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Paper Authors
Mrs. Ramya Sri Kotha,P. Sushmitha,Nalla Amrutha Reddy, M. Vinisha

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A SENTIMENT ANALYSIS SYSTEM TO IMPROVE TEACHING AND LEARNING

[1]Mrs. Ramya Sri Kotha,[2]P. Sushmitha,[3]Nalla Amrutha Reddy,[4]M. Vinisha
[1]Assiatant Professor,[234]Students
Department Of CSE
Malla Reddy Engineering College for Women

ABSTRACT:

The act of recognizing and categorizing user opinions from a text into various sentiments (e.g., positive, negative, or neutral) or emotions (e.g., happy, sad, furious, or disgusted) in order to ascertain the user's attitude toward a certain topic or entity is known as sentiment analysis, or SA. SA is crucial in many domains, including education, where evaluating the efficacy of learning tools depends heavily on student input. In order to evaluate the work of the instructor, several colleges collect this kind of input during or after a course using a student response system (SRS).1. Social media may also be used to get feedback from students on the quality of the instruction, the performance of the teachers, and other aspects of the course. Due to the availability of free courses from an increasing number of carefully chosen universities, online learning portals such as Courser have drawn a large number of students in recent years.Every year, two million students enroll in these massively open online courses and post comments on the discussion forum about the instruction and course material. Students also leave blog comments on their educational experiences.

I. INTRODUCTION

At the moment, most research on sentiment analysis focuses on the sentiment polarity that the text expressly conveys. It mainly uses statistical machine learning methods to categorize the text into positive and negative emotions. There hasn't been much study on how the book could influence pupils' feelings [1-4]. Student sentiment analysis looks at how language and text cause students to experience certain emotions, such as happiness, sadness, anger, and joy, and attempts to predict how students would feel after reading the text. The online student evaluation of teaching is a vital part of the network that supports and grows for teachers at various universities. Long-term users of online teacher evaluations at universities have accumulated massive amounts of textual data on these tests. However, due to the non-structural aspects of the teacher assessment materials, routines cannot be adhered to. The statistical analysis of the data indicates low data consumption. If things keep going this way, not only will the teaching evaluation data fall short of its full potential in enhancing the quality of instruction provided by teachers, but students' enthusiasm to participate in the assessment will also diminish. Analyzing and examining the emotions that students encounter via assessment texts is essential to understanding their mental states and information retrieval [5]. Due to the complexity of human emotions and the even larger variety of emotions among students, research is difficult and is still in its early stages [6]. In order to extract textual aspects that impact students' emotions, previous studies often used manually generated feature extraction approaches, ignoring contextual signals and word order in the text, and failing to fully capture the complex linguistic phenomena found in the text. Furthermore, it may be difficult to fully capture the complexity of a broad variety of interrelated human emotions since most common student sentiment analysis approaches now in use employ several labels [7, 8].

The goal of this proposal is to solve the shortcomings of most existing models, which are ill-suited to assess complex student emotions and ignore the interactions between emotions. The teaching assessment text emotion analysis model makes use of the CNN-BLSTM model and attention mechanism. The suggested model has the following improvements over the current emotion analysis models:The suggested model's

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ability to extract text features is enhanced by using the CNN model to construct convolution windows of various lengths for the purpose of extracting the text's binary and ternary properties. Additionally, sequence properties are extracted using BLSTM, resulting in highly reliable text features for subsequent classification.(2) Given that the traditional analytical models ignore the relationship between emotions, the proposed model includes an attention mechanism. By adaptively merging context and student emotion data, it may identify significant text aspects that impact students' emotions. This effectively raises the classification accuracy of emotions.

This section provides an overview of sentiment analysis in learning settings and using deep learning methodologies. 2.1 Sentiment Assessment Through Deep Learning Deep learning has drastically changed the problem-solving strategy that traditional machine learning (ML) techniques previously used. The creation of a Dynamic Convolutional Neural Network (DCNN) for phrase sentiment modeling, for example, is described by the authors of [9]. The network handles phrases of different lengths and recognizes word relationships. On Twitter terms, the writers experimented with binary and multiclass prediction. The author in [11] uses a Convolutional Neural Network (CNN) with a convolution layer and pre-trained word vectors utilizing more than 100 billion words from Google News for sentence-level classification tasks. Despite the simplicity of his approach, it yielded excellent results for the several corpora that were used. The second conclusion drawn by the researchers is that pre-trained vectors are extractors of universal qualities that may be used to a range of classification tasks. Using a valence scale, the authors of [20] provide a CNN-LSTM model to predict text attributes. Two parts make up the model: an LSTM and a regional CNN. Unlike the regular CNN, which uses the whole text as input and weights it according to the valence scale, the regional CNN uses individual phrases as regions. Finally, this regional data is progressively combined into each area using LSTM for prediction with valence scale for each area. The experimental results show that the proposed method outperforms the ANN-based, lexical, and regression-based methods published in previous studies. In [18], they provide simple, trained models with annotations, whereby two classes—positive and negative—are added to each phrase at the sentence level. Additionally, they use LSTM to model the terms of intensity and denial, which represent the language functions of the lexical sensations. The results show that the models are able to faithfully capture the linguistic meaning of strong, denial-based, and emotive language. The authors of [15] used semantic criteria using a lexical-based approach to determine the etymology of words and their links to other words. After that, they used a DeepCNN to record the morphological details of every word at the character level using pre-trained vectors. Then, they used a BiLSTM bidirectional network, which creates a representation of the attributes of the whole phrase by using word-level pre-trained vectors. The model was trained using 100 billion Google News keywords from Word2Vec [14] and TwitterGlove [17] from Stanford University. In this investigation, they assert an accuracy of 86.63%. 2.2 Emotional Analysis in Learning Environments In order to create an evaluation in this respect while taking user feedback into account, a research paper published in [10] recommends using hybrid learning methodologies based on SVM and Hidden Markov Model (HMM) in an online learning environment. The authors propose that e-learning blogs become more complicated and challenging when sentiment analysis is applied to them. [8] provides a sentiment analysis methodology to collect student feedback and evaluate a course's quality in two steps. Based on each student's papers, views have been divided into good and negative categories using machine learning algorithms. Next, the extraction of opinion is used to extract characteristics from the user-generated materials for a certain course, including resources, exams, and teachers. In SA-E [1], the authors evaluate student input that is obtained in real time via Twitter tweets using two machine learning algorithms: Naïve Bayes and SVM. This enables them to ascertain, in real time, if the attitudes of the pupils are good or negative. The purpose of the evaluation and feedback-gathering process was to improve teaching. Users of the social network Facebook provide sentiment data to a tool called SentBuk [16]. It evaluates student opinions and classifies them as positive, negative, or neutral in order to spot significant emotional alterations. The SentBuk system has been enhanced by integrating this data, enabling it to suggest tasks to students based on their emotional states. Insightful remarks are also given to the course teacher based on these emotions. SentBuk's classification algorithm employs a hybrid methodology that blends traditional machine learning techniques with lexical analysis. The relevance of student sentiment in this attempt is highlighted in [4], where an ANN-based strategy is proposed to estimate students' dropout rates from MOOC courses using sentiment analysis. Running text is used in [12] to collect student feedback, and supervised and semi-supervised machine learning techniques are applied for sentiment analysis to identify important features in addition to orientations. In the work of [7], sentiment analysis is used with supervised machine learning algorithms of type SVM, Naïve Bayes, nearest neighbors (KNN), and ANN to identify the polarity of the student comments based on predefined teaching and learning criteria. In this study, a combination of machine learning and natural language processing (NLP) techniques was used to student feedback data. The optimal performance of every algorithm was ascertained by contrasting the outcomes with many evaluation standards. Based on feedback from students, they look into NLP and machine learning techniques in [19] to help teachers and university administrators deal with problems related to students' learning. The system they developed looks at comments students make in online course surveys and real sources to assess the polarity of sentiment, expressed emotions, and student contentment. To determine the reliability of the system, they also contrasted the results of the direct test.

II. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM:

SA has a number of technical challenges. Firstly, a term's meaning might change depending on the circumstances. In the context of education, for example, the word "early" indicates a negative meaning in the sentence "The lecture is too early!" yet a positive connotation in the context of customers in the line "The courier arrived early." Second, applying SA to multilingual material might be difficult. For example, people in India often leave comments in a transliterated form of Hindi in order to express their opinions. Moreover, multilingual data is not handled by them. Finally, previous research has not attempted to validate their systems by comparing the results of their analysis with traditional direct-assessment methods.

DISATVANTAGES:

1. Categorize feelings and emotions. There are two categories for sentiments.
2. Both positive and negative emotions are distinguished, and the method calculates satisfaction or dissatisfaction based on the eight categories of anger, anticipation, disgust, fear, joy, sorrow, surprise, and trust.
3. To aid in analysis, the SA system has a data-visualization component and is capable of processing multilingual information.

PROPOSED SYSTEM:

Our suggested SA approach enhances teaching and learning by performing temporal sentiment and emotion analysis of multilingual student feedback in terms of teacher performance and course satisfaction. The method divides feelings into two groups: positive and negative, and then further divides emotions into eight categories according to Robert Plutchik: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. This allows for the computation of pleasure or dissatisfaction. Figure 1 depicts the system architecture, which is divided into five main sections: data collection, data preprocessing, sentiment and emotion identification, pleasure and dissatisfaction computation, and data presentation. The system uses the free and open-source R programming

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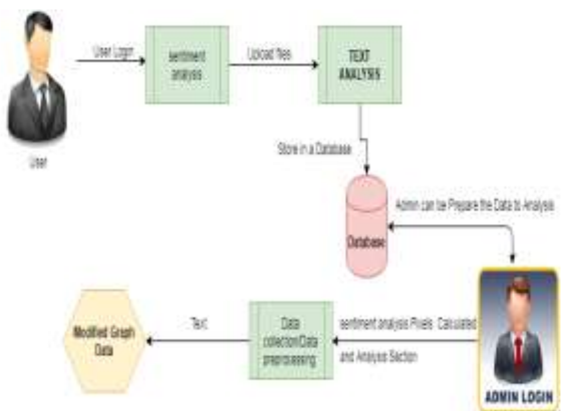
language (www.r-project.org) to prepare data and identify sentiment.

ADVANTAGES:

1. The establishment of norms. Content that has been shortened is normalized by mapping it to commonly used Internet slang terms using a glossary. For instance, the terms "gud" and "awsm" correspond to "good" and "awesome," respectively.
2. Stemming. The tm_ map function in R's SnowballC package is used to translate terms in student comments to their base word in order to aid word matching even further. For instance, "move" replaces "moving," "moved," and "movement."

SYSTEM DESIGN

ARCHITECTURE DIAGRAM



III. IMPLEMENTATION MODULES:

SENTIMENT ANALYSIS (SA)

It is possible to evaluate course results directly or indirectly. Exams, assignments, quizzes, and project reports are examples of real student work that are taken into account during direct assessment. Student observations of the educational process and the quality of instruction serve as the foundation for indirect evaluation. In order to ascertain students' interest in a course and pinpoint areas that might be improved by corrective action, SA of student feedback examines text provided by students, whether in official course surveys or informal remarks from online platforms.

DATA COLLECTION

Both data from a university SRS and student reviews of a Coursera course make up our first data corpus. About 4,000 student comments from the August 2015 to August 2016 course as well as 1,700 comments from students after the course is over are included in the Coursera dataset. About 500 student comments and evaluations for lecture and lab sessions after midterm and final semester exams for a course taught by one instructor over the last ten years are included in the SRS dataset.

Data preprocessing:

The SA system prepares the collected data for further processing at this point. This process consists of three steps.

The tokenization process. The R tokenize function divides student comments into words, or tokens.

lowering the case. To make it easier to match terms in student comments with words in the NRC Emotion Lexicon, characters are changed to lower case. The tm_map function from the R tm package is used for this phase.

Elimination of superfluous content To increase the efficiency and reaction speed of the system, stop words and punctuation are eliminated as they are not significant to SA.

Sentiment and emotion identification: In this stage, the preprocessed data is analyzed by the SA system to find sentiment and emotion occurrences. It associates words with positive or negative sentiment and the eight fundamental emotions using the NRC Emotion Lexicon5, commonly referred to as EmoLex. Forty languages are supported by the dictionary, including major Indian languages including Tamil, Hindi, Marathi, Gujarati, and Urdu. It has annotations for 8,116 Hindi and 14,182 English unigram words.

IV. CONCLUSION

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There is broad agreement that evaluations of learning behavior and teaching effectiveness, both direct and indirect, need to be consistent. For instance, it would be anticipated that students who do well in a course will give the instructor good marks and positive remarks; on the other hand, students who do badly are likely to be unhappy. We examined student surveys and comments from a university SRS system for 25 different courses over a two-year period in order to verify our SA method. We then compared the average course grade on a 0–100 scale with the proportion of positive feelings students had about each course.

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