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Psychological State Detection based on Online Music Comments

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Abstract

In this paper, machine learning was used to analyze comments in NetEase's Cloud Music. A new feature vector was proposed to classify the comments as positive, negative, likes, and confidence. The study draws a histogram of users' psychological state based on the classified data and also compares the performance of the four classifiers (Naive Bayes, SVM, Maximum Entropy, and Ensemble). The findings show that: 1) music comments are related to people's psychological state; 2) machine learning can be used to analyze the sentiment of music comments with high accuracy; 3) the users' overall psychological state can be accurately reflected in the results.

Keywords

Music Comments, Psychological State Detection, Machine Learning.

1. Introduction

Mental health can be defined as a state of well-being, under which everyone can exploit their potential and lead a successful and happy life[1]. However, with the development of society, many people are suffering from psychological sub-health symptoms. Research has shown that about three out of every hundred people in the world are suffering from stress [2]. Many severe physical and mental problems, such as depression, insomnia, violent tendency, and even self-injurious behaviors, are strongly associated with psychological stress [2]. [3] believed that violence occurred frequently because of the increased level of psychological stress. An investigation into shootings revealed that shootings involved the release of firearms in college buildings or on campus grounds. From 2013 and 2016, there were 76 incidents of gun violence in the United States [3]. Also, a study concerning the population-based matched cohort (the study used all individuals in Denmark bereaved passed away between 1997–2014) suggested that mental stress may be a factor of excess mortality [4]. Furthermore, excessive stress is correlated with mental illness. In other words, long-term stress may adversely influence people's health. [1] performed research about mental illnesses and concluded that major depression and anxiety are two of the twenty of the known causes of disease.

To release stress, people interacted with music in some way to reduce pressure, such as music therapy. Music is considered therapy because its effectiveness can help patients to reduce their activity disturbances, aggressiveness, and anxiety [5]. Different genres of music have diverse effects on people. [6] designed an experiment for adults and teenagers to determine the effects of several genres of music (i.e. grunge rock, new age, designer). They concluded that listening to grunge rock led to significant increases in hostility and a decrease in relaxation, but new age music and designer music enables people to relax and reduce hostility, mental clarity [6].

The wide application of social media has had a profound impact on people's lives. The proportion of American adults using social media platforms increased from 7% to 65% between 2005 and 2015 [7].

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Moreover, according to the survey, about 65% of adults use social media and 73% of teens are connected to the internet through social media [8]. People share thoughts, express emotions, record daily habits on textual and image posts. The vast majority of these online actions are stored, and can be fully used in various ways. Sentiment extracted from Twitter can be utilized to improve the forecasting power of social media [9]. Another method harnessing sentiment is through a predictive model that maps social media data to tie the strength of the human connection together [10]. This type of data can also be mined to measure author sentiment through analysis of the text.

Reliable and visual content can be obtained from the individual's posts, which may help to analyze people's psychological state. [11] leveraged Tweeter postings to identify the spread of flu symptoms. [12] applied the Ailment Topic Aspect Model to more than 1.5 million tweets in order to discover correlations between behavioral risk factors and ailments. [12] used behavioral cues extracted from Twitter postings to predict depression. They demonstrated the feasibility of using social media data to develop health-related tools.

The data used in this article comes from NetEase's online music platform, which is one of the largest social media platforms in China, where people can comment on all types of music. It can be found that most of the music comments are lyrical because users are willing to express their own emotions after listening to music [13]. Therefore, it can be identified that the use of music comments to analyze psychological state can effectively provide accurate information for the analysis.

2. Data

Nearly 10,000 user comments were used for data analysis. These comments come from NetEase's Cloud Music's top 30 songs in 2019. There are more than 13,000 likes for these songs. The list consists of music from top lists from different music genres (ex. classical music, rock music). For example, song names such as "Get Me", "Dance Monkey", "All Falls Down" and "Life is Good". This list also contains specific effects of distinct genres of music and the number of people who had listened to that music. NetEase's Cloud Music community has more than ten million users every day, including clients from different platform applications (such as iPhone, Android, and Windows). Due to the semi-anonymous nature of the music platform, users are more prone to express their own feelings about music [14]. This requires the use of the music platform to analyze the mental well-being of users. Moreover, this study adopted the definition of mental health published by the World Health Organization (WHO). The role of this organization is to guide international health within the United Nations' system and to lead partners in global health responses. Because it is difficult to calculate stress directly, a snowball approach was used to arranging our dataset.

Table 1. Summary of Statistics. This table shows a summary of the statistics of user comments related to the top 30 most popular songs on the NetEase's platform.

	Classic	Country	Rap	Light	Pop	Rock	Total
Number of Comments	1736	1259	1657	1675	1684	1634	9645
Number of Likes	2009	2776	2093	1862	2614	1762	13116
Average Comments	347	252	331	335	337	327	1929
Average Likes	402	555	419	372	523	352	2623

3. Methodology

3.1 Attributes Definition

Music comments contain many attributes including text, expression, publishing time, likes, and source songs. First, it is necessary to integrate and classify the data according to these attributes. According to the release time of the comments, the comments were aggregated together in the same period (i.e., the same month), and then numbered based on the classification of each song (such as rock, folk songs, etc.). To describe the linguistic attributes of the text, the stress level reflected in the

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text was digitized with the help of "Language Inquiry and Word Count Dictionary", a simplified version Chinese LIWC psycholinguistic dictionary developed by Chinese psychologists and linguists [15]. This has been proven to be effective. It composed of approximately 4500 words and categorized into over 60 categories [16]. Second, Baidu sentiment analysis API was used to calculate the confidence of each text. It is an open API under Baidu AI (one of the most advanced AI platforms in China). Based on deep learning, Baidu sentiment analysis extracts a polarity category and confidence. Finally, comments are classified into positive and negative reviews by different classifiers, and the psychological stress level is derived from the number of comments in each class.

3.2 Classification

Three steps were taken to classify the dataset (see Figure 1). Firstly, specific features were extracted from the comments. When extracting features from tweets, hashtags and emoticons must be considered as specific features and should be classified independently [17]. However, in the comments from NetEase's Cloud Music, emoticons can be automatically converted to text, so emotions can be simply treated as text.

Figure 1. Methodology Steps. This figure illustrates the steps takes in this research.

Secondly, the unigram approach was used to represent comments as a collection of words. In unigrams, comments are represented by its keywords. LIWC was used to create keyword lists of different emotions: negative keyword list and positive keyword list. Counts of positive and negative keywords are two different features in comments. To obtain accurate results, the judgment must show whether the comment expresses a kind of emotion or comment on the song itself. Also, a new property, confidence, was introduced to determine the weight of this data in the model training process. For instance, comments with the first person will gain a higher confidence score. Keywords cannot all be treated equally as research shows that adjectives, adverbs, verbs, and other keywords can express emotion better than other words [16]. Some elements such as adjectives, verbs, and adverbs will be focused on. These elements are used to express subjective feelings. Each keyword is weighted according to LIWC. The emotional bias will be calculated based on the number, classification, and weight of the keywords listed in the comment. Furthermore, the psychological stress level of the user is measured when they publish the comment.

Finally, after creating a feature vector, Naive Bayes, Support Vector Machine, Maximum Entropy, and Ensemble classifiers are used to classification.

Naive Bayes classifier (Russell & Norvig [2009])

Naive Bayes classifier is a weak classifier based on Bayes theorem. It takes advantage of all features that are in the feature vector and analyzes them separately because they are assumed to be of independence of each other. It is simple and fast with good prediction performance. If the conditions for independent features are met, its performance will be better than other classification methods (such as logistic regression), and only a small amount of training data is required. The conditional probability of Naive Bayes is defined as

$$P(X|y_j) = \Pi_{i=1}^{m} P(x_i|y_j) \tag{1}$$

'X' is the feature vector, defined as $X = \{x_1, x_2, ... x_m\}$, and y_j is the class label. In this work, there are different independent features, likewise, counts of positive and negative keywords, confidence, and likes. These are effectively utilized by Naive Bayes classifier for classification. But the

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relationships between features are not considered by it. Therefore, it cannot take advantage of the relationships between text and likes.

SVM Classifier (Vapnik et al. [1992])

SVM Classifier uses a hyperplane to separates the texts and a large margin for classification. SVM uses a discriminative function defined as

$$g(X) = \omega^T \phi(X) + b \tag{2}$$

Φ () is served as the non-linear mapping which is from input space to the high-dimensional feature space. 'X' is defined as the feature vector, 'b' is regard as the bias vector and 'w' is the weights vector. 'b' and 'ω' are learned automatically in the training set. A linear kernel is used for classification, maintaining an extensive gap between the two classes.

Maximum Entropy Classifier (E.T. Jaynes [1957])

In the Maximum Entropy Classifier, it is assumed that there is no relationship between those features. The classifier always tries to maximize the entropy of the system by estimating the conditional distribution of class labels. The conditional distribution is defined as

'X' is the feature vector and 'y' is the class label. Z(X) is the normalization factor, λ_i is the

$$P_\lambda(y|X) = 1/Z(X) \exp\{\textstyle\sum_i \lambda_i f_i\ (X, y)\} \tag{3}$$

weight coefficient, and f_i (X, y) is the feature function.

$$f_i(X, y) = \begin{cases} 1, & X = x_i \ and \ y = y_i \\ 0, & otherwise \end{cases} \tag{4}$$

In this feature vector, the relationships between the part of the counts of keywords, counts of likes, and confidence are used for classification.

Ensemble classifier

Ensemble classifiers can become different types depending on the situation. They attempt to make good use of this feature, so the base classifiers will be able to do the best classification. Naive Bayes, SVM, and Maximum entropy are used as basic classifiers. It is generated by voting rules.

4. Result

4.1 Data Processing

The dataset was analyzed to ensure that the text is correct and usable. After selection, the dataset contains 7423 texts. Baidu's sentiment analysis API was leveraged to calculate the confidence of each text. The result is an available dataset with different features, such as counts of positive and negative keywords, likes and confidences. The data with confidence being less than 0.5 was also removed because it can be ignored.

4.2 Classification

The four different types of classifiers are also widely used in text classification. They can also be used for sentiment classification of music comments.

In this research, 1000 comments were selected as the training set, and 200 comments were chosen as the test set. Figure 2 shows the performance of these classifiers. The performance of all these classifiers are almost similar. Then, the above four classifiers were used to process all of the comments

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in the dataset, so four classification results were obtained for each comment. Because the result of the Ensemble Classifier is based on the other three classifiers, the following classification result will not appear: two of the classifiers are considered positive, the other two are considered negative.

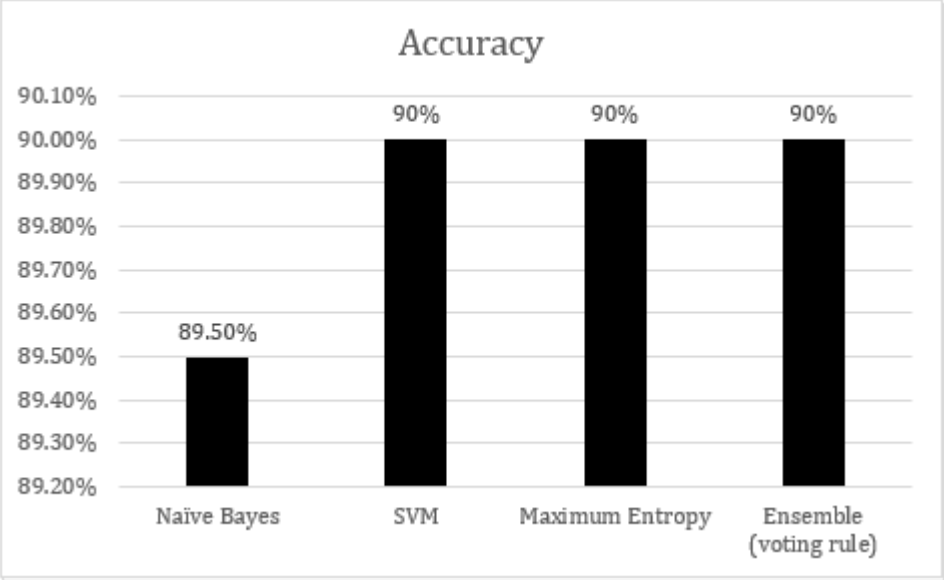

Figure 2. Performance of Different classifiers in Comment Sentiment Analysis.

Table 2. Summary of Statistics. This table shows the final dataset for analysis.

Date	Positive Comments	Negative Comments	Total Number
2015	58	5	63
2016	73	24	97
2017	37	13	50
2018	269	241	510
2019	1002	681	1683
2020	3563	1457	5020
ALL	5002	2421	7423

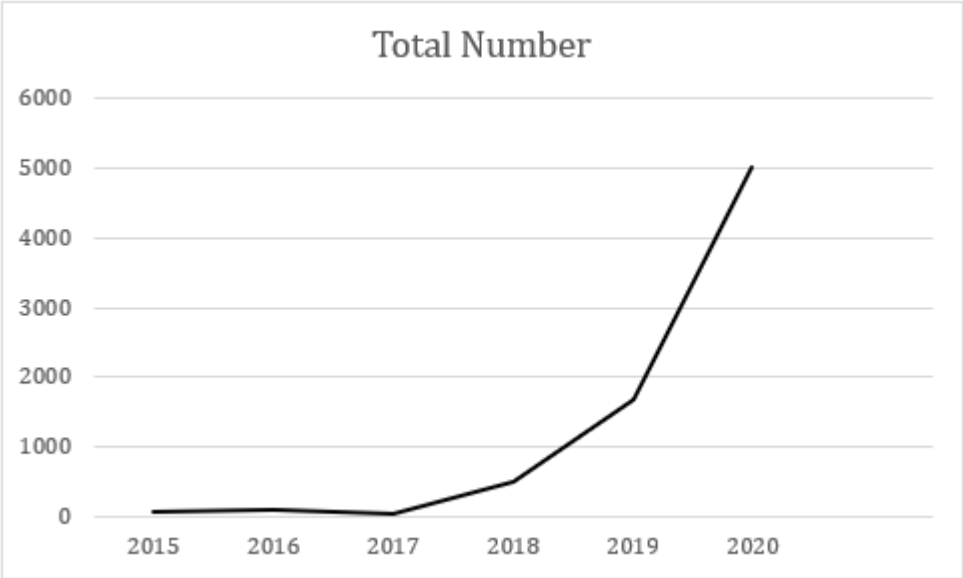

Figure 3. Trend of annual data volume

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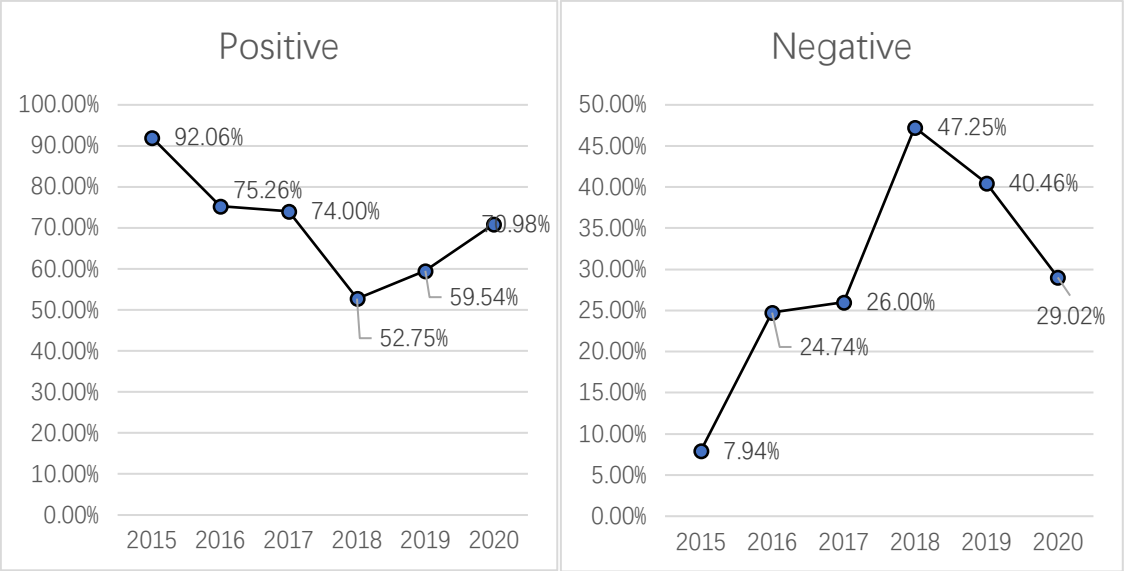

(a) (b)

Figure 4. Proportion of positive comments and negative comments

As can be seen from the charts, Figure (a) and (b) show the ratio of positive comments to negative comments is about seven to three. In general, users' psychological status tends to be good, and most users do not have much psychological stress. A large number of comments in the dataset were published in 2019 and 2020. Due to the comment renew mechanism of NetEase Online Music, most comments of popular songs before 2017 are no longer visible, so there are only a few comments of 2015, 2016, and 2017.

5. Conclusion

This research demonstrates the feasibility of using machine learning to analyze the sentiment of music comments. This also proves that it can be used to detect the psychological state of people who comment because most of the comments are expressions of their emotions caused by users through music. This study leveraged four different classifiers: Naive Bayes Classifier, SVM Classifier, Maximum Entropy Classifier, and Ensemble Classifier. Also, it compared their performance. In addition, the result indicates that the general psychological state of the public is stable and positive.

Future research will focus on the psychological analysis of each individual. Personal music record comments will be used to calculate their psychological stress levels. The changes in their psychological status over time will be displayed in the form of charts.

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