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 of self-awareness of their goals. Learning diaries are also a very informative feedback source for instructors regarding the student emotional wellbeing. However the amount 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 emotion changes 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

Keywords

Emotion detection, sentiment analysis, learning diaries, visualization

1. INTRODUCTION

Instructors are constantly looking for ways to understand and address their students' challenges during the learning process. Emotional obstacles, in particular, are known to hinder 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, in order to be aware of the 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 student's personal diaries to uncover their feelings towards the learning experience as a whole (i.e., the instructor, the learning material and topics, and about themselves and their performance) can lead to improvements in the quality of instructor-student relationship and the 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 to educational settings, particularly to the analysis of students' learning diaries. Applying SA to the educational field holds many possibilities for improving the communication pathways and the learning opportunities between an instructor and their students. That is, it is well documented that students' emotions towards 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 students that need particular attention is of vital importance. Through automatic analysis of the sentiments and emotion 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 emotion information without disturbing the student's 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, we go beyond polarity and identify expressions of emotions such as joy, sadness, anxiety, frustration and how these emotions evolve over the period of the diary, for a richer understanding of the student's texts. 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 processes. In addition, Goleman [7] adds that students should also be able to recognize and accurately label their emotions and how they may lead their actions.

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

Our system main contribution relies on 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 creation of personalized feedback to students that so require, hence improving student motivation and performance [25]. In addition, students themselves can use the system to assess and be aware of their learning and motivational progress according to their own needs.

2. BACKGROUND

2.1 Learning Diaries

Learning diaries are containers for writing that is usually recorded over a period of time [16]. They are progressively included in educational settings as a means facilitating or of 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 a vehicle for reflection for the student which otherwise might not be possible to do in the classrooms. The diary usually accompanies 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] explains, subjectivity represents facts and also emotions, feelings, views and beliefs.

2.2 Sentiment Analysis on Student's Texts

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

Work on SA with student texts has 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 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 Rodrigues et al.,'s work in that we use texts from more than one student and we 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 a positive feedback, even if what has to be communicated is negative, for example, 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 the 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 what words are associated more with emotions, and they also created sentiment adjustment strategies to help a student, for example if a student typed that they felt frustrated after being criticized by a teacher, the system would suggest to the student to communicate with the teacher.

Hence, it is reasonable to say that the emotion information in the learning diaries has the potential to prompt the teachers to shape and personalise 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 in the psychological field prominently 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 Ortony et al., [18]; and Shaver et al., [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 subtlety 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 fit well our purposes. We further extended Plutchik's basic set of emotions to include two emotions that have been found relevant in learning context: frustration and anxiety [12]. We include frustration and anxiety in particular, as they can impede the progress of the student towards their learning goals [14]. Plutchik's categorization of emotions further provides us with a conceptualization to blend 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. Figure 1, illustrates the overview of our proposed system. The system accepts students' learning diaries as input, and first 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).

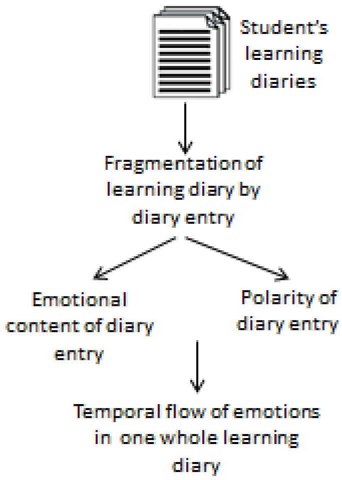

Figure 1. System flow diagram

3.1 Uploading Students Learning Diaries

Our system allows a user (e.g., the instructor) to enter a student's name and to 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, they record the date of the new diary entry which is what the system uses to fragment the whole learning diary into diary entries. Figure 2 illustrates an example where a student's learning diary had three diary entries.

(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. Extract of the learning diaries, fragmented by date of entry

3.2 Extractions of Emotions

In order to have a richer exploration of the emotions expressed, beyond the emotion polarity of learning diaries, we extract emotions from the learning diaries by comparing each sentence in a diary against the NRC lexicon [15]. The lexicon has been manually annotated into eight emotion categories according to Plutchik's [22] eight basic emotions: Joy, Trust, Anger, Sadness, Fear, Disgust, Surprise and Anticipation. 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 with a word in the lexicon we mark that word with a score = 1 within the matched emotion category, and when the word does not match any word in the lexicon; we mark it with a score = 0. Currently the lexicon includes emotional annotations for 6468 unique words. Further description of the lexicon can be found in Mohammad and Turney [15]. .

In our work, an emotional score *(eScore)* is calculated for each one of the Plutchik's [22] 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 [22] 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. 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).

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.

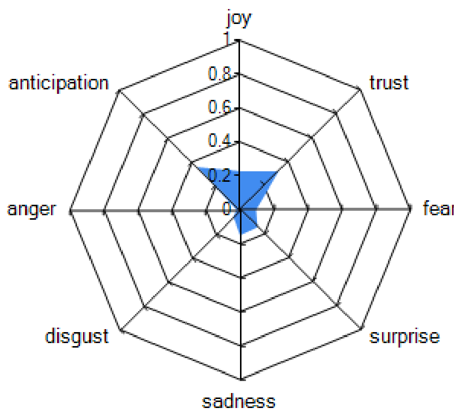

Figure 3. Distribution of emotions within diary entry

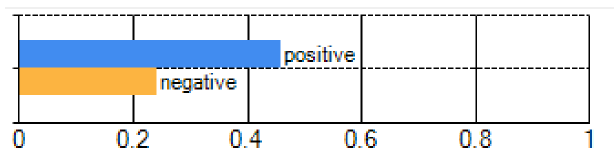

Figure 4. Diary entry's positive and negative sentiment average

3.3.3 Topics

Most frequent topics found in the diaries are displayed as a word cloud, convenient for identifying frequent topics conveyed by students (see Figure 5). Before building a word cloud, we apply a stop word removal procedure and a Porter's stemming algorithm [24]. These steps help the significant linguistic components of text to be focused and considered by removing unimportant data.

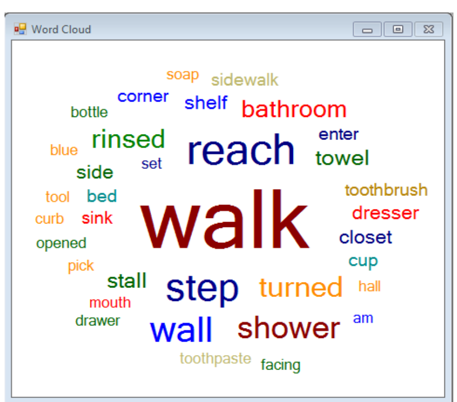

Figure 5. Word cloud view of topics present in the uploaded learning diary

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 a selecting a combination of emotions. Figure 6a shows visualization when all the emotions are selected and Figure 6b shows an example where one emotion (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 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 radar chart, i.e., number of emotional words for the given category divided by the number of emotional words. We count that for all the words in the given month and we get a value between 0 and 1.

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 1st 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 three entries in their diary 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. Diary entries description by gender with average word count (Avg) and standard deviation (STD).

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

Since the diary entries did not have a date time-stamp on them, for our preliminary evaluation each entry was given a date in the form of month-year. Hence each entry had the format entryNumber_monthYear.txt. This format made it easier to place the diaries in a time sequence.

We tested all the 35 diaries, 18 diaries written by females and the 17 diaries 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 those students whose anxiety and / or frustration levels are increasing. It is also possible to determine a correlation 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 had a parallel relationship over the three diary entries. Figure 8 gives an example where such a relationship was observed. In the other 27

[1] James W. Pennebaker personal communication

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, that is 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.

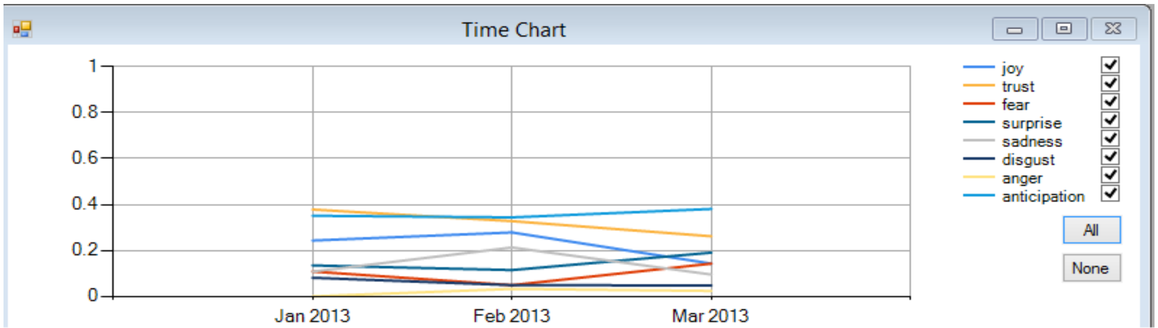

Figure 6a. View of the flow of all the eight Plutchik [22] emotions within a learning diary.

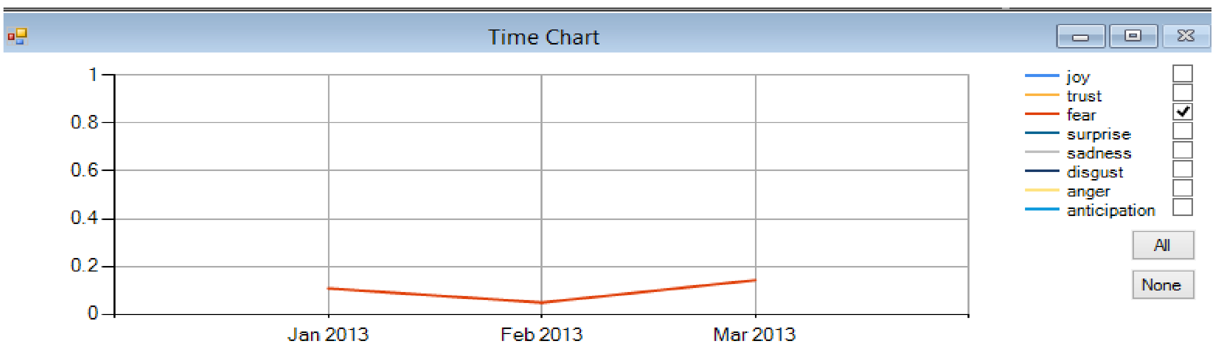

Figure 6b. Fear flow within the learning diary.

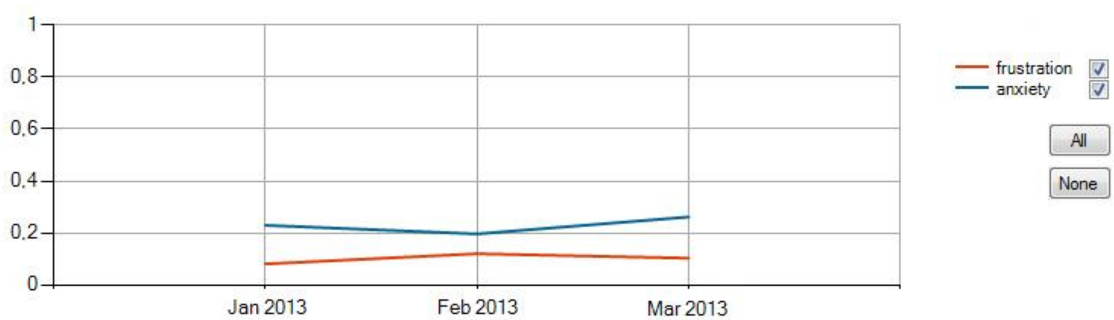

Figure 7. Frustration and anxiety emotional flow within a learning diary.

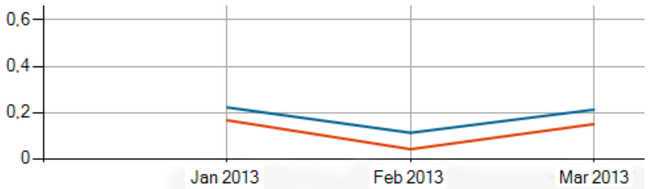

Figure 8. Example where Frustration (red line) and Anxiety (blue line) have a parallel relationship

Table 2. Distribution of anxiety and frustration within the dataset

	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 levels 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 majority of participants expressed relative low frustration and majority of the participants express more anxiety than frustration. With more testing, we hope to establish a threshold whereby if frustration and anxiety levels in a student's diary pass this threshold, a signal is given to the instructor.

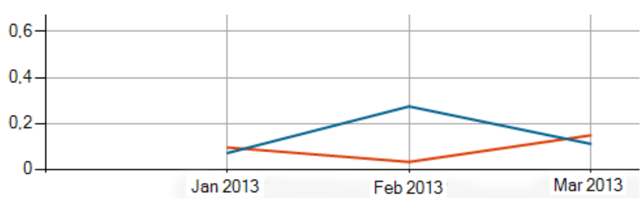

Figure 9. Example where Frustration (red line) and Anxiety intertwine (blue line)

4.3 Implications

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 good instructor's feedback, among other things, will encourage motivation and self-esteem, which are directly related to the student's emotional state.

Our visualization system can provide important insights on the students' pedagogical wellbeing, which is a vital part of the learning experience, since aaccording 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 taking the student emotional state information into account, instructors can have a holistic picture of the students' progress. Our system can also serve as a self-evaluation space in which the students can assess and be aware of their learning and motivational progress. Hence, our visualization system can positively contribute to enhancing the traditional educational setting by providing a mean of surveying the students' wellbeing and, at the same time, by aiding instructors to personalize their feedback. This will result in an overall improved learning experience.

5. CONCLUSION

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

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

Future versions of the system can be incorporated in e-learning environments, where the 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 deeper linguistic analysis to better understand the expressed emotions. Furthermore we plan to include event analysis within the next version of the system so as to better inform an instructor of any events that might have led to the observed emotions.

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