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Traditional Sentiment and emotion identification system to improve teaching and learning

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Abstract— Sentiment analysis (SA) is the process of identifying and classifying users' opinions from a piece of text into different sentiments—for example, positive, negative, or neutral—or emotions such as happy, sad, angry, or disgusted to determine the user's at-titude toward a particular subject or entity. SA plays an important role in many fields includ-ing education, where student feedback is es- sential to assess the effectiveness of learning technologies. Many universities obtain such feedback via a student response system (SRS) during or at the end of a course to analyze the teacher's performance.1 Student feedback about teacher performance, the learning experience, and other course attributes can also begathered through social media. In recent years, online learning portals like Courser have attracted many students by providing free courses from a growing number of selected institutions.2 millions of students join these massive open online courses each year and share their opinions about the course con- tent and quality of teaching on the course's discussion forum. Students also comment about their educational experiences in blogs.

1. INTRODUCTION

sentiment analysis (SA) is the process of iden- tifying and classifying users' opinions from a piece of text into different sentiments for ex- ample, positive, negative, or neutral or emotions such as happy, sad, angry, or dis- gusted to determine the user's attitude towarda particular subject or entity. SA plays an important role in many fields including education, where student feedback is essential to assess the effectiveness of learning technologies. Many universities obtain such feedback via a student response system (SRS) during or at the end of a course to analyze the teacher's performance Student feedback about teacher performance, the learning experience, and other course attributes can also be gathered through social media. In recent years, online learning portals like Coursera (www.coursera.org) have attracted many students by providing free courses from a growing number of selected institutions Millions of students join these massive open online courses each year and share their opinions about the course content and quality of teaching on the course's discussion forum. Students also comment about their educational experiences in blogs, online forums such as College Confidential (www. collegeconfidential.com), and teacher review sites such as Rate My Professors (www.ratemyprofessors.com) This feedback not only yields useful insights for university administrators and instructors but also plays a key role in influencing student decisions on which universities to attend or courses to take

2. SENTIMENT ANALYSIS

Course outcomes can be assessed directly or indirectly. Direct assessment considers samples of actual student work including exams, assignments, quizzes, and project reports. Indirect assessment is based upon student observations of the learning experience and teaching quality. SA of student feedback is a form of indirect assessment that analyzes text

written by students whether in formal course surveys or informal comments from online platforms to determine students' interest in a class and to identify areas that could be im-proved through corrective actions SA raises many technical challenges. First, word mean-ing varies across different domains. For ex- ample, in an education context the word "early" connotes a negative sentiment in the sentence "The lecture is too early!" but in a consumer context it connotes a positive one in the sentence "The courier arrived early." Sec-ond
in the sentence "The lecture is too early!" but in a consumer context it connotes a positive one in the sentence "The courier arrived early." Second which translates into English as "He teaches very well in the class," as "Woclass main achha padhate hain." These types of challenges motivate the need to develop a context sensitive, multilingual SA system Most SA studies have focused on user-review corpora—for example, product, movie, and hotel reviews—with researchers generally classifying the reviews into positive, negative, and sometimes neutral. SA has not been ex-tensively applied to education, though work in this area has grown recently as described in the "Related Research" sidebar. However, most of these approaches limit the classifica-tion of sentiments to the two or three catego-ries indicated above, without considering the wide range of emotions that can also affect student feedback. Moreover, they do not pro-cess multilingual data. Finally, previous re-searchers have not attempted to validate their systems by comparing the results of their analysis with those of traditional direct- as-sessment methods.

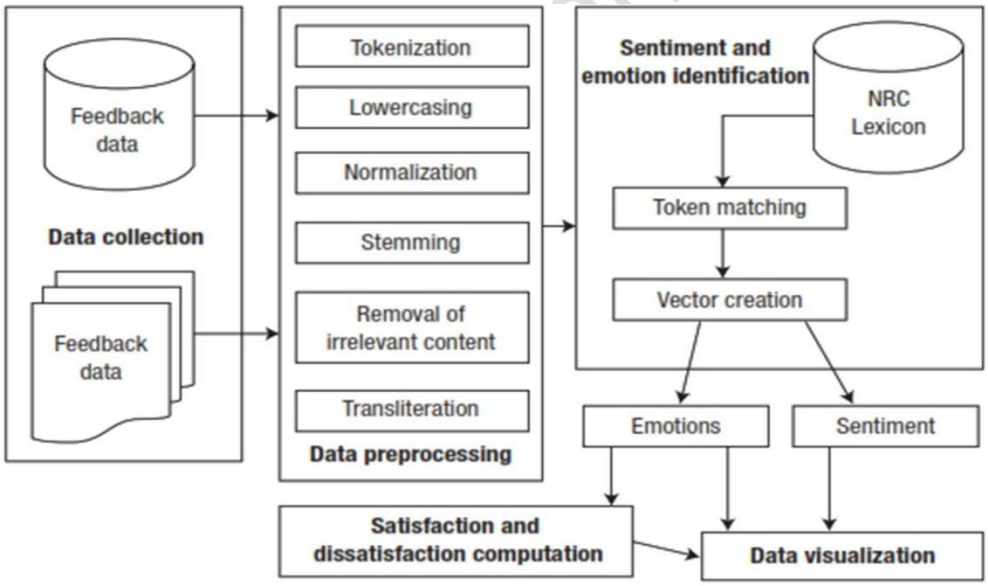

FIGURE 1. Proposed sentiment analysis (SA) system architecture. After preprocessing input data student feedback obtained from both formal sources such as course surveys and informal sources such as blogs and forums—the system uses natural language processing in conjunction with the NRC Emotion Lexicon to clas-sify sentiments and emotions. Sentiments are classified into two categories, positive and negative, and emo-tions are classified into one of eight categories—anger, anticipation, disgust, fear, joy, sadness, surprise, and trust—from which the system computes satisfaction or dissatisfaction. The SA system can process multilin-gual content and includes a data-visualization component to facilitate analysis.

3. RELATED WORK

In recent years, researchers have begun to ap-ply sentiment analysis (SA) to the education field using various machine learning and nat- ural language processing techniques. In 2011, Zied Kechaou, Mohamed Ben Ammar and Adel M. Alimi performed sentiment classifi-cation of e-learning blogs and forums using a supervised hybrid technique that combined hidden Markov models with support vector machines (SVMs). They performed experiments using three feature-selection methods mutual information, information gain, and chi statistics and determined that the chi-statistics method outperformed the other two. Two years later, Myriam Munezero and her colleagues performed emotion analysis of student learning diaries and classified them into RobertPlutchik's eight emotion categories. They also computed frustration and anxiety from these eight emotions. In 2014, Nabeela Altrabsheh, Mihaela Cocea, and Sanaz Fallahkhair performed SA of student feedback using naive Bayes (NB), complement NB (CNB), SVM, and maximum-entropy classifiers using unigrams as features. They concluded that an SVM with a radial ba- sis function kernel and the CNB technique achieved good results for real-time feedback analysis. They also observed better performance without including the neutral class The following year, Trisha Patel, Jaimin Undavia, and Atul Patel analyzed feedback from meetings of students' parents using the General Architecture for Text Engineering (GATE) tool and its ANNIE application to classify comments as positive or negative. Several studies were published in 2016. Fran-cis F. Balahadia, Ma. Corazon G. Fernando, and Irish C. Juanatas proposed an SA system to evaluate teacher performance in courses from student responses in both English and Filipino. They calculated sentiment scores from qualitative and quantitative response rat- ings using an NB algorithm and graphically represented the percentage of positive and negative sentiments to help university administrators be aware of students' concerns. V. Dhanalakshmi, Dhivya Bino, and A.M.Saravanan performed SA on feedback from a student evaluation survey of Middle East College in Oman. They used the RapidMiner tool to classify the comments into positive and negative on the basis of features like teacher, exam, module content, and resources. The researchers compared the performance of their approach using NB, SVM, k-nearest neighbors, and neural-network classifiers. Brojo Kishore Mishra and Abhaya Kumar Sahoo used CUDA C programming with a GPU architecture to evaluate faculty performance. They categorized faculty members as excellent, very good, good, average, or poor on the basis of average marks given by students in feedback form. The researchers favorably compared their approach in terms of time execution to a similar performance evaluation using a CPU architecture

4. PROPOSED SA SYSTEM

Our proposed SA system helps to improve teaching and learning by performing temporal sentiment and emotion analysis of multilingual student feedback in terms of teacher performance and course satisfaction. The system classifies sentiments into two categories, positive and negative, and emotions into Robert Plutchik's eight categories anger, anticipation, disgust, fear, joy, sadness, surprise, and trust from which it computes satisfaction or dissatisfaction. Figure 1 shows the system architecture, which has five main components: data collection, data preprocessing, sentiment and emotion identification, satisfaction and dissatisfaction computation, and data visualization. The system uses the open-source R language (www.r-project.org) to perform data preprocessing and sentiment classification.

5. DATA COLLECTION

Our initial data corpus consists of student feedback about a Coursera course as well as data obtained from a university SRS. The Coursera dataset includes approximately 4,000 student comments made during the course, which ran from August 2015 to Au- gust 2016, and 1,700 student comments made after completion of the course. The SRS dataset includes about 500 student comments and ratings for lecture and lab sessions after midterm and final semester examinations for a course taught by one teacher over the past 10 years. It also includes student surveys and comments for 25 courses taught by different teachers at the university over the past 2 years, which we used in conjunction with direct as- sessments of student performance to evaluatethe system's reliability

6. DATA PREPROCESSING

During this phase, the SA system prepares collected data for further processing. This in- volves six steps.

Tokenization. Students' comments are split into words, or tokens, using the tokenize func- tion in R.

Lowercasing. Characters are converted tolower case to ease the process of matching words in student comments to words in the NRC Emotion Lexicon. This step is per- formed using the tm_map function in R's tmpackage.

Normalization. Abbreviated content is nor- malized by using a dictionary to map the con- tent to frequently used Internet slang words.

For example, "gud" and "awsm" are mapped to "good" and "awesome," respec- tively.

Stemming. To further facilitate word match- ing, words in student comments are convertedto their root word using the tm_map function in R's

SnowballC package. For example, "moving," "moved," and "movement" are all converted to "move." Removal of irrelevant content.

Punctuation and stop words, which are irrele- vant for SA, are removed to improve system response time and effectiveness.

Transliteration. To address the issue of use of mixed language in student comments, the text is transliterated using the Google Trans- literate API.

7. SENTIMENT AND EMOTION IDEN- TIFICATION

During this phase, the SA system analyzes the preprocessed data to identify instances of sen- timent and emotion. It uses the NRC Emotion Lexicon, also known as EmoLex, to associate words with positive or negative sentiment and the eight basic emotions. The lexicon supports 40 languages including several Indian ones like Hindi, Tamil, Gujarati, Marathi, and Urdu. It includes annotations for 14,182 uni- gram words for English and 8,116 for Hindi. Each word in the lexicon has an emotion vec- tor (E) containing a Boolean value (b) for each sentiment (s) and emotion (e):

$$\vec{E} = \vec{E}_e + \vec{E}_s,$$
$$\text{where } \vec{E}_e \in \{b_0,\ldots,b_7\} \text{ and } \vec{E}_s \in \{b_8,b_9\}, \forall b_i \in \{0,1\}.$$

If a word in a student comment matches a word in the lexicon, the corresponding emo- tion vector is returned; if the word matches more than one word in the lexicon, the sum of the corresponding emotion vectors is re- turned. In this way, an emotion vector is cre- ated for each comment representing the differ- ent emotions and sentiments contained within. For example, for the sentence "Sir, you are great!" the SA system would return the following emotion vector:

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
0	0	0	0	0	0	0	1	0	1

This equates to the positive sentiment, as trust and positive parameters have a b value equal to 1

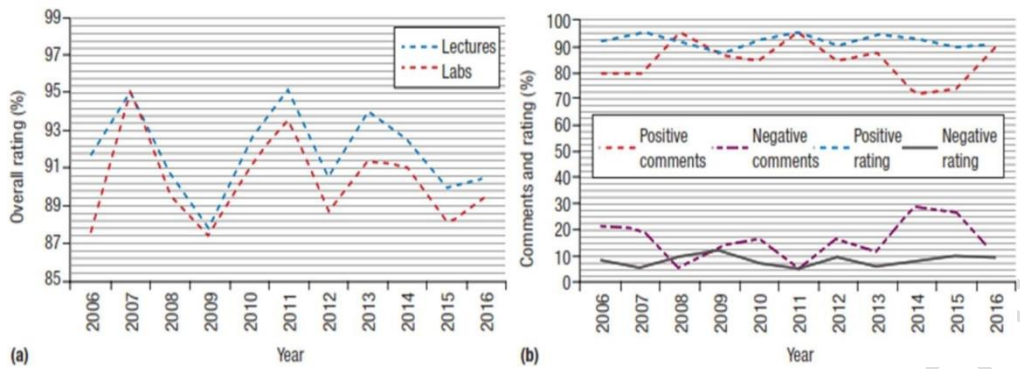

FIGURE 2. Temporal sentiment analysis. (a) Student ratings of a teacher's performance in lectures and lab sessions of one course over a 10-year period. Students rated the performance in lectures slightly higher, and average overall perfor-mance exceeded 90 percent during the last six years. (b) Percentage of positive and negative student comments about andratings of the same teacher; on average, 85 percent of comments were positive and 15 percent were negative

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To enable temporal analysis of sentiments and emotions, the SA system generates a mean emotion vector (E) for each month and year:

$$\vec{E}_j = \frac{1}{n}\sum_{i=0}^{n-1}\sum_{j=0}^{p-1}\vec{E}_{ji}, \forall \vec{E}_{ji} \in N \text{ where } N \geq 0.$$

Here, n represents the number of comments in each month and year and p represents the emotion and sentiment parameters such that p ∈ {anger, anticipation, disgust, fear, joy, sad-ness, surprise, trust, negative, positive}. This vector is created to avoid any anomalies that might result from an increase in the value of a particular emotion in that month or year.

8. SATISFACTION AND DISSATISFACTION COMPUTATION

Satisfaction and dissatisfaction are crucial pa-rameters in education. The SA system derives these from six of the eight emotion parameters namely, joy, trust, anticipation, anger, disgust, and sadness. Anticipation and trust clearly connote satisfy action, but in some circum-stances, joy could have a negative connationfor example, a student could feel joy at skip-ping a boring class. Therefore, in computing student satisfaction, we multiply the sum of anticipation and trust by a constant (α = 0.6) to give these parameters more weight. We em-ploy the same mechanism in computing student dissatisfac-tion to give more weight to anger and disgust than to sadness. The calculations are as fol-lows:

$$Satisfaction = [\alpha(TA) + (1-\alpha)(J)]/n$$
$$Dissatisfaction = [\alpha(AD) + (1-\alpha)(S)]/n,$$

where TA = trust + anticipation, J = joy, AD = anger + disgust,
S = sadness, and n = max(TA or AD, J or S). Consider two examples. For the sentence "He is good at teaching," the SA system returns the following emotion vector from the NRC lexi-con:

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
0	1	0	0	1	0	1	1	0	1

Here, $TA = 2$, $J = 1$, and $n = \max(TA, J) = 2$. Satisfaction is thus calculated as $[0.6(2) + 0.4(1)]/2 = 1.6/2 = 0.8$. For the sentence "He is bad at teaching and every student has doubts about the class," the system returns the following emotion vector:

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
1	0	1	2	0	2	0	1	2	0

9. Data visualization

To facilitate analysis of student feedback about course satisfaction and teacher perfor- mance, our SA system has a data visualization component that creates sentiment and emo- tion word clouds as well as line graphs of changes in sentiments and emotions over time.

Sentiment and emotion word clouds.

Students use a variety of words to convey their sentiments or emotions while giving feedback. Visualizing frequently used posi- tive words ("great," "excellent," interesting," and so on) and negative words ("dull," "con- fusing," "terrible," and so on) in
the form of word clouds can help identify stu- dent learning behavior—for example, whether or not they are taking an interest in lectures and lab sessions.

Temporal sentiment and emotion analysis.

As indicated earlier, our SA system groups to- gether positive and negative comments and ratings in student feedback by month and year. This makes it possible to track teacher performance and course satisfaction overtime. Figure 2a plots overall student ratings(ranging from 0 to 100 percent) of one teacher's performance in lectures and lab ses- sions of a university course from 2006 to 2016; the graph shows that students rated the teacher's performance in lectures slightly higher than that in lab sessions and that theaverage overall rating was more than 90 per-cent during the last six years. Figure 2b plots the percentage of positive and negative student comments about and ratings of theteacher over the same period; the graph re- veals that, on average, 85 percent of com- ments were positive and 15 percent were neg- ative. Sentiment polarity can also be tracked across different teachers and courses over time to analyze overall teaching quality at agiven institution.

10. CONCLUSION

Our proposed SA system has great potential to improve teaching and learning in universities by analyzing sentiment, emotion, and satis- faction parameters in student feedback to help administrators and teachers understand prob- lematic areas and take corrective actions. The large volume of information contributed by students to course surveys, discussion forums, blogs, and other sources is a largely underuti- lized resource that can be effectively lever- aged with the application of machine learning techniques, which are continually improving. A comparison of our proposed system's re- sults with direct assessments of class perfor- mance demonstrates its reliability. Despite its promise, the system has some limitations. It is only as good as the data it analyzes, so care must be taken in collecting feedback from stu- dents. SRSs must be well designed to ensure that they are engaging, and instructors must make a concerted effort to ensure that as many students as possible provide complete and ac- curate feedback. In future work, we plan to adapt the SA system API to integrate with SRSs and online learning portals to enable real-time analysis of student feedback. We will also add other Indian languages to extend the system's multilingual capabilities.

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