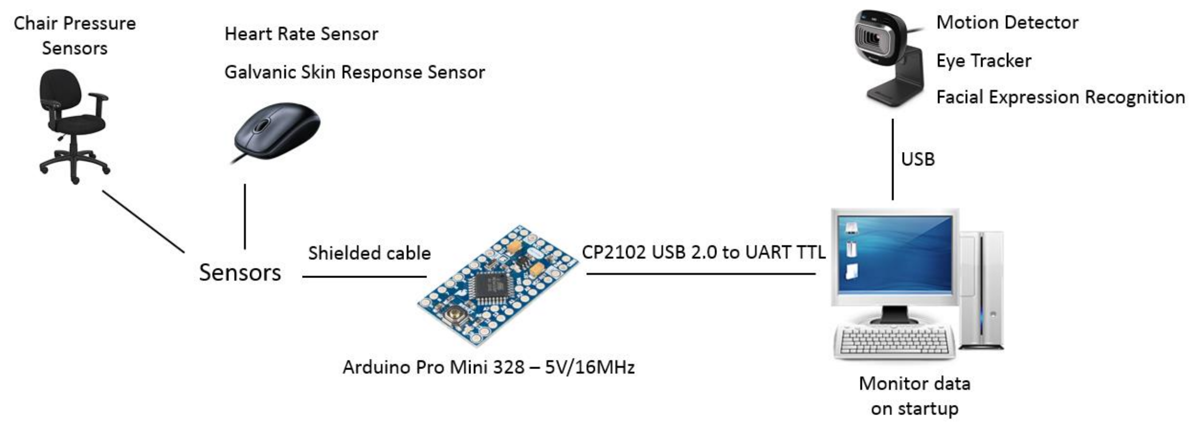

Figure 1. Affective state reading framework

Data acquisition will be done through the chair, mouse and webcam. These are connected to a microcontroller for data processing or directly to the computer. The monitoring is done on startup, without any external input from the student or the teacher.

Chair sensors

The chair will contain a set of pressure sensors in the seat and the back to indicate the posture. Changes in posture indicative of boredom (e.g., people tend to lean back when they are bored) can be measured using a pressure sensor embedded on the seat and the back of a chair (Woolf et al., 2009; D'Mello, Chipman and Graesser, 2007). Changes in posture, measured using chair pressure sensors are indicative of levels of engagement in that people tend to lean forward in their seats when they are engaged (Mota and Picard, 2003) or when they are experiencing the state of flow, a state of highly focused engagement where skill level matches challenge level of a task (D'Mello, Chipman, and Graesser, 2007). This offers us the ability of measuring affective states such as anger, frustration or boredom. Improving the posture analysis can be done using the camera and motion detection algorithms.

Mouse sensors

The mouse will have a heart rate sensor and a galvanic skin response sensor incorporated. The sensors will be inside the mouse, which will be used normally. Electrodermal sensors can be used to measure galvanic skin response (GSR), which has been linked to variations in emotion (Critchley, 2002) and emotional response (Bradley, Moulder, and Lang, 2005), indicative of emotions such as anxiety, frustration (Scheirer et al., 2002), and boredom (Merrifield, 2010). Cardiovascular measures such as heart rate can be used to determine levels of arousal (Jang et al., 2002; Hoover and Muth, 2004), and changes in heart rate have been found to occur during periods of anger, fear, (Lisetti and Nasoz, 2004), and boredom (Merrifield, 2010). A combination of heart rate and variability have further proven useful in discriminating emotional states (Jang et al., 2002) as well as the level of stress induced by specific aspects of a test environment, such as aircraft takeoff and landing (Cacioppo, Berntson, Sheridan, and McClintock, 2000). Based on these series of studies and using these sensors, we could profile affective states such as anger, frustration, fear, anxiety or boredom. An important thing to consider here is the place of the sensors on the mouse as different people have different mouse grips, and the sensors need to be in contact with the hand. Such mice already exist on the market but do not offer any API to access the sensor information (Mionix Naos QG).

These sensors will be connected to an Arduino Pro Mini board to help gather all the data, process it for a more readable manner and send it further to the computer. The board can be placed right next to the computer system unit and be connected to the sensors via shielded cables.

Camera

The web camera can be any normal web camera on the market as long as it has a decent resolution. Feature extractions from speech and facial expression classifiers have been utilized to assess valence (positive or negative nature of the emotion) and arousal components (Woo Kim, Jin, Fuchs, and Fouad, 2010). Using a web camera to distinguish facial expressions has also been used to determine specific emotions such as anger, disgust, fear, joy, and surprise (Woolf et al., 2009). Eye-tracking can be used to assess emotional arousal via pupilometry (Partala and Surakka, 2003) or to assess cognitive workload via blink rates (e.g., Scerbo et al., 2001), pupil amplitude variation (Ahlstrom and Friedman-Bern, 2006), pupil dilation (Pomplun and Sunkara, 2003), and saccade peak velocity (Di Stasi et al., 2010), attention via number of fixations on each area of interest (Hyona, Radach, and Deubel, 2003), and drowsiness via blink rate and blink duration (Ryu and Myung, 2005).

Every data acquisition here is done through software. Using Emotion API from Microsoft Azure we can recognize anger, contempt, disgust, fear, happiness, neutral, sadness or surprise. With the help of eye tracking techniques, we can measure attention and workload. Using Face API from Microsoft Azure, we can recognize each student and save personal data and also monitor class attendance automatically.

As we can see, all of this is done with non intrusive devices, in a seamless fashion, without requiring any involvement from outside actors. The students simply sit down at their computers and take part in the lab normally. There is no awkward transitions, interruptions, or indications of disparity.

All the information is then processed in real time on the computer, giving each data acquisition device a certain weight in order to measure and calculate the student's affective states. The weights are given after a series of user test periods and also based on the reliability of the data acquisition devices. For example, the heart rate could have more impact in observing a certain affective state than the posture or we could find out that it is not reliable due to a bad sensor position in the mouse leading to inconsistent results.

All the computers are connected to the lab network and the teacher can monitor in real time the classroom state. Note that the teacher should not be able to see individual information for a given student, but the classroom as a whole. Data can also be stored to keep track of progress or to help discover recurring patterns that need to be improved (Figure 2).

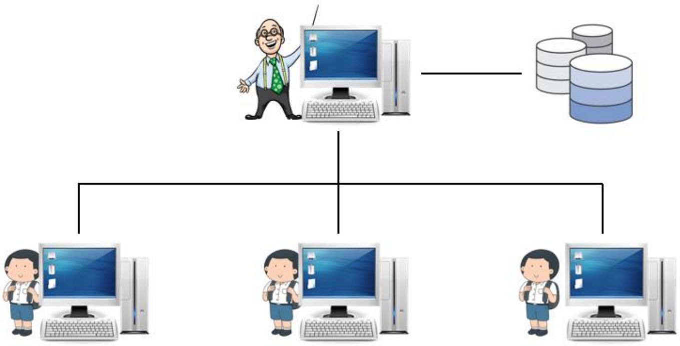

Figure 2. System setup in the classroom

This system enables teachers to have a grasp on the affective state of their classroom, but to become effective it is critical that they are able to recognize and adapt to students cognitive and affective state. It creates an opportunity to make a more effective and efficient teaching environment. I believe that this system has also a place in an environment without a physical teacher, where, by analyzing the data in real time, the teaching or training system can also adapt in real time to the students cognitive and affective states, similarly to the way a teacher could.

Unfortunately, the teachers do not always show eagerness or enthusiasm in changing their teaching methods over the years. More studies also remain to be done in order to refresh and improve the act of teaching based on the cognitive and affective states of the students. Acquiring all this data has no significance if we do not know how to use it.

A point could also be made that student engagement requires greater human involvement, not greater technology involvement. It is important to note that technology tools like this one are not replacing humans' abilities but merely augmenting them. Instructors can incorporate the findings from sentiment analysis into their approaches without relying solely on them.

Privacy

Based on my research and knowledge, I have not found any direct series of government laws that address this issue, however, the university administrators have final say over these decisions. The lawfulness aspect of the project still remains a part that surpasses my scope of knowledge right now and I cannot give more information regarding it. It is truly a delicate matter that needs to be taken care in order to avoid creating problems such as the outcry resulted in 2014 when Harvard University secretly photographed students with the goal of improving attendance collection.

As far as I can see it, the best approach would be to provide disclosure to students up front and require their acceptance to let them know exactly how their information is being collected and how it will be used. I believe that there should not be created any context in which the data is being used to affect an individual student's trajectory or what's available to them or their grades. The professor will not be presented in any way, shape or form information about specific students' emotional behaviors, but rather the classroom as a whole.

However, it is true that people who know they are being analyzed tend to not give accurate results due to different forms of the psychic staring effect or even some spend time early on "pulling faces" and trying to game the system, but they eventually retreat to their normal stance, allowing for accurate analysis. A good non intrusive system, that doesn't change or add to the student's daily routine in the laboratory will definitely help in gathering more reliable data.

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