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Towards Building Incremental Affect Models in Self-Directed Learning Scenarios

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Abstract: Self-reflection and self-evaluation are effective processes for identifying good learning behavior. These are essential in self-directed learning scenarios because students have to be responsible for their own learning. Although students benefit from doing fine-grained analysis of their own behavior, which we observed in our previous work, asking them to perform tasks such as analysis and making annotations are tedious and take significant amount of time and effort. In this paper, we present our work on the development of incremental affect models that can be used to minimize effort in analyzing and annotating behavior. Incremental models have an added benefit of adaptability to new information, which can be used by future systems to provide up-to-date affect-related feedback in real time.

Keywords: self-directed learning, self-regulation, annotation, affect modeling, incremental

1. Introduction

Self-reflection and self-evaluation are self-regulatory processes that can help students understand their learning behavior (Zimmerman, 2002). Students who understand their behavior can change it so they can perform better in succeeding learning sessions. Although self-reflection and self-evaluation are important, much effort is required which often discourage students from actually using them. When available, teachers or peers can also help students regulate their learning behavior by directing their attention to what they did wrong or by giving them suggestions for learning better. Unfortunately, teachers or peers are not always available especially when students study on their own. Furthermore, students also need to learn how to regulate their own behavior so they do not become dependent on external evaluation and feedback.

In our previous work, we developed a self-reflection and self-evaluation support tool that can help students observe their own behavior and encourage them to evaluate it (Inventado *et al.*, 2013). The tool captured screenshots of the students' desktop and webcam, which they later reviewed and annotated after learning. The tool also asked students to evaluate their performance according to their analysis after annotation. Our results confirmed the significance of self-reflection and self-evaluation in learning wherein students discovered aspects of their learning behavior they did not know about, identified problems in their learning behavior and formulated strategies that could improve their performance. Much like other existing research, our results highlight the value of understanding one's learning behavior despite the significant amount of time and effort required.

The aim of the work discussed in this paper is two-fold wherein we want to: 1) minimize the effort required for observing and annotating learning behavior and 2) utilize students' annotations for creating affect models that future systems can also use to provide real-time feedback.

2. Data Characterization

The data we used for our experiments were taken from our previous work, wherein data was collected from five separate two-hour learning episodes from four students over a span of one week (Inventado *et al.*, 2013). In a learning session, students had complete control over when, where and how they learned. Specifically, two of the students' task involved writing an academic paper, while the other two students created research presentations. After each session, students reviewed their learning session and annotated their *activities*, *intentions* and *affect* using a software tool we developed. Activities referred to any activity done while learning (e.g., using Google Chrome, using Microsoft Word, reading a paper, sending a text message). Intentions indicated whether the student performed a learning or non-learning related activity. Affect referred to how students felt while performing an activity and was differentiated using academic emotion labels (i.e., delighted, engaged, confused, frustrated, bored, surprised or neutral) which are commonly used to describe emotions in learning settings (Baker *et al.*, 2012; D'Mello *et al.*, 2008).

Students' annotations were processed so that contiguous annotations with the same activity and affect labels were merged. This resulted in a total of 1,015 annotations with an average of 50.75 annotations in each learning session. Each annotation was used as a training example consisting of four features (i.e., time elapsed in seconds, activity, intention and activity duration) and a corresponding affect label. The distribution of the affect labels was— Engaged (39.61%), Neutral (30.34%), Confused (11.33%), Bored (9.06%), Delighted (7.09%), Frustrated (2.07%), Surprised (0.39%) and Disgusted (0.10%).

3. Incremental Affect modeling, Results and Analysis

Much research such as that of (Baker *et al.*, 2012) and (D'Mello *et al.*, 2008) have modeled students' affect as they used computer-based learning environments. These learning environments were built specifically for teaching a particular domain and students' actions were constrained by the design of the environment. In a self-directed learning environment however, students' behavior is unconstrained and information such as learning goals, learning progress and possible actions are only partially available.

Affect models are usually built from many students' behavior and generalize over how they commonly react to events while learning. These models are often static so they are highly dependent on the data they were trained on. However, the methodology used in our previous work was quite different wherein students annotated their affect at the end of every learning session as a part of helping them self-reflect and self-evaluate. The availability of students' annotations enabled us to build incremental models that adapted to new data after every session.

In order to build and evaluate the performance of incremental affect models in self-directed learning scenarios, we built one model for each student (i.e., personalized model). In the first step of the process, each model was trained on data from the first session. The resulting model was then evaluated by using it to predict affect in the second session. Data from the second session was again used for training and the updated model was evaluated on the data from the succeeding session. This process was repeated until the model was tested on data from the last session. The whole process resulted in four personalized affect models which were updated and evaluated four times. We used a data stream mining toolkit called Massive Online Analysis (MOA) (Bifet *et al.*, 2010) which contained implementations of the different machine learning algorithms we used to conduct our experiments.

Table 12: Performance of personalized incremental affect models over sessions.

		Incremental Affect Model Performance – Accuracy (Kappa)			
Algorithm	**Student**	**Session 2**	**Session 3**	**Session 4**	**Session 5**
iOVFDT	1	0.274 (0.080)	0.440 (0.275)	0.636 (0.469)	0.356 (0.162)
	2	0.640 (0.412)	0.497 (0.263)	0.511 (0.319)	0.406 (0.212)
	3	0.203 (-0.005)	0.668 (0.273)	0.706 (0.465)	0.592 (0.190)
	4	0.000 (-0.045)	0.163 (0.140)	0.000 (-0.007)	0.567 (0.402)
Weighted Naïve Bayes	1	0.302 (0.130)	0.378 (0.171)	0.505 (0.263)	0.872 (0.678)
	2	0.659 (0.429)	0.473 (0.264)	0.437 (0.216)	0.302 (0.059)
	3	0.328 (0.130)	0.618 (0.267)	0.837 (0.680)	0.810 (0.327)
	4	0.702 (0.495)	0.451 (0.137)	0.267 (-0.307)	0.525 (0.260)

Table 1 presents the results of the two best performing algorithms we used from our experiments. We can see that there were no constant improvements in the models' performance over time. A probable reason why this happened was because students' activities were used as a feature for modeling and according to the data, students were engaged in activities which they did not perform in previous sessions. Initially, collecting more training data would seem to be a good solution however, we also need to consider that the state space for activities in a self-directed learning environment is infinite. A few years or months from now, students could use new software or engage in new activities that we cannot foresee at the moment. Despite the decrease in the models' performance, we also see performance increase in succeeding sessions indicating that the models adapted to the new data. Unfortunately, due to the limited data we collected, we could not identify the best algorithm. We aim to collect more data in the future to perform better analysis.

4. Conclusion and Future Work

In this paper, we discussed the creation of incremental affect models for students in self-directed learning scenarios. Students learning in this kind of environment are not bound by any rules, thus making it difficult or even impossible to collect training data that could model the student well. It is advantageous to create incremental models because they can continuously accommodate new information, which also gives them the potential to perform better than static models.

Our observations for this experiment were limited by the number of sessions in which we gathered data. Collecting data over a longer period may reveal more interesting results. Currently, preliminary evaluations indicate that the resulting models have the capability of predicting affect using simple features making it worthwhile to investigate further. Using better features can further improve the performance of these incremental models.

The self-reflective and self-evaluative methodology we used highlighted the value of annotating one's own behavior despite the effort it required. The incremental affect models we built using the data from our methodology may be used by future systems to help minimize annotation effort by using the affect predictions as suggestions so that students can confirm affect annotations instead of identifying them manually. Furthermore, these affect models may also be used by future systems to predict students' affect and provide affect-based feedback in real-time because the data it uses is readily available.

The methodology we presented can be easily extended to other domains where people benefit from self-reflection (e.g., work, exercise). It can be used to predict other factors (e.g., stress, motivation) using features that can also be annotated (e.g., cost, effort).

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