Incorporating Affect into Educational Design Patterns and Frameworks

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Abstract

In this paper we aim to bring together research in affective computing and educational design. We review the literature and describe the design of a methodological and technical framework for studying pedagogical designs that are informed by the affective state of learners. The proposed framework integrates techniques for affect recognition using physiology and text, and describes an approach to studying the affective dynamics of collaborative activities. We aim for this exploratory work to improve our understanding of how to best design group learning activities, and then to communicate these outcomes in the form of educational design patterns.

1. Introduction

Experienced teachers and tutors learn to recognise and take into account students' emotional states during an activity, and to act accordingly. For example, when students are engaged in discussion on the topic matter and one student becomes enraged at the opinion of another student, the discussion becomes personal, and progress is stalled. During the course of a collaborative learning session, students are likely to move through a variety of emotions from excitement, anxiety and engagement to anger, neutrality or boredom. Our evidence-based understanding of how and when to intervene or of how emotional states in general unfold during collaborative interaction and how this influences learning, is very limited.

The design of collaborative learning activities has yet to be informed by the underlying affective dynamics that learners experience. Although emotions have generally been recognized as having an important impact on learning, particularly in the context of collaborative activity, researchers have found this aspect of learning difficult to research and model. However, recent advances in biomedical engineering, neuroscience and data mining have stimulated research attention to this issue. We are at a point where significant accuracy in recognising basic emotional states is feasible via a number of approaches. The identification of affective and mental states provides a magnifying glass for closer understanding of the processes involved in collaborative learning activities.

Computer Supported Collaborative Learning (CSCL) researchers evaluate activities and systems using quantitative and qualitative data that describe impact on the cognitive aspects of engaging in activities. In contrast, almost no experimental research has been performed to evaluate the affective aspects of these group activities. The focus in CSCL has been on cognition almost exclusively, and even within Psychology and related disciplines the affect and the cognition-affect relationship has been neglected. This is changing quickly as advances in technology are making the systematic study of affect more feasible, and as a response to research that has highlighted the vital role emotion plays in decision making and learning. For example, neuroscientists have recently shown how a person with full cognitive abilities intact, but lacking in normal emotional response, is incapable of making decisions essential for life [1]. In Education, there has been increasing evidence to show how emotional states inevitably affect learning. For example, there are clear correlations between emotional states and pretest results (due to different levels of engagement with learning activities), and with learning [2]. These studies have focused on using information about the mental/affective state of an individual subject to improve the user/learner experience. To date, the dynamics of collaborative activities have only been studied using social psychology techniques [3].

The new data collection and processing techniques developed by this and other projects, can now allow for the recording of verbal interaction (speech and text) and physiological signals of learners engaged in collaborative activity (both online and face to face). Ergonomic sensors that record physiological signals while students collaborate (in a laboratory scenario) can be integrated with software that processes these signals, merges it with behavioral information (i.e. what learners type simultaneously), and identifies the affective states that individuals go through as they collaborate. Herein, we propose this combination of technologies and techniques as the first research environment designed to study the affective and physiological aspects of collaborative learning.

Other researchers are also developing learning technologies that employ affect recognition, but with a focus on the improvement of Intelligent Tutoring Systems. Graesser [4] reported the evaluation of an affective tutor (extension of their ATutor), for which 28 college students discussed Computer Science topics with ATutor's natural language dialogue system. Dialogue (based on the text students wrote), posture (recorded with sensors placed on a chair) and facial features (recorded with a camera) were used to detect the students affective state and this information was used to adapt ATutor's responses. In a related project [5] the affective states of 61 High School students playing Tower of Hanoi were identified based on signals from 4 sensors (camera, pressure mouse, skin conductance, and posture chair). The authors studied congruence (appropriateness of teaching intervention with respect to learners' frustration level) and interventions. These projects studied data mining algorithms trained with the subjects' data (behavioral and physiological signals and text) and optimized to make accurate automatic classifications of affective states. These affect recognition strategies were used to improve the adaptability of a software tool that interacts with a single student.

We take a distinct, but complimentary, focus and aim to use affect recognition to generate evidence and insight into the way people collaborate and learn in group activities Our second aim is to use this new knowledge to improve educational design. Extensive research in social psychology [3, 6] has demonstrated the complexity of studying the effect of emotion on collaborative activities. We hope to address this issue with the tools being developed.

Section 2 reviews some of the literature on emotion recognition and on educational design patterns. Section 3 puts forward an approach to extend current educational design patterns in order to make them affect-aware (informed by affective factors). It also proposes the creation of new affect-specific patters. This research framework would use a multimodal emotion recognition component that employs a combination of physiological and speech/textual recordings processed using pattern recognition techniques. Section 4 concludes with a call for studying how affect should influence educational design.

2. Background

Approaches to affect recognition – prospecting tools

Recent literature has produced successful recognition techniques that classify physiological and neurophysiological signals, behavioural data and text / speech into different sets of emotions. A commonly used model to represent these emotions, includes 'arousal' and 'valence' axes [7] as shown in Figure 1.

Most current projects build the recognition systems using a common set of data mining techniques: 1) One or more signals are recorded for each subject while they elicit an emotion, 2) researchers then look for features of those signals that can be used to build classifiers, and 3) different pattern recognition approaches are evaluated [8]. These systems can provide a window for looking into the affective dynamics of collaborative activities.

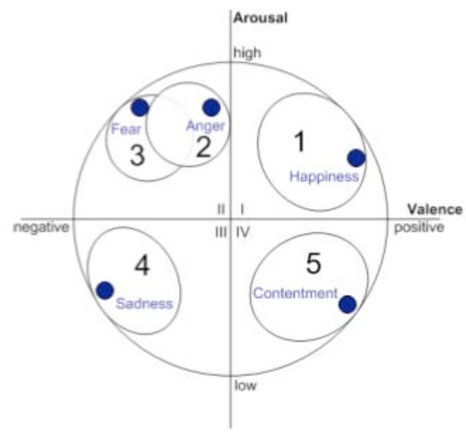

Figure 1: Emotion model (reproduced from [9])

When *physiological signals* are used there are two approaches to building the emotion recognition component. The tradeoffs are similar to those faced by the speech recognition community in its beginnings: the quality of the signal processing and recognition depends on the complexity of the dataset. First there are the systems trained to work on a single subject. They can achieve relatively good performance, but might not generalize to other subjects. Picard [10] developed one such system, training machine learning algorithms with data from 20 sessions where 1 subject elicited 8 emotions while 4 sensors recorded heart activity (electrocardiogram - ECG), face muscle activity (electromyogram - EMG), blood volume pressure (photoplethysmyograph) and skin conductance, achieving 81% classification accuracy. They analysed a total of 40 features, identifying the best 11 features for their subject. Although the set of features may differ for other subjects, the methodology described is quite general.

A second approach is to seek a 'universal' recognizer. Researchers at Samsung [11] developed a system aimed at recognizing emotions in a wide population in a standardized way. They recorded the elicitation of 4 emotions with 3 sensors on 125 subjects achieving ~30% accuracy using a support vector machine (SVM) algorithm. Ekman [12] also seeks this type of recognizer analysing features in people's faces while they are in different affective states. Using their Facial Action Coding System (FACS) researchers are building 'universal' recognition systems that record and analyze high-speed photographs and that in lab conditions can be as accurate as a trained human.

In a recent study we recorded 3 subjects who each elicited a sequence of 8 emotions on 3 different days while 3 sensors recorded their ECG, EMG and skin conductivity. We evaluated 8 classifiers and achieved up to 95% accuracy on a single subject using 10-fold cross validation. In this study Naïve Bayes, Bayesian Networks, Support Vector Machines, and Neural Networks classified 3 physiological signals (ECG, EMG and SC) for the 3 individuals who elicited 8 emotions. In this preliminary study neural networks had the best accuracy (95% for a single subject), followed by SVM which had a much better time performance. The method used in this preliminary study utilised a subject-elicited, lab setting, where the elicitation was timed so the training data was easier to collect. In the next step we will need to refine the approach, so the recordings from all the datasets will be annotated. The strong consistency of classifier accuracy (> 90%) across the nine primary data sets (3 for each of 3 subjects subject) shown in our first study is already a good indication of the potential for more complex experimental settings.

Other recognition systems combine other types of signals for their recognition including:

- Language, using features from the speech or using text to speech and then text classification.
- Behaviour, using features such as sitting position, breathing patterns or facial expressions.

Patterns in collaboration

Educational design patterns describe reusable solutions to the design of learning tasks and environments. Essentially, a design pattern provides a generic, reusable solution to a recurring design problem or situation. The key is to describe the solution in a way that makes the solution reusable for similar problems. Patterns describe forces.

For example, there is the pattern for '`Group nomination`' (pattern *title*). The *problem* addressed by this pattern is how to get students to generate a number of original ideas on a topic in a short amount of time. The *context* is an activity for decision-making around a certain topic or problem without a specific solution. The resolution implies, not only creating ideas or solutions, but also choosing the best idea. The ideas should be distinct but students are not expected to elaborate them until a later stage. Each pattern includes a list of *forces* or constraints. Typically, these include elements such as number of participants, duration, workload, etc. Here is where discoveries on affect could be included to enhance the efficacy of the pattern. A new type of force could be added that would include the general motivation or mood of the group. *Examples* of the activity for this pattern include synchronous co-located (face-to-face) or online sessions. In the *solution*, the pattern describes the actual activity, including forces, as such:

1. Posting ideas, since no criticism or elaboration is allowed in this step, group dynamics are often supervised by a tutor for better results.
2. Discussing the ideas to obtain clarifications and evaluation.
3. Idea-prioritising, each participant is asked to assign a mark for each idea.
4. Idea-reporting, reporting the highest idea to other groups.

3. A research framework

The first challenge posed by the study of affect in collaboration is setting up controlled yet meaningful collaborative activities in which data can be recorded. This is difficult because of all the experimental factors that come into play [10]. For example, should the subject elicit the state on cue or should it be triggered by an event? Should the experiment take place in a lab or in a real-world setting?

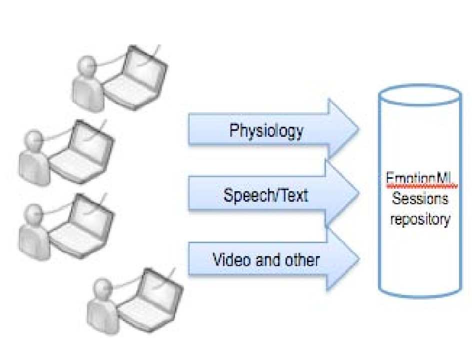

Figure 2: schema of recording and processing activities

We opt for identifying a small set of emotions, that can be recognized reliably and that are shown to influence the collaborative process. A tentative list of these would include: ‘boredom’, ‘anxiety’, ‘anger’, and ‘excitement’. Here we describe how we will identify them within actual collaborative activity.

Physiological signals: While participating in the collaborative activity, subjects will be connected to sensors that record key physiological signals (ECG, EMG, EEG, SC) as they discuss a topic in a group. Subjects will work in front of a laptop with a webcam on which data will be logged including chat text or voice and video when the activity is face to face. It is not expected that students will use this recording equipment in real learning situations, outside this research project. Chat logs (or voice to text transcriptions for face to face scenarios) will also be tagged for their affective content with an emphasis on identifying strong emotional cues. These two data sets will be annotated with EmotionML (a W3C markup language). This annotation format will also allow us to integrate the resulting systems into IMS Learning Design compliant systems [13], adding affect to real-world learning design platforms. The recordings and expert annotations will be supported with interviews and self-assessments, similar to the Self Assessment Mannequin [14] and other approaches [15] used in emotion research.

Text. We are exploring techniques to classify statements based on their affective content. The framework is designed to combine thesaurus and corpora based approaches. The Wordnet Affect [16] is a hierarchical thesaurus of affective domain labels in which affective concepts are annotated, and will be at the core of a thesaurus based approach (others include Storm [17]). Basically a statement containing emotionally charged terms would indicate a high arousal, and possibly a valence position (i.e. ‘I hate the way you work’ would tell us something about the feelings a person has about a collaborator).

The corpora based approach will be based on ‘sentiment analysis’ research [18, 19] where opinions with regards to an entity are classified on a scale similar to the valence used in emotion models

These annotated datasets will be used to train two sets of classifiers, one for the physiological signals and another for the text [20]. We will combine two pattern recognition strategies, each aiming at creating an accurate real-time classifier.

With a framework for identifying affective states, we can analyse when their changes co-occur with significant events during a collaboration activity. Having real time recognition will allow us to introduce interventions (i.e. a tutor coming in and providing a recommendation) and identify its effects, both from outcomes and affective perspectives.

Since the aim is to build classifiers that can be used to understand how people collaborate, having classifiers that are accurate even if only on a few people and situations is more important than aiming for what have been termed ‘universal’ classifiers. For each of the techniques we will produce a classifier with optimum offline accuracy. These classifiers will then be studied in combination during actual collaborative activities.

Pattern recognition strategies such as those used to detect successful learning processes will be used to detect combinations of affective sequences that produce satisfactory results. An important aspect of our data that we need to take into account is the timing of events, as described in the annotated EmotionML record for the session. We want to extract the sequences of ‘affective events’ (those that we can recognize automatically) that characterise a particular session. A data mining technique which considers this temporal aspect is sequential pattern mining [21]. It finds sequential patterns that occur in a dataset with at least a minimal level of frequency called support.

The quality of the session, as assessed by a human tutor, and the subjects themselves, will be used to identify successful ones from unsuccessful ones. This side of the experiment introduces new challenges, such as the Hawthorne effect, where the behaviour of test subjects is temporarily altered because they are aware of being participants in a study. Normally they show increased performance. This will be addressed using a crossover design, so we will aim at having students in the same groups in our lab experiments as they are in real courses that we run in Engineering and Education (where our subjects normally come from).

4. Conclusions

We have proposed to study how emotions affect collaborative learning activities. We describe the design of a framework that will allow us to study and introduce affective forces into educational design patterns. Design patters provide a formalism for describing the results of studying affective dynamics for learning in a reusable way. By analysing collaborative scenarios and identifying patterns of successful sequences, we will be able to improve our understanding of how to better design group learning activities.

Activity patterns such as ‘brainstorming’ or ‘peer review’ describe the tradeoffs that an instructor must consider when running this activity. We will include analysis of the affective factors.

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