Exploiting Sentiment Analysis to Track Emotions in Students' Learning Diaries

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ABSTRACT
Learning diaries are instruments through which students can reflect on their learning experience. Students' sentiments, emotions, opinions and attitudes are embedded in their learning diaries as part of the process of understanding their progress during the course and the self-awareness of their goals. Learning diaries are also a very informative feedback source for instructors regarding the students' emotional well-being. However the number of diaries created during a course can become a daunting task to be manually analyzed with care, particularly when the class is large. To tackle this problem, in this paper we present a functional system for analyzing and visualizing student emotions expressed in learning diaries. The system allows instructors to automatically extract emotions and the changes in these emotions throughout students' learning experience as expressed in their diaries. The emotions extracted by the system are based on Plutchik's eight emotion categories, and they are shown over the time period that the diaries were written. The potential impact and usefulness of our system are highlighted during our experiments with promising results for improving the communication between instructors and students and enhancing the learning experience.

Categories and Subject Descriptors
I.2.7 **[Artificial Intelligence]**: Natural Language Processing – *Text Analysis*

General Terms
Design, Experimentation, Human Factors

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Emotion detection, sentiment analysis, learning diaries, visualization

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1. INTRODUCTION
Instructors are constantly looking for ways to understand and address the challenges that their students face during the learning process. Emotional obstacles, in particular, are known to hinder a learner's progress: students learn and perform better when they feel joy, satisfaction and contentment about a particular subject [13]. One approach that instructors use to be aware of their students' emotional welfare is the incorporation of learning diaries which are reflective of a student's journey throughout the duration of a course [16]. Understanding students' personal diaries to uncover their feelings toward the learning experience as a whole (i.e., the instructor, the learning material and topics, and themselves and their performance) can lead to improvements in the quality of the instructor-student relationship and the manner of teaching [2].

Over the past two years, a large number of sentiment analysis (SA) programs have been developed to discover the sentiment content of texts in various genres including news headlines for polarity and emotions [28], movie reviews for polarity [20] and Twitter posts for emotions [11]. However, not much work has been done in applying SA in educational settings, particularly in the analysis of students' learning diaries. Applying SA to the educational field holds many possibilities for improving the communication pathways and learning opportunities between instructors and their students. That is, it is well documented that students' emotions toward the learning experience have an important influence on learning outcomes [9] and that happy learners are generally more motivated to accomplish their set goals throughout the course [13]. Hence, the prompt detection of students' emotional problems or of students that need particular attention is of vital importance. Through the automatic analysis of the sentiments and emotions expressed in students' learning diaries it is possible to promptly identify students that are in need of immediate and personalized feedback. Additionally, using SA on students' text is less invasive than, for instance, personal interviews, which is desirable for instructors as they obtain information on a student's emotions without disturbing his or her learning [25].

SA is framed within the area of natural language processing (NLP) and is broadly defined by Pang and Lee [20] as the computational treatment of opinions, feelings, emotions, and subjectivity in texts. Current work in SA focuses on classifying sentiments based on the polarity/valence (positive, negative, neutral) of text [20]. In this paper, for a richer understanding of the students' texts, we go beyond polarity classification and identify expressions of emotions such as joy, sadness, anxiety, and frustration and how these emotions evolve over the period of time when the diaries are written. Our work is relevant to the education community as an application of SA in the educational context. As Goleman [7] points out in his book, Emotional Intelligence, expert teachers are able to recognize a student's emotional state, allowing them to respond in an appropriate manner that has a positive impact on the learning process. Goleman [7] also adds that students should also be able to recognize and accurately label their emotions and how they may guide their actions.

Hence, in order to provide instructors with a fast method to identify students' emotional states, this paper presents a functional system that takes students' learning diaries as input and gives a graphical visualization of the changes in emotions in the analyzed learning diaries as output. In addition, our system illustrates the polarity scores and the various topics covered in the diaries.

Our system's main contribution relies in providing the instructor with new perspectives for the detection, analysis and prompt addressing of the emotions that the students express. Our system also facilitates swift interventions and the creation of personalized feedback to students who so require, hence improving student motivation and performance [25]. It is not the aim of the system to predict a student's learning process or progress; it simply provides a window into the emotional well-being of students during their time of writing the learning diaries. The instructor is allowed to monitor and respond accordingly when emotions such frustration and anxiety are observed to be extreme or lasting for a too-long period of time. Not all of the emotions might need to be addressed. In addition, students themselves can use the system to assess their learning and motivational progress according to their own needs.

2. BACKGROUND

2.1 Learning Diaries

Learning diaries are containers for writing that are usually recorded over a period of time [16]. They are included in educational settings as a means of facilitating or assessing learning. They may provide valuable insights into what students think and feel during lectures and any problems that they might be having. They are vehicles for reflection for the student, without which might not be possible to do in the classrooms. The diaries usually accompany a program of learning or a research project. Moreover, the diaries can come in many different forms and be used to fulfill different purposes [16]. Thus the nature of learning diaries makes them largely subjective. As Altrabsheh *et al*. [1] explain; subjectivity represents facts and also emotions, feelings, views, and beliefs.

2.2 Sentiment Analysis on Students' Texts

Sentiment Analysis (SA) is a field that works on making sense out of textual material [1], and using it to analyze students' learning diaries can help instructors understand the learning behaviors of students. SA, however, has not been widely applied to the educational sector. A majority of the SA research has been built around user reviews corpora (e.g., movie reviews, product reviews, etc.) [20, 19]. This is because these reviews, similar to learning diaries used in the paper, are subjective and contain information about the user experience with the product or movie [10].

Works on SA with student texts have been applied to various forms of texts, especially those retrieved from e-learning platforms. Santos *et al*. [26], for instance, used SA to analyze emotional reports written by students while they were conducting an activity. Our work differs from theirs in that we go beyond the analysis of emotional valence (how pleasant or unpleasant an emotion is) into the identification of the categories of emotions present in text. In another relevant work, Rodrigues *et al*. [25] extracted emotions from essay texts produced within the classroom and also within an adaptive learning environment that supported dynamic task recommendation. They made use of emotion dictionaries and word-spotting techniques in order to classify the texts into four emotion categories: joy, anger, sadness and fear. Our study differs from the work by Rodrigues *et al*. [25] in that we use texts from more than one student and then analyze and visualize the emotions and their changes over a period of time.

2.3 Feedback in Education and Learning

SA has also been investigated to improve the feedback given to students [1]. It is important to notice that good feedback, among other things, will encourage motivation and self-esteem, which are directly related to the student's emotional state. As Hattie and Timperley [8] explain, it is beneficial to give positive feedback, even if what has to be communicated is negative (e.g., when a student has solved a problem wrongly). Analyzing students' learning diaries can also help in understanding the different issues that students go through, including their lack of understanding of a subject. These learning diaries can in fact become an important source of feedback to the instructor. Through this type of feedback, a student can convey his or her feelings in short expressions or words [1]. Analyzing online students' feedback, Feng *et al*. [5] created patterns to find which words are associated more with emotions, and they also created sentiment adjustment strategies to help students in certain situations like being frustrated after being criticized by a teacher.

Hence, it is reasonable to say that the information on emotions in the learning diaries have the potential to prompt the teachers to tailor their teaching styles in a manner that better matches the learner's requirements.

2.4 Categorizing Emotions

It is beneficial to investigate the kind of emotions students express and experience during the learning process, and how these emotions evolve over a period of time [25]. Lists of primary or "basic" emotions have been put forward prominently in the psychological field by Frijda [6], Ekman [4], and Plutchik [22], among others. The basic emotion categories used in these lists include anger, sadness, joy, love, surprise, happiness, fear and disgust (see [18, 27], for a detailed compilation of primary emotion lists). It is difficult, however, to settle on a category of emotion labels given the gradations and subtleties of the way emotions are expressed in language [29]. Furthermore, in literature, there is no consensus on which basic emotions to use. Thus we decided to concentrate on Plutchik's eight emotions: joy, sadness, fear, anger, anticipation, surprise, disgust and trust, as these adequately fit our purpose of identifying several basic emotions and in addition, they can be used to derive two other emotions that have been found relevant in the learning context: frustration and anxiety [12]. We include frustration and anxiety in particular, as they can impede the progress of the students toward their learning goals [14]. Plutchik's categorization of emotions further provides us with the conceptualization of blending the eight primary emotions to obtain secondary and tertiary emotions, such as frustration and anxiety [22].

3. SYSTEM DESCRIPTION

For the purposes of emotional analysis of learning diaries, we have designed and implemented an automated system that performs several actions. The system accepts students' learning diaries as input and then fragments the diaries by the date of each diary entry. It then extracts the emotions present in the diary entry, their negative and positive attributes, and the topics present. Finally, using the extracted diary entry time elements, the system produces a fine-grained visualization of the emotional information flow in the entire diary (i.e., all the analyzed entries). Figure 1 illustrates the overview of our proposed system.

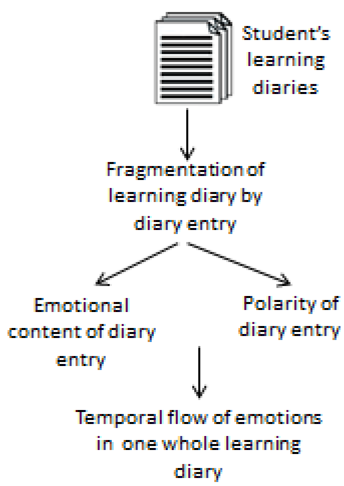

Figure 1. System flow diagram.

3.1 Uploading Students' Learning Diaries

Our system allows a user (e.g., the instructor) to enter a student's name and upload the learning diary belonging to that student for analysis. Upon uploading the diary, the system fragments the diary time-wise. Usually when a student updates a learning diary, the date of the new diary entry is recorded which makes it possible for the system to fragment the whole learning diary into individual diary entries. Figure 2 illustrates an example where one student's learning diary had three diary entries. Figure 2 shows the time stamp of the diary entry along with the textual content belonging to that time stamp. From these diary entries, we are able to create several visualizations (see Section 3.3).

(1.1.2013) This morning I woke up and turned off my alarm. I went

(1.2.2013) When you walk into my room there is a doctor to the rig

(1.3.2013) When I am finished with this experiment I am going to

Figure 2. Student's learning diary, fragmented by entry date.

3.2 Extractions of Emotions

In order for a richer exploration of the emotions expressed that goes beyond the emotion polarity of learning diaries, we extract emotions from the learning diaries by comparing each sentence in a diary against the NRC word-emotion association lexicon [15]. The lexicon has been manually annotated into eight emotion categories according to Plutchik's [22] eight basic emotions: joy, sadness, fear, anger, anticipation, surprise, disgust and trust. The annotations also include scores for whether a word is positive or negative. Each score in the lexicon is simply a Boolean marker, denoting whether the given word belongs to a given emotion category. In our calculations, when a word in a learning diary matches a word in the lexicon, we mark that word with a score of 1 within the matched emotion category, and when the word does not match any word in the lexicon, we mark it with a score of 0. Currently, the lexicon includes emotional annotations for 6,468 unique words. Further description of the lexicon can be found in an article by Mohammad and Turney [15].

In our work, an emotional score *(eScore)* is calculated for each one of Plutchik's eight categories represented in each diary entry as follows:

$$eScore_{(category)} = \frac{eWords_{(category)}}{eWords_{(all)}}$$

where:

- $eWords_{(category)}$ is the number of words in the uploaded learning diary that have nonzero emotional score for the category according to the NRC lexicon.
- $eWords_{(all)}$ is the number of words in the uploaded learning diary that have nonzero emotional score for any category according to the NRC lexicon.

Using the eight categories of emotions, we were also able to calculate frustration and anxiety as follows [23]:

$$Frustration = Average\left(eScore_{(Anger, Surprise, Sadness)}\right)$$
$$Anxiety = Average\left(eScore_{(Anticipation, Fear)}\right)$$

where *Frustration* is given by the average eScore of anger, surprise and sadness; and *Anxiety* by the average eScore of anticipation and fear.

3.3 Data Visualization

Our system visualizes obtained scores with a variety of graphical forms. The visualization shows the following:

3.3.1 *Emotion Distribution*

Emotional scores, calculated over a sequence of diary entries, are visualized on a radar chart that directly resembles Plutchik's wheel of emotions.

This radar chart (Figure 3) has eight independent axes, corresponding to the individual primary emotions. For each axis, we calculate a point of average emotional score over the given diary entries (i.e., for each diary entry, we calculated the *eScore* and then summed up all the *eScores* and divided the resulting value by the number of entries). Then these points become vertices of a filled polygon, thus providing a convenient visualization for the eight primary emotional scores. As frustration and anxiety are mixed emotions [22], they are not included in the radar chart. Those two emotions are visualized separately in a time chart (see Section 3.4).

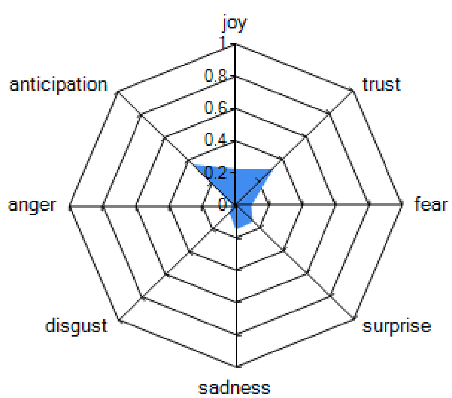

Figure 3. Distribution of emotions within a diary entry.

3.3.2 *Emotion Polarity*

In addition, polarity attribute scores are visualized on a bar graph (see Figure 4). Since "positive" and "negative" annotations are directly present in the NRC lexicon, in Figure 4, we make use of this information. The visualization shows the positive/negative average values for the given range of diary entries.

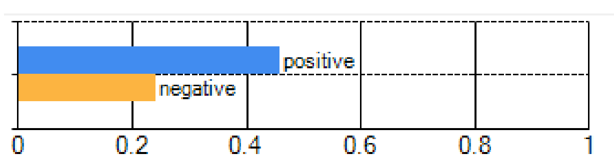

Figure 4. A diary entry's positive and negative sentiment averages.

3.3.3 *Topics*

Most topics found frequently in the uploaded student's diary are displayed as a word cloud, which is convenient for identifying frequent topics conveyed by one particular student (see Figure 5). Before building a word cloud, we apply a stop-word removal procedure and Porter's stemming algorithm [24]. These steps help to focus on the linguistically significant components of text by removing common words that are not topics, such as "without", "soon", "sometime", etc.

Figure 5. Word cloud view of topics present in the uploaded learning diary.

3.3.4 *Temporal Flow of Emotions*

Our system also allows for the visualization of the temporal flow of emotions in the learning diaries. The temporal flow-charts are divided into two views: The first view (Figure 6a and Figure 6b) displays the flow of the eight primary emotions. The second view (Figure 7) displays the mixed emotions, frustration and anxiety. In each of the views, a user has the choice of visualizing all the emotions or selecting a combination of emotions. Figure 6a shows visualization when all the emotions are selected, and Figure 6b shows an example where one emotion (i.e., fear) is selected.

For the temporal flow-chart, we build average emotional scores for each time entry and thus obtain a calendar-like view of emotional changes in the writings. In the given examples, the entries are given for three different dates; hence, the graphs are built for three time points. The Y-axis values for the flow chart are calculated in the same manner as for the *eScore*, (i.e., number of emotional words for the given category divided by the number of emotional words).

4. PRELIMINARY EVALUATION

4.1 Dataset

We performed a preliminary evaluation of our visualization system with samples of diaries from the Newman *et al.* [17] corpus[1]. The diaries used were written by first year college students, where they described their experience of going to college. There were a total of 18 female participants and 17 male participants, and each participant wrote in their diary three entries in three different occasions in sequential order, for a total of 54 entries written by females and 51 entries written by males. Table 1 shows a description of the entries.

Table 1. Description of diary entries by gender with average word count (Avg) and standard deviation (STD).

Female				***Male***			
Diaries	Entries	Avg	STD	Diaries	Entries	Avg	STD
18	54	459	119	17	51	384	105

[1] We obtained the corpus through personal communication with James W. Pennebaker, a professor of psychology.

Since the diary entries did not have a date time stamp on them, for our preliminary evaluation, each diary entry was assigned a date in the month-year form. Hence, each diary entry had the format entryNumber_monthYear.txt, transforming the sequential order of the diary entries into three-month time stamps. This format made it easier to place the diaries in a time sequence that allowed us to generate the flow of emotion charts, as shown in Figures 7, 8, and 9. We tested all 35 diaries, of which 18 diaries were written by females and the 17 diaries were written by males.

4.2 Results

With our system, it is possible to visualize the variation over time in all the emotions, including frustration and anxiety, as detected in the students' diaries. This allows the identification of students whose anxiety and/or frustration levels are increasing. It is also possible to determine the proportionality between anxiety and frustration that the students are experiencing.

In our preliminary evaluation, eight participants (five female and three male) showed frustration and anxiety levels that were proportional to each other over the three diary entries (i.e., both anxiety and frustration increased and decreased proportionally at the same time). Figure 8 gives an example where such a relationship was observed. In the other 27 participants (13 female and 14 male), anxiety increased while frustration decreased or vice versa. Moreover, within the dataset, we observed that with 30 participants, their three diary entries contained more anxiety than frustration, as indicated by the Y-axis values in Figure 7. No participant's diary showed more frustration than anxiety over the three diary entries, and five participants' diaries intertwined (i.e., they showed more anxiety than frustration in one diary entry and then more anxiety than frustration in another). Table 2 shows a summary of the results.

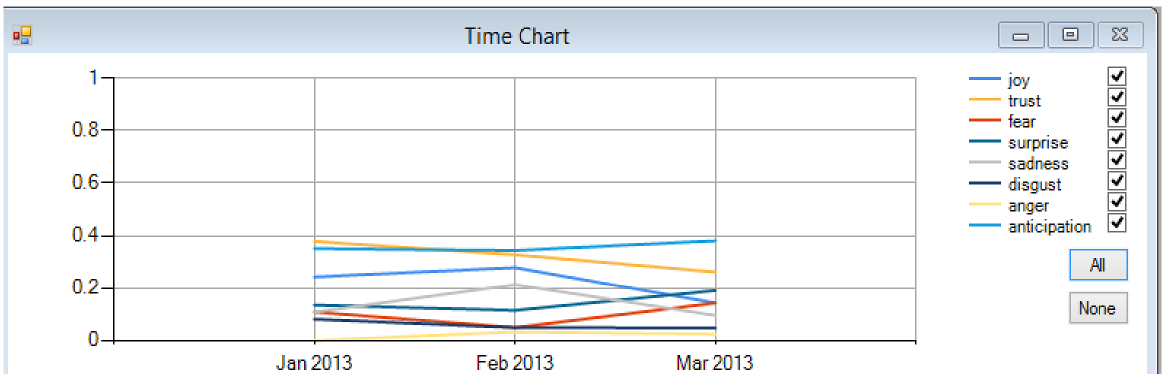

Figure 6a. View of the flow of all the eight Plutchik [22] emotions within a learning diary.

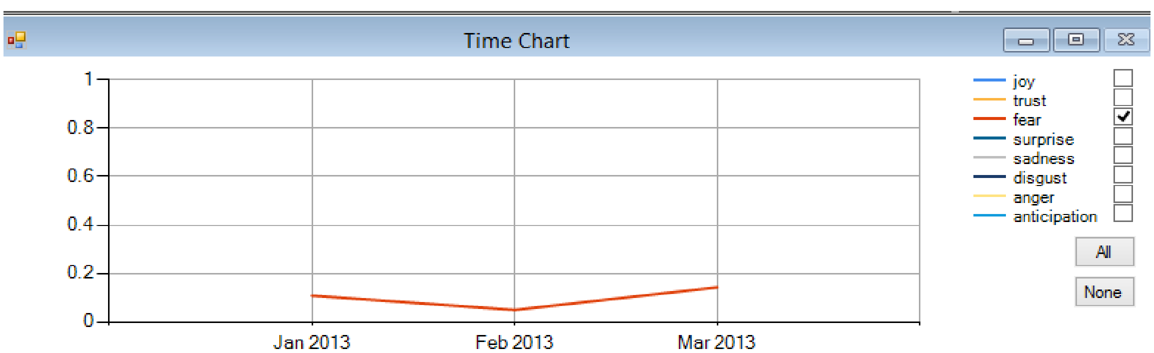

Figure 6b. Fear flow within the learning diary.

Figure 7. Frustration and anxiety emotional flow within a learning diary.

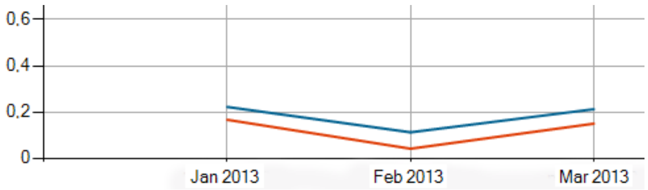

Figure 8. Example where frustration and anxiety have a parallel relationship.

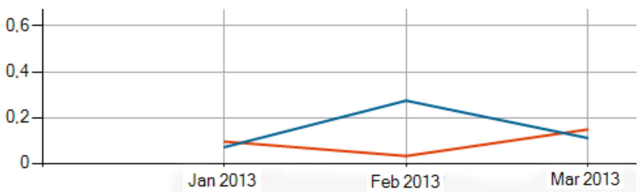

Figure 9. Example where Frustration and Anxiety intertwine.

Table 2. Distribution of anxiety and frustration within the students' diaries (all entries included).

	Female	***Male***	***Total***
More anxiety in each of the three diary entries	17	13	**30**
More frustration in each of the three diary entries	0	0	**0**
Intertwined	1	4	**5**
Total	**18**	**17**	**35**

Figure 9 shows an example where the frustration and anxiety levels are intertwined. Interestingly, only one participant registered anxiety levels of 0.4. Otherwise, all the participants had frustration and anxiety levels less than 0.4, with frustration in particular, registering levels less than 0.2 within 34 participants.

Thus, within the dataset, we see that the majority of participants expressed relatively low frustration whereas most of the participants expressed higher anxiety levels. This could be interpreted from the context within which the diaries were written: the students were expressing their anxiety toward their new college life experience. An interesting direction to explore is the selection of an empirical threshold, whereby if frustration and anxiety levels go beyond it, a signal is given to the instructor.

4.3 Implications

Our visualization system can provide important insights into the students' pedagogical well-being, which is a vital part of the learning experience since according to the "Explaining Student Performance" report (2005) by the European Commission, data from PISA (Programme for International Student Assessment) suggests that students who have higher levels of performance in their scores are less anxious about the learning process. Also, the report showed that there is a positive correlation between interest and enjoyment of a subject and the students' PISA achievements[2].

By observing the flow of emotions within a diary, an instructor is given the opportunity to timely address any issues or concerns that might be causing any of the negative emotions such as frustration. It is important to notice that an instructor's feedback, among other things, will encourage motivation and self-esteem, which are directly related to the student's emotional state.

By taking the information on the student's emotional state into account, instructors can have a holistic picture of the students' emotional progress. Our system can also serve as a self-evaluation platform in which the students can assess their emotions and motivational progress. Hence, our visualization system can positively contribute to enhancing the traditional educational setting by providing a means of surveying the student's well-being and, at the same time, helping instructors to personalize their feedback. This will result in an overall improved learning experience.

From the students' perspective, we are aware that allowing for student self-evaluation might prompt them to manipulate the content of their diaries; however, with the system, there are no wrong or right emotions. The emotional flow of a student is not part of that student's performance assessment. With that emphasized, we believe that the students will use the system as a reflection tool and will not try to manipulate the content of their diaries as to improve their grades.

5. CONCLUSION AND FUTURE WORK

In this paper we have explored the automatic analysis and tracking of emotions within student' learning diaries. The developed system presented here aimed to function as an aiding system for improving instructors' teaching methods and feedback and serving as a reflection medium for students.

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[2] http://ec.europa.eu/education/more-information/doc/basic_en.pdf

The preliminary evaluation showed that the system successfully presented information in an easy-to-understand manner and that the emotional flow of the students during the learning experience, as expressed in their learning diaries, can be meaningfully extracted.

Future work involves studying student diaries that have longer time stamps and analyzing their long-term implications. We also plan to continue the validation of our emotion detection system by comparing the results and performance with other systems on the same learning diaries dataset.

Future versions of the system can be incorporated in e-learning environments or learning management systems (LMSs), where text-based documents produced by the students can be automatically analyzed and the results combined with student profile information. The combination can be used to customize teaching material for students. Also, we plan to conduct a deeper linguistic analysis to better understand the expressed emotions. As the current version of the system makes use of a keyword based approach for detecting emotions, we plan to extend the capabilities of the system by incorporating approaches such as phrase- and sentence-level emotion analysis and common-sense analysis for broader emotion detection. Advantageously, using the keyword approach allows the system to handle the use of slang words and misspellings and even handle keyword sets of different languages.

Furthermore we plan to include event analysis within the next version of the system so as to better inform an instructor of any events such as sitting for an exam, receiving bad news or passing a course, that might have led to the observed emotions.

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