A Study on the Analysis of Students' Emotions in the Classroom Based on School Forums

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Abstract. In this paper, we first crawl the campus forum data using the Scrapy crawler framework to obtain the classroom evaluation dataset, and then use sklearn to perform random partitioning of the dataset. Then the jieba library is used to segment the training set comment data, and feature extraction and feature vectorisation are carried out. Subsequently, a plain Bayesian model constructed by training with the test set data is tested on the data to be tested, and course optimisation suggestions are made based on the test classification results, which are constructive guidance for the reform and improvement of course quality.

Keywords: Campus forum · Plain Bayes · Students · Classroom · Sentiment analysis

1 Introduction

The continuous advancement of the education process has led to a gradual increase in the quality of teaching and learning required in higher education. Problems such as the quality of teaching not matching the needs of the educated and the inefficiency of student learning are important causes of poor classroom teaching. Scientific analysis and decision-making of classroom data can bring guidance to teaching and learning and significantly improve teaching quality. As a medium for students to make objective evaluations of classroom quality, the campus forum carries a large amount of data related to teaching evaluation. In order to deeply understand students' demands on classroom quality and explore the relationship between students' emotional experience and course quality, this study conducts an investigation of classroom quality factors based on student review data from the students' perspective, perceives students' attitudes towards the classroom, and then based on the classification of the plain Bayesian model ideas and correlation analysis to reveal the relationship between students' affective experience and classroom quality in order to improve teaching quality and promote quality education and teaching and the sustainable development of high quality classroom teaching.

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2 Emotional Analysis

2.1 Sentiment Analysis Process

This study takes the school campus forum as the object, firstly, using the Scrapy web crawler framework technology, crawl the forum data of the campus forum students' comments on the class, and classify the users' emotions into four categories: positive, low, bored and indifferent. Then, the collected data was pre-processed, and the pre-processed data was subjected to word separation operation, then feature extraction and feature vectorisation, and for the vectorised features, the data from the test set was put into the training set for training of the plain Bayesian model, and the training reached the accuracy requirement before testing the data from the test set. The flow of sentiment analysis is shown in Fig. 1.

2.2 Research Methodology

2.2.1 Data Sources and Pre-processing

Data pre-processing refers to the acquisition of textual data after acquisition, as the campus forum is a real-time online social medium for users and data information is constantly changing [1]. In this paper, a total of 20,666 pieces of data were crawled using the Scrapy framework, a fast and high-level web crawling framework [2], since the beginning of the implementation of the OBE concept in China in 2015, and the data crawled was collated, invalid and blank comments were removed, and the comments of relevant educators were also removed to ensure the validity of the data results. In order to ensure the validity of the data, the comments of the educators were also removed, and some comments that were not relevant to the study were also removed, resulting in 18,532 valid comments as the target data for the analysis.

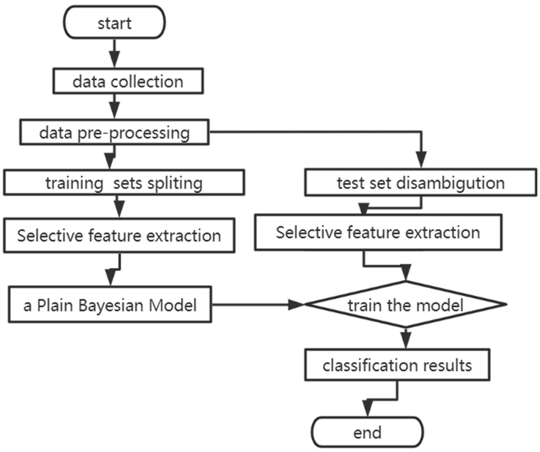

Fig. 1. Emotional analysis flow chart.

2.2.2 Splitting Words

The 18,532 valid forum comments were processed using the HIT language technology platform to remove the deactivated words from the comments, and then the jieba third-party library in python was used to split the comments into words, for example, the comment data "I like data structures course" was split into "I", "like", "data structure", "course". At the same time, the whole dataset is randomly divided into a training set and a test set using the ShuffleSplit algorithm in sklearn in python.

2.2.3 Feature Extraction and Vectorisation

The results of the split comment data were evaluated by the TF-IDF keyword evaluation method. The number of occurrences of the word is counted, the more occurrences of the word, the more important it is, while it is the opposite of the number of occurrences in the document set it is in [3]. The TF is used to represent word frequency and is calculated as shown in equation $\mathrm{TF_i} = \frac{\text{Number of occurrences of the word i in the document}}{\text{Total number of occurrences of all entries in the file}}$. The Inverse Document Frequency (IDF) refers to the fact that if the file containing word i is smaller, the IDF will be larger, $\mathrm{IDF}_i = \log(\frac{\text{Total number of documents in the file set}}{\text{Number of documents containing entry i}})$. And the TF-IDF is calculated as

$$\mathrm{TF}\text{ - }IDF_i = TF_i \times IDF_i$$

The keywords in the comments were extracted by the TF-IDF algorithm, and comments with scores greater than or equal to 0.75 were judged as positive emotions, those greater than or equal to 0.5 and less than 0.75 were judged as low emotions, those within the range of 0.25 to 0.5 were judged as disgusting emotions, and the rest were indifferent emotions. The keyword extraction results are shown in Table 1. At the same time, to ensure the accuracy of the prediction results, the keyword results in each emotion type were obtained by using manual statistics of 5000 comment data and compared with the evaluation results of the TF-IDF algorithm, and the accuracy rate was as high as 92.3%, therefore, the keyword extraction was effective.

Using the CountVectorizer vectorisation tool, the words in each comment are converted into a corresponding word frequency matrix.

Table 1. Key words corresponding to the four mood types.

Emotional value	Type of emotion	Keywords
0.75–1	**Active**	like, hope, teaching aids, delight, happy, lively, very good, recommend, support, hard work, love, learn
0.5–0.75	*Downturn*	boring, unintelligible, unsupportive, can't learn, can't keep up, bad attitude, so fast
0.25–0.5	*Aversion*	annoyed, upset, beat up, get lost, blah, blah, bleep, nag, annoying
0–0.25	*Indifference*	posed, indifferent, meaningless, not my business, not much to do with, dozing, sleeping, playing on the phone, listening to songs, swiping video screens

2.2.4 Building a Parsimonious Bayesian Classification Model

Plain Bayes is one of the most commonly used generative models for classifiers, converting joint probabilities into conditional probabilities using Bayes' theorem, which in turn determines the classification outcome by comparing the magnitude of the probabilities [4]. The joint probability distribution of a plain Bayesian p(X, Y) is converted to a conditional probability, expressed as $p(Y|X) = \frac{p(Y)P(X|Y)}{P(X)}$ [5]. Since a total of three classes of the plain Bayesian model are provided in sklearn's navie_bayes library, according to the need to classify the words in the review data in this experiment, and then to count the frequency of occurrence of the words, the type that fits the type of polynomial distribution, the polynomial distribution is the probability distribution of a particular combination of occurrences of each category after the experiment has been done n for a consecutive time in satisfying the category. Assume that denotes the number of times the category x_i i occurs and p_i denotes the probability that the category i occurs in a single experiment. When the precondition $i = 1, kx_i = n$ is satisfied, the random vector $\mathrm{X} = [x_1, x_2 ... x_k]$ consisting of the random variable x_i satisfies the following distribution function $f(x, n, p) = \frac{n!}{\prod_{i=1}^{k} x_i!} \prod_{i=1}^{k} p_i^{x_i}$ [6]. For this experiment, the size of the lexicon of the data to be tested is set to k and the occurrence of a word in a review is considered to be a distribution experiment satisfying the categories of k. The set of comments is considered to be composed of n entries, so that the set of comments is a category-compliant experiment for n times. Since the size of the lexicon k is large, the matrix after eigenvectorisation is a sparse matrix. By analysing the lexicon, the sentiment probability of occurrence of each lexical item, i.e. the value of p_i, was counted. At the same time, the probability is found by counting the word frequency of the entries in the lexicon of the test set, i.e. the value of x_i and the number of entries in the review article n.

The training and test samples follow sklearn's random partitioning of the dataset, so the number of training samples may appear to be small, while the training samples simply rely on word frequency statistics without contextualising them, both of which may lead to a lower accuracy rate of sentiment analysis. To improve this problem, a 5-fold validation was constructed using the k-fold method in sklearn, and the initial samples were divided into 5 equal parts. To avoid the problem of inaccurate training and testing results, the training and testing sets were divided according to the ratio of 3:2, and a total of 5 simulations were conducted. The training model was used to test the results more accurately.

3 Experimental Results and Analysis

3.1 Analysis of the Classification of Emotional Disposition

Using the method of this study to analyse the emotions of the sample to be tested, four categories of emotional tendency degrees were obtained as shown in Fig. 2. The graph shows the students' emotional disposition towards the classroom, with 58.8% positive, 18.4% negative, 10.8% disgusted and 15% apathetic. This result indicates that students overall have a positive affective disposition towards the classroom, suggesting that students are largely comfortable with the current implementation of the classroom and are able to complete the classroom learning objectives.

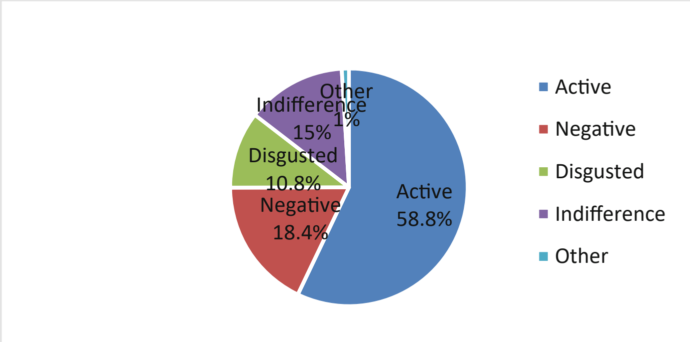

Fig. 2. Students' tendency to analyse their emotions about the classroom

Table 2. Table of sentiment values for the top 12 keywords

Keywords	Emotional value	Keywords	Emotional value	Keywords	Emotional value	Keywords	Emotional value
like	0.91	delighted	0.78	pendulum swing	0.23	playing with mobile phones	0.21
beep	0.42	so fast	0.61	Can't understand	0.73	thank you for your hard work	0.78
recommend	0.81	blah blah blah	0.48	support	0.79	love it	0.89

3.2 Analysis of Keywords and Sentiment Values

In this paper, the top 1000 keywords extracted were analysed for sentiment using a plain Bayesian model, of which 558 showed positive sentiment, 184 negative sentiment, 108 boredom, 140 apathy, and 10 others. The sentiment values of the key keywords with the top 12 scores were also calculated as shown in Table 2.

4 Conclusion and Recommendations

This paper explores and analyses students' emotional attitudes towards the classroom from the students' perspective, applying the polynomial distribution model of the plain Bayesian clock in a comprehensive manner, and using the students' campus forum classroom evaluation data as the basis, with a prediction accuracy of 91.2% and an average comprehensive evaluation index of 68.38%. The results of the sentiment analysis of the course facilitate a deeper understanding of student needs for the course from the data and provide new ways for teachers to improve the quality of their teaching. On the one hand, the emotional analysis of the course can increase the emotional aspect of the social presence between students and teachers, thus enhancing students' interest and satisfaction in learning in terms of teacher-student emotions; on the other hand, it can increase students' understanding of the professional course system and the OBE education concept, guiding them to draw up learning goals and make good study plans. For course teachers and course teams, the data can be used to explore students' learning knowledge and emotional needs, so that they can better build course teams, iterate on new lecture content, create learning situations and meet students' learning needs. In the face of such a large amount of evaluation data, this study still has some limitations, as it lacks balance in exploring the needs of the curriculum from the stdents' perspective only, and a more in-depth investigation should be carried out from both teaching and learning dimensions.

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