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Analysis of Students' Emotion from a Text Corpus

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Abstract: Emotions play an important role in e-learning environments. Previous studies have investigated the prediction of learners' emotions using various features such as acoustic-prosodic features, mouse movements, facial features, and body postures. In addition to these features, linguistic features are also useful for identifying learners' emotions especially in text-based e-learning systems. Therefore, this study attempts to analyze the linguistic features for different types of emotions. To accomplish this goal, we first collect a text corpus of emotion sentences from student-teacher dialogs in mathematics learning. Each sentence is then annotated to provide analysis results such as the linguistic features, proportions, annotator agreements, and annotation accuracy for different emotions.

Keywords: Emotions, natural language processing, language resources

Introduction

Emotions have drawn more attention in the field of e-learning. Previous studies have shown that emotions may have a positive or negative impact on learning outcomes [1][2][3]. For instance, Rodrigo et al. has summarized that boredom may have a negative impact on student achievement, and confusion may have both positive and negative effects [2]. Therefore, researchers have investigated different methods for prediction of learners' emotions to improve learning [4][5][6]. Litman and Silliman used acoustic-prosodic features to detect student's emotions in their ITSPOKE tutoring system [4]. Horiguchi et al. proposed the use of mouse and face movements to explore relationships between mental states and learners' behaviors [5]. Graesser et al. integrated multiple features such as facial features and body postures to identify learners' emotions in their AutoTutor system [6].
In addition to the features mentioned above, linguistic features are also useful for emotion prediction. By incorporating the linguistic features, text-based e-learning systems [7][8] can be enhanced by identifying student's emotions from text inputs and providing personalized suggestions accordingly. To accomplish this goal, the first step is to analyze the linguistic features for different types of emotions occurred in learning environments. Therefore, we first collect a text corpus of emotion sentences from student-teacher dialogs in mathematics learning. Each sentence is then annotated to provide analysis results such as the linguistic features, proportions, annotation agreement and accuracy for different emotions.

1. Text Corpus Collection

We collected a text corpus from a junior high school in Taiwan. Three mathematics teachers and 149 students were involved in the collection process. The teachers and students

Table 1. Text corpus analysis — Emotion types, example sentences, and linguistic features.

Emotion	Example sentence	Linguistic feature
Delight	I made a big progress this time. Oh! Great! This question is so easy.	progress, great, easy, simple
Contempt	This question is so stupid and deserves no response. This question is too elementary. Even a kid can do it.	stupid, basic elementary, kid
Boredom	That's so bored. I have addressed such kind of questions many times before. I don't want to waste my time on such a tedious question.	bored, boring, tedious
Frustration	That's too bad. I will be failed. Forget it. That's too hard.	bad, fail, hard, difficult
Confusion	This question is ambiguous. I do not understand the meaning. Why the question can be solved in this way?	ambiguous, why, weird, confuse,

communicated with each other to discuss mathematical problems in the classroom. A total of 759 sentences with emotions were collected from the student-teacher dialogs to form a text corpus. We herein defined five emotion types: Delight, Contempt, Boredom, Frustration, and Confusion according to the previous studies [1]. Since not all sentences in the corpus contained an emotion type, we added Others to handle out-of-domain emotions.

2. Results

2.1 Linguistic Features of Different Emotions

Table 1 presents several example sentences for the five emotion types. As indicated, students may express Delight when they satisfy their performance or the questions are easy. Nevertheless, if the questions are too simple, then students may express Contempt. Students may also express Boredom when they feel bored due to the pointless or senseless questions. Conversely, students may express Frustration when they worry about their performance or the questions are hard. On the other hand, students may express Confusion when they are confused due to the ambiguous or incomplete questions. By observing the emotion sentences in the corpus, we summarize a number of linguistic features for different emotion types, as shown in the last column of Table 1.

2.2 Annotation Results

In order to analyze student's emotions, the three mathematics teachers annotated the corpus to create a gold standard of the emotion types. Each sentence in the corpus was first annotated with one of the five emotion types by two teachers (annotators). If there is a disagreement between the two annotators, then this sentence will be judged by the third teacher (adjudicator) for final decision. After all disagreements were resolved by the adjudicator, the proportions of the emotion types and the accuracy of the two annotators can be calculated from the corpus. Table 2 shows the annotation results. The results show that around 74% of the sentences in the corpus contained an emotion type, and the remaining 26% were out-of-domain sentences. Additionally, among the five emotion types, Delight and Confusion were the two major types.

For the analysis of agreement, Table 2 shows that the agreement between the two annotators A1 and A2 was 81.16%. Additionally, the agreement of Contempt and

Table 2. Annotation results.

Emotion	Num. of sentence	Proportion	A1-A2 Agreement	A1 Accuracy	A2 Accuracy
Delight	194	26%	93.30%	94.85%	98.45%
Contempt	53	7%	62.26%	77.36%	84.91%
Boredom	81	11%	69.14%	88.89%	80.25%
Frustration	99	13%	59.60%	79.80%	78.79%
Confusion	134	18%	84.33%	92.54%	91.79%
Others	198	26%	87.88%	89.90%	97.98%
Sum/Avg.	759	100%	81.16%	89.33%	91.70%

Frustration were relative low, indicating that these two emotion types were more ambiguous. Another observation is that the accuracy of A1 and A2 were 89.33% and 91.70%, respectively. Such human (expert) results can be viewed as the upper bound for automatic emotion classification using machine learning algorithms.

3. Conclusion and Future Work

In this study, we have collected a text corpus with different types of emotions. We also annotated this corpus to analyze the linguistic features, proportions, annotator agreements, and annotation accuracy for different emotions. Future work will be devoted to developing machine learning algorithms using the analysis results to automatically identify learners' emotions and provide personalized suggestions in mathematics e-learning systems.

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