Adapting Feedback Types According to Students' Affective States

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Abstract. Affective states play a significant role in students' learning behaviour. Positive affective states can enhance learning, while negative ones can inhibit it. This paper describes the development of an affective state reasoner that is able to adapt the feedback type according to students' affective states in order to evoke positive affective states and as such improve their learning experience. The reasoner relies on a dynamic Bayesian network trained with data gathered in a series of ecologically valid Wizard-of-Oz studies, where the effect of feedback on students' affective states was investigated.

1 Introduction

This paper reports on the development of an affect state reasoner, which is able to tailor different feedback types according to student's affective state during their interaction with a learning environment.

Affective states interact with and influence the learning process [1, 2] and therefore detecting student's affective states and helping them regulate their affect is important. Most of the related work in the field focusses on detecting emotions in different input stimuli, ranging from spoken dialogue (e.g. [3]) to keyboard and mouse interactions [4]. Only a limited amount of research has been undertaken into how those detected emotions can be used in a tutoring system to enhance the learning experience. One example is Conati et al. [5], who developed a pedagogical agent that is able to provide support according to the emotional state of the student and their personal goal. Another example is Shen et al. [6] who tailor the learning material according to a student's affective state. D'Mello et al. [7] use the student's affective state to respond via a conversation.

In this work, we report on the development of an affective state reasoner, which aims to change negative into positive affective states by adapting the feedback type. It is a dynamic Bayesian network trained with data from Wizard-of-Oz studies (WoZ) where the effect of different feedback types on students' affective states was investigated (*c.f.* [8]).

2 The iTalk2Learn platform

iTalk2Learn is a learning platform for children aged between 8-12 years old who are learning fractions. It includes an exploratory environment called Fractions Lab. The platform is being designed to detect children's speech in real time which, together with their interactions, are analyzed in order to provide adaptive support.

2.1 Intelligent support

Figure 1 provides an overview of the different layers of support in the platform. Similar to [9] it consists of three main layers: the analysis or evidence detection

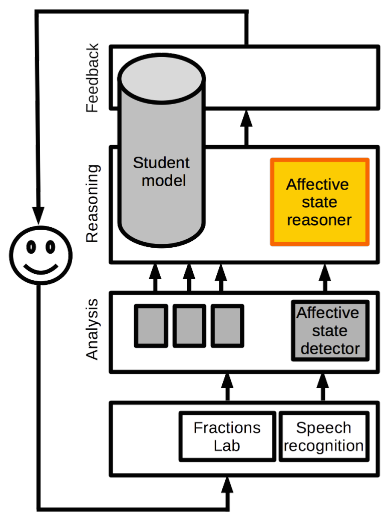

Fig. 1. Components of the intelligent support.

layer, the reasoning layer, and the feedback generation layer. In the evidence detection layer, the student's interactions with the platform are identified. It includes the affective state detector, where the student's affective state is detected via their speech and their interaction with the learning environment.

Based on the evidence detection component, the reasoning layer decides if and what feedback should be provided. This layer includes a student model and the affective state reasoner. The student model includes the affective state of the student as well as information about actions that the student preformed, such as whether they followed the advice that was provided by the feedback. The affective state reasoner uses the information from the student model to decide what type of feedback should be provided as described below.

The feedback generation layer receives the output from the reasoning layer and with further information from the student model decides how the feedback should be presented; for example high- or low-interruptive feedback.

2.2 Affective state reasoner

The aim of the affective state reasoner (see the orange box in Figure 1) is to tailor the feedback according to the affective state of the student, in order to evoke a positive affective state and thus enhance their learning experience. We focus on a subset of affective states identified by Pekrun [10]: flow, surprise, frustration, and boredom. We also add confusion, which has been identified elsewhere as an important affective state during learning for tutor support [11].

The affective state reasoner is a dynamic Bayesian network, based on data gathered in ecologically-valid WoZ studies [8] which investigated the impact of different feedback types on the affective state of students. The feedback types include problem solving support, reflective prompts, talk aloud and talk maths prompts, task sequence feedback, and affect boosts. The data from those studied showed that, to be effective, different student affective states require different feedback types. For example, when a student is confused, affect boosts or guidance feedback are more effective than others at enhancing the student's affective state. Figure 2 shows the dynamic Bayesian network of the affective state reasoner. We trained the network with the data from the WoZ studies annotated by three researchers. For the annotations we used the Baker-Rodrigo Observation Method Protocol (BROMP) and the HART mobile app that facilitates coding in the classroom [12] . Kappa based on the the annotation was .56, $p<.001$. We also annotated the affective states after the WoZ studies using screen and voice recordings. This was then compared against the field annotations. Kappa between the consolidated annotation and the HART data was .71, $p<.05$.

For the trained dynamic Bayesian network we employed a 10-fold cross-validation that shows encouraging results so far (accuracy=82.35%; Kappa=0.58; recall true=0.69). The affective state reasoner receives the affective state of the

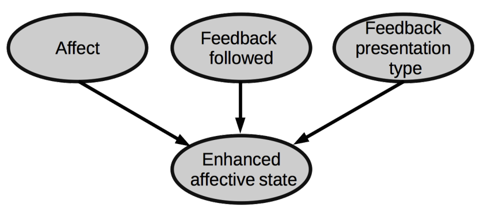

Fig. 2. Dynamic Bayesian network of the affective state reasoner.

student (based on speech and interaction) as well as information about previous feedback followed. For each feedback type the enhanced affective state is predicted. This is used to determine which feedback type will be the most effective at enhancing the affective state. After appropriate feedback has been provided to the student, the CPT of the network is updated according to the student's affective state (and whether the previous feedback was followed) after feedback was delivered. In this way, the affective state reasoner is able to accommodate individual differences.

3 Conclusion and future work

We have developed an affective state reasoner, which is able to tailor different types of feedback according to the affective state of the student, in order to enhance their affective state. The affective state reasoner is a dynamic Bayesian network trained with data from WoZ studies, which investigated the effect of feedback on affective states. The results of the trained network are encouraging. The next stage in our research is to test the model with a new set of data, collected from future studies.

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