Aspect-Based Emotion Analysis on Speech for Predicting Performance in Collaborative Learning

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***Abstract*— This full research paper focuses on a natural language processing (NLP) driven approach to extract emotions from the speech in collaborative learning environments and analyze how they correlate with the learner's performance. Social competency is one of the base competencies that have been the target of many educational researchers in engineering and computing education during the past several years. Studies show that the low level of individual's performance is not just due to lack of intellectual or cognitive competencies but also lack of social skills impact performance in both educational and industrial domain. For this reason, Engineering Education is encapsulating social skills into the curriculum to prepare students for the fourth industrial revolution (i.e., Industry 4.0). Towards this goal in earlier work [1], we proposed a model to identify the correlation between the sentiments extracted from students' speech in teams and their performance. The results of polarity sentiment analysis showed a strong positive correlation between students' positive feelings in teams and their individual performance in the course. This study takes a further step and conducts multi-class emotion analysis on students' speech in teams. The process consists of two steps:1) extracting different classes of sentiment such as joy, anger, anxiety, etc., and identifying their correlation with students' performance using collaborative speech in an introductory programming course (CS1), 2) Aspect-Based Emotion Analysis (ABEA). The approach we adopt is the supervised machine learning method and rule-based models on speech datasets. After pre-processing the text, we identify multi classes of sentiments. Aspect extraction is accomplished through the Part of Speech (POS) tagging, and patterns are extracted from the identified aspects. Finally, we use the combination of emotion classes and aspect patterns as feature vectors to train the K-Nearest Neighbor (KNN) algorithm to predict students' performance.**

Keywords—*Aspect-based emotion analysis, Emotion, Collaborative learning, NLP, KNN, Performance prediction, CS1, Quantitative analysis*

I. Introduction

Emotion is an essential component of the attitude that has a key impact on the learning process and promotes team effectiveness [2]. According to research, the poor level of an individual's success is triggered not only by the lack of cognitive capacity but also are impacted by the individual's attitude and lack of soft skills in both the educational and industrial realms [3]. As a result, it is important to consider different dimensions of the attitude like affect, behavior, and cognition (i.e., ABC of attitude [4]) into the curriculum to improve the students' learning experience and prepare them for the fourth industrial revolution [5]. Sentiment analysis is one way to capture emotional states and has been largely applied in the commercial domain, however during the past decade it drew the attention of researchers in the field of engineering education [6]. Different methods are proposed by educators to analyze students' emotions and sentiments in the academic setting [7]. The most common approaches to extract emotions are either text analysis on students' asynchronous discussions, and reflective writings [1] or speech analysis on their conversation about the course topics [5, 24]. Some of the studies take a further step in analyzing emotions by conducting aspect-based emotion analysis that deals with emotions linked to each important aspect of the topic [8].

In this experimental research, we analyze students' speech in an active learning introductory programming course, to identify how their emotions during teamwork associate with their performance in the course. In the previous study [5], we conducted polarity-based sentiment analysis on collaborative verbal discussions in CS1 class to determine the relationship between positive sentiments and students' performance. Our analysis showed a strong positive correlation between students' positive sentiments in teams and their performance. In this study, we do sentiment analysis with more granularity by extracting different classes of emotion [i.e., happy, sad, angry, surprise, fear] from speech. We further conduct aspect-based emotion analysis to extract the aspects related to each emotion and have a better understanding of what subjects were explored as student expressed their emotion. Finally, we fit the extracted aspects and emotions to train the KNN algorithm to predict student's performance.

In the next section, the overview of the related research in the field of aspect-based emotion analysis is presented. The remainder of the paper is set out as follows: in section three we present our research methodology, data collection, and preprocessing approach, in section four the result of data analysis including multi-class emotion detection, and aspect-extraction, performance prediction are presented. Finally, the paper concludes with a discussion about further data analysis and the path to future work.

II. Background

Different frameworks are developed for emotion analysis in the educational domain either by measuring the polarity of sentiments (i.e., positive, negative, or neutral) or by classifying emotions into various classes like happy, sad, angry, or disgusted [6].

Although emotion analysis fine-grains the sentiment in determining the feeling behind an argument or comment, [9] Aspect-based emotion analysis, also known as feature-based sentiment analysis, goes a little forward by classifying features of the subject about which the emotions are expresses.

Aspect-based emotion analysis has application in different domains and several methods are proposed to achieve it. For example, in the commercial domain, it can be used to analyze users' reviews about a piacular product and extract the most interesting aspect of that item [10]. In one study the authors propose aspect extraction from iPod unlabeled review dataset by two models of POS tagging and TD-IDF (Term Frequency Inverse Document Frequency) feature extraction technique [10]. In the first model, after preprocessing the review corpora, they extract all the aspect words in the dataset by POS tagging method starting from noun phrases and extending it to adjectives and adverbs. The frequency of the most interesting aspects is measured, and positive, negative, and neutral emotions are classified. They apply the second model of aspect extraction, TF-IDF, to measure the frequency of the terms in the dataset and the importance of each term. The author used Naïve Bayes, Support Vector Machine (SVM), KNN, and Decision Tree classifiers to calculate the accuracy and determine the proper classification of aspects by both models. The result of their analysis shows on the iPod review data set the TF-IDF model results in a higher performance metric.

Our finding on the existing research shows opinion mining and generating aspect-sentiment pairs is mostly applied to the customers' reviews about specific products. In [11] the authors propose a compound noun lexicon model named ASPERC, for extraction of aspect-sentiment pairs. The three main phases of the model are the generation of 1) compound noun lexicon, 2) aspect-sentiment pair rule, and 3) aspect-sentiment pair extraction. The result of this study shows the proposed model has decent performance on two domains of laptops with 76% precision and restaurants with 77.03% precision. However, for efficient training of the model high number of sentences are required otherwise training of the model would be costly with fewer data.

In another study [12] the authors propose a POS tagging approach for extortion of opinion phrases about product features from customers' reviews by using adjectives, adverbs, verbs, and nouns. For this experiment, they use customer reviews of 5 electronic products from amazon. The result of this study shows an average of 0.73% precision in feature extraction for all five products. The extracted patterns can serve to provide a product feature summary to guide both the users and merchants to make a better choice.

Akhoundzade, R., et al. [13] suggest a hybrid approach for opinion mining that included rule-based approaches, neural networks, word embedding-based models, and clustering methods. The aim of the authors is to decide whether people have a positive or negative attitude toward the functionality of cellphones, tablets, and laptops on an e-commerce website. After identifying the sentiment words, they solved the problem in two steps: (1) extraction of aspects and (2) identification of users' positive or negative tendencies against certain aspects. For aspect extraction first the most frequent phrases are selected based on adjective and descriptive rules, and by clustering methods and cosine similarity metric, the final aspects are selected. For evaluation of the method, they used the recall and precision and F1 metric. Their findings show that using unsupervised clustering methods combined with cosine similarity results in a higher F score.

Another important application of aspect-based sentiment analysis is in the educational domain. Researchers have used different methods to analyze students' reflections and feedbacks to improve the pedagogical practices. For example, in [14] the authors propose a model that classifies sentiment polarity (i.e., positive, and negative) feedback that is generated through peer assessment in Higher Education. The authors conduct the experiment with different n-grams and TF-IDF techniques and classification models like SVM. Their findings show SVM was the best classifying model which increased the efficiency and effectiveness of the model.

In another study [15] the authors extract aspects from students' feedback to help administrators with the evaluation of the University's performance. In this study, they define a domain ontology in the preprocessing phase for aspect extraction and apply the OpenNLP parser for POS tagging and the SentiWordNet lexical tools to define the WordScore. the accuracy of the proposed model is measured by the Naive Bayes Classifier. With overall accuracy of 0.89, the result of this study shows the proposed method is helpful in analyzing student input so that administrators could make decisions to enhance the university's results.

In the next section, we propose our model of aspect-based emotion analysis using POS tagging and KNN classifier to predict students' performance based on the identified feature vector.

III. METHODOLOGY

Most of the existing work on aspect extraction and opinion mining is conducted on the textual reviews or feedbacks in the commercial or educational domain. The innovation of our research is aspect-based emotion analysis in the educational domain by using students' verbal speech during teamwork in class.

In this study, we identify the correlation between students' emotions in their speech during teamwork and their performance in the course. The performance metric is considered to be students' overall grades in the course which includes their grades on class activities, four major assignments, and two tests. Next, we conduct aspect-based emotion analysis using the POS tagging method and apply KNN supervised machine learning algorithm on the combination of aspects and emotions as feature vectors, to predict students' performance. We propose the following hypothesis to answer the research question.

H1: Students' positive emotion of 'happiness' during teamwork is correlated with their performance in the course.

In the following, we present our methodology for aspect-based emotion analysis, data collection, and pre-processing of the collected data for analysis.

A. Aspect-based emotion analysis

Our proposed method consists of two main steps. The first step is to identify different classes of emotion and the second is to extract aspects related to each emotion. For emotion analysis, we used the Text2Emotion python package which parses the texts and identifies the embedded emotions in the context. It outputs the emotions into five classes of joy, anger, sadness, surprise, and happiness. Next, we did aspect extraction using a rule-based grammatical tagging method called POS tagging. In this method, we mark up the tokens in each sentence with related parts of speech tag such as nouns, adjectives, verbs, adverbs, etc. The list of identified POS tags used in this research is presented in Table 1.

TABLE 1: ASPECT FEATURE EXTRACTION PATTERN'S

Tag	Description
NN	Noun, singular
NNS	Noun plural
NNP	Proper noun, Singular
NNPS	Proper noun, Plural
RB	Adverb
RBR	Adverb, Comparative
RBS	Adverb, Superlative
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund/present participle
VBN	Verb, past participle
VBP	Verb, present, non-3rd person singular present
JJ	Adjective
JJR	Adjective, comparative
JJS	Adjective, superlative

Different combinations of POS tags create multiple POS patterns. We identified 14 unique POS patterns in the dataset out of which three POS patterns were selected heuristically as candidates for aspect extraction. We used expert analysis to identify the candidate POS patterns that better reflect the emotional tone of the sentence in the context of this study. The identified patterns are presented in Table 2.

TABLE 2. POS PATTERNS FOR ASPECT-BASED EMOTION ANALYSIS

Description	POS Pattern
Adjective + adverb (Pattern 1)	JJ + RB/RBR/RBS
Adverb+ verb + noun (Pattern 2)	RB/RBR/RBS + VB/VBD/VBG/VBN/ VBP + NN/NNS/NNP/NNPS
Adverb+ adjective+ noun (Pattern 3)	RB/RBR/RBS + JJ + NN/NNS/NNP/N NPS

After identifying the POS patterns for aspect extraction from students' speech, we applied the KNN model to predict students' performance. KNN is a machine learning approach that predicts objects by learning data that is closest to them based on the distance metric. We trained the model by passing the feature vector which consists of POS patterns and multiple classes of emotions (i.e., happy, sad, fear, surprise, anger) and considered the target value as the performance score.

For evaluating the performance of the proposed model, we used the Mean Squared Error (MSE) metric [16]. MSE is the most common loss function for regression algorithms, which calculates the sum of the squared distances between target variable and predicted values (Equation 1) [16]:

$$MSE = \sum_{i=1}^{t}(F_i - A_i)^2 / t \quad (1)$$

B. Data Collection and preprocessing

We conducted this experiment on an active learning introductory programming class (CS1). In this course, the first half of the class time was dedicated to mini-lectures and low-stake quizzes about the course topic, and the second half of the class time was dedicated to pair programming in which students worked in teams to solve the given problems. The total number of participants in this study was 28 students who formed 14 teams. We recorded the team's conversations during the class activity for an average of 40 minutes in every class session throughout the semester.

The collected audio data from students' conversations were filtered and processed for noise removal and quality improvement [5]. Next, the data was transcribed into text format for analysis. The transcription datasets were vectorized based on speech initiation points such that each vector denotes when a student started speaking both in active and reactive manner.

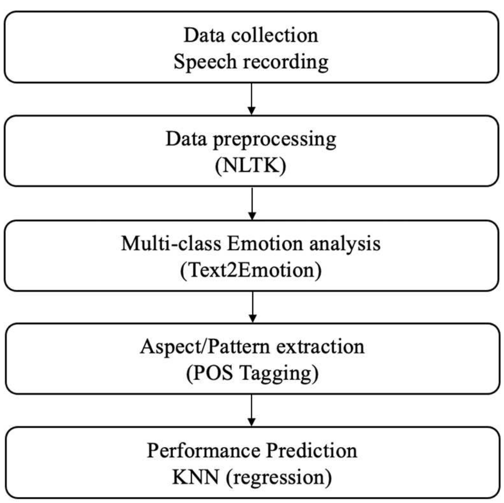

Figure 1. Research methodology

Data preprocessing is an important step in natural language processing to clean the text so that it can be encoded into numeric vectors and comprehended by a machine. We employed the NLTK package from python to conduct the common steps of lower casing, stemming, lemmatization, stop word removal, digit and noise removal on the dataset to preprocess the textual data. The next step was tokenization, in which strings were spitted into a sequence of tokens. A custom dictionary was developed to remove the tokens that frequently appeared in the dataset but didn't have any significance in the context of this study. Figure 1 shows the general flow of the research method.

In the following section, we present our findings from the data analysis.

IV. DATA ANALYSIS

In this section, we present the result of data analysis in three parts. First, we discuss our findings on multi-class emotion analysis and test the hypothesis to identify the correlation between happiness emotion and performance. Next, the result of aspect extraction and POS pattern identification is presented. Finally, we discuss how we train the KNN model to predict students' performance based on the emotions they expressed in the speech and the POS patterns.

A. Multi-Class Emotion mining

To categorize unlabeled vectors into different classes of emotion we applied the Text2Emotion python package [17]. Text2Emotion package detects five emotion classes of happy, angry, sad, surprise, and fear as well as the values that represent the intensity of each emotion. The output of Text2Emotion is a set of numeric values for each of the five emotions. In this research, the emotion associated with the maximum value was considered as the emotion for that specific vector. Figure 2 visualizes the frequency of each emotion class for all participants.

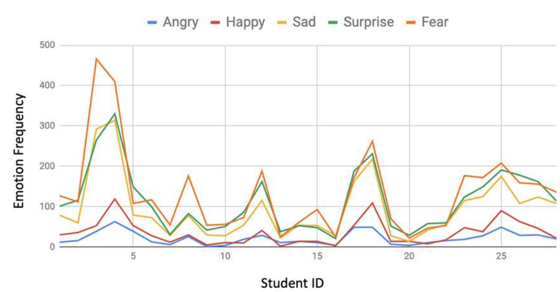

Figure 2. Multi-class emotion frequency

Next, we identified if there is any correlation between students' happiness emotion and their performance. To answer this question, we used the Pearson correlation coefficient [18] to measure the linear relationship between happiness emotion, and performance. The Pearson correlation coefficient is calculated by multiplying the covariance of two features by the product of each data sample's standard deviation. It is the process of normalizing the covariance between two features [18]. The coefficient value is signified by r_s (Equation 2) where r_s can be anywhere between -1 and 1. The interpretation is that the closer to r_s is +1 and -1, the stronger the monotonic relationship is between the two variables. The strength of the correlation can be described using the following guide for the absolute value of r_s [19]; r_s = 00-.19 “very weak”, r_s =.20-.39 “weak”, r_s = .40-.59 “moderate”, r_s = .60-.79 “strong”, r_s = .80-1.0 “very strong”.

$$r_s = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{2}$$

Where n is the total number of cases.

The calculated coefficient value (r_s) for the association of happiness emotion and performance is 0.12. Although technically there is a positive correlation between “happiness” emotion and performance the strength of this association is weak.

Next, we test the hypothesis by using the two-tailed p-value statistical method with a confidence value of 0.05. This is to determine if there is a statistically significant correlation between happiness emotion and performance. The calculated p-value is 0.540 which is higher than the confidence level, therefore the null hypothesis cannot be rejected. This indicates the association between happiness and performance is statistically significant.

B. Aspect Extraction Using Rule-Based POS Tagging Patterns

We applied the NLTK package to identify the POS patterns presented in Table 2 and extracted aspects based on the identified POS patterns. The frequency of POS patterns for each participant is presented in Figure 3.

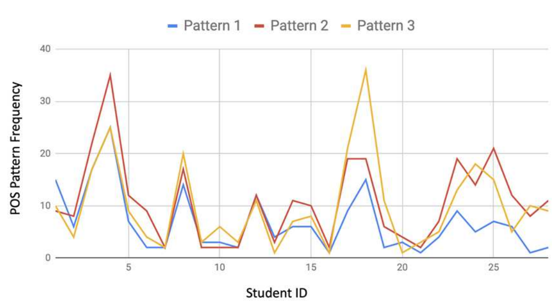

Figure 3. Frequency of aspect patterns for each student

C. Performance prediction using KNN Regression

We applied the KNN model for predicting the performance of each student by fitting the model with the feature vector consisting of POS patterns and multi-class emotions (happy, sad, fear, surprise, anger) the target value as the performance score. The target is estimated using local interpolation of the targets aligned with the training set's closest neighbors. For this algorithm, the best k-value denotes the number of near neighbors which is determined by the data. To calculate the optimum k-value, we applied cross-validation [20], and GridSearchCV methods [21]. The optimal value of k is usually the square root of the total number of samples. For the experiment, we identified the k-value=15 to be an optimal score for running KNN regression. Figure 4 shows the mean squared error versus the k-value. At k-value = 15, we see that there is a decrease in the mean squared error rate of 0.012.

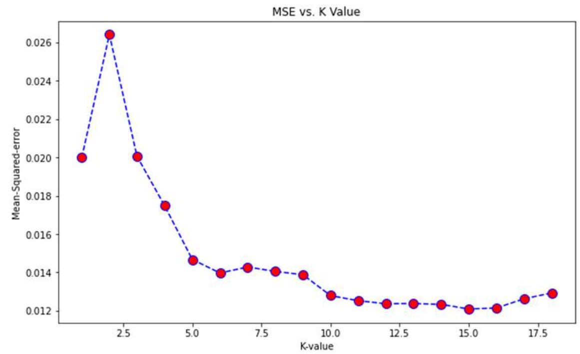

Figure 4: k-values versus the mean squared error rate

Before fitting the data into the model, we encoded the aspects and emotions from categorical type to binary 0’s and 1’s using the one hot matrix and normalized the target feature so that it ranges from 0 to 1. This is because the KNN model does not accept categorical data as input. The steps we followed for fitting the model as follows: 1) shuffled the dataset, 2) split the dataset into 10 percent testing and 90 percent training the model, 3) fit the model with training features and labels, and 4) predict the test data and get the nearest neighbors for the data.

To determine the performance of our model Root Mean Square Error (RMSE) evaluation metric was applied. RMSE is used for measuring the difference between the predicted and actual values to determine the accuracy of the model. The mean or average of the squared deviations between predicted and actual target values range from 0 to infinity, the lower score is an indicator of better performance. In our model, the MSE score is 0.01 which is a decent score for performance.

V. Discussion

In this study, we extracted different classes of emotion from students’ speech as they worked in teams. Our finding from the data analysis shows a weak yet statistically significant correlation between student’s “happiness” emotion and their performance in the course.

We did further analysis to identify a pattern between the correlation of different types of emotions and students’ performance. For this, we applied the same Pearson coefficient value and two-tailed p-value to measure the strength of association between the parameters. These numbers are presented in Table 3. Data shows a weak positive correlation between emotion classes of “happy” and “fear” with performance and a negative weak correlation between "angry", "sad", and "surprise" emotions with performance.

TABLE 3: POSITIVE AND NEGATIVE CORRELATION COEFFICIENT AND P-VALUE

	Performance		
	Pearson's r_s	Strength of relation	p-value
Angry	-0.1028	Weak Negative	0.60248
Happy	0.12085	Weak Positive	0.540
Sad	-0.01708	Weak Negative	0.9312
Surprise	-0.0390	Weak Negative	0.843
Fear	0.0190	Weak Positive	0.9234

For predicting students' performance based on the feature vector we tried different machine learning models such as SVM and random forest regression. SVM is a supervised machine learning model which can be used for both classification and regression problems [22]. Random Forest (RF) is the supervised ensemble-based machine learning algorithm technique that works well on classification and regression [23].

For evaluating the performance of each regression method we used the same Mean Squared Error (MSE) metric. The calculated MSE of SVM is 0.02 and for the random forest is 0.02. The comparison of the SVM values for the three regression models of KNN, SVM, and random forest shows a better performance with KNN on our dataset.

VI. CONCLUSION

Students' emotional states impact their learning experience and performance in the academic setting. This has drawn the attention of researchers to study different dimensions of affect and emotion in engineering education and make appropriate interventions. One of the emotion analysis methods that has been widely applied in related research is sentiment analysis. Sentiment analysis methods either measure the polarity of students' emotions or categorize emotions into different classes like anger, sadness, happiness, etc. These methods are mostly applied to students' feedback, discussion forums, and reflective writings. The innovation of this research is analyzing student's speech as they work in teams in class and identify how their emotions correlate with their performance. Our finding shows there is a weak yet positive correlation between students' happiness and their performance. We further propose to predict students' performance based on emotional states. For that, we did aspect-based emotion analysis to identify the context of the expressed emotions. Post tagging approach was used to identify different parts of speech and we identified three POS patterns based on combinations of the tags. We used both emotion and POS patterns as feature vectors to predict the performance, which is students' grades in the course. We fit the data into the KNN regressor to train the model. The prediction showed the MSE value of 0.1 which indicates a decent performance.

This study was conducted on a CS1 class with 28 participants as a case study. In future work, we will expand the number of participants and run the experiment on different classes to evaluate if we observe the same correlation between students' emotions and performance. This finding would help both instructors and students. Instructors can observe the climate of teams based on the emotions that students express in their discussions and apply appropriate pedagogical interventions. Providing emotional feedback to students will help them be aware of their feelings and behavior in teamwork and make adjustments accordingly to have a positive team experience. The application of this model can be extended beyond computing and engineering education into the industrial domain as well.

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