Deep Learning-Based Emotion Classification of Chinese Song Lyrics

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Abstract

Nowadays, the development and convenience of music streaming services has led to the phenomenon that listen music has gradually been an indispensable part of people's daily routine. Due to the reason that song lyrics effectively convey a range of emotions, serving as a medium for expressing the emotional state either from songwriters or singers, the application of music sentiment analysis has witnessed widespread adoption in various domains, including information retrieval systems and personalized recommendation systems (Edmonds & Sedoc, 2021; Wang & Yang, 2019). Although numerous studies have investigated the current advancements in music emotion classification, merely a few of them have successfully incorporated enough linguistic perspectives and machine learning techniques to effectively classify the emotions conveyed in music, especially Mandarin song lyrics. Thus, this study aims to apply linguistic features to deep learning model to complete music emotion classification task. Adhering to Ekman's six basic emotions (Ekman, 1992) with necessary modifications, this research labels Mandarin song lyrics into five different emotion types, *non*, *happy*, *sad*, *angry*, *fear*. In addition, linguistic features of sentiment-related lexicon (e.g., positive, negative, hypothesized, and escape-related words), lexical diversity (e.g., entropy and code-switching words), and subjectivity (single and plural pronouns) were extracted and trained by deep learning model, GRU, with both pretrained lyric embeddings and embeddings from CKIP GloVe as baseline models. The result shows that GRU model with CKIP GloVe and selected features performed with accuracy of 0.52, which is higher than the baseline model (Accuracy: 0.41). Moreover, the outcome also suggests that by removing some handcrafted linguistic features such as *first_single_pronoun*, *second_single_pronoun*, and *second_plural_pronoun*, the performance gained improvement. Overall, this study demonstrates the potential of employing linguistic features in deep learning approaches for Mandarin song lyrics' emotion classification.

Keywords: emotion classification, Mandarin song lyrics, deep learning, linguistic features

1. Introduction

Due to the ubiquity of smartphones, easy accessibility to the Internet, and the flourishing of music streaming platforms, the number of mobile music users has witnessed a remarkable surge. By the mid-point of 2022, the total number of mobile music users reached a staggering 616.2 million, reflecting a notable growth rate of approximately 7.1% compared to the end of 2021 (Mulligan, 2022). As a result, music streaming services have become an integral part of individuals' daily routines. The profound impact of music, known for its ability to evoke human emotions effortlessly, has prompted researchers to conduct sentiment analysis in the domain of music. The development and improvement of methods for automatically classifying music by mood can greatly enhance music recommendation systems on music streaming platforms. Because by enlarging the possibility of user interaction and amusement, users can search songs in accordance with their present moods instead of the recommendation system of current platforms that often rely on popular songs, listening histories of users, and music styles to provide advice to users (Rajendran et al., 2022).

Given that human beings possess the cognitive capacity to comprehend information, make judgments, and express opinions on a wide range of topics, their sentiments can be easily influenced by various factors, whether positively or negatively. Consequently, the investigation of human sentiments aims to systematically and efficiently identify, assess, extract, and analyze emotional information (Shukla et al., 2017). In general, sentiment or emotional analysis and detection encompass three primary approaches: polarity, valence and arousal, and emotions. Polarity represents the simplest approach, dividing sentiment into binary categories. Valence and arousal, on the other hand, consider the dimensional aspects of human emotions. In addition to positive and negative valence, arousal provides information about the level of excitement, agitation, soothing, or calmness experienced by individuals when reflecting on an event (Kensinger, 2004). Then, when discussing emotions, two widely accepted perspectives are the theories proposed by Plutchik and Ekman. Plutchik's "Wheel of emotions" encompasses eight fundamental emotions, including joy, trust, fear, surprise, sadness, anticipation, anger, and disgust. These emotions interact with each other to generate more complex emotional states. In contrast, Ekman's perspective suggests that for survival, humans possess six basic expressive emotions: happiness, anger, surprise, sadness, fear, and disgust (Ekman, 1992; Plutchik, 1980). Drawing upon the essence of human beings and various theories and approaches, sentiment analysis emerges as an active research field that encompasses diverse subjects such as movie reviews, tweets, text documents, comments, public statements, and, in the context of this study, music.

Based on the abovementioned emotion-related theories and approaches, many researchers have put a lot of effort into detecting and analyzing sentiment and emotions in music. In the field of machine learning, the traditional machine learning approach and deep learning-based approach are two primary ways to develop autonomous emotion classification of songs. In addition, among these studies, some concentrates on audio features such as rhythm, keys, and pitch, some apply lyric-based features including term frequency, n-grams, and so on, and some employ multi-model to combine both audio features and lyric-based features (Mulligan, 2022). However, it is still hard to prove which kind of features are influential because the results of the previous studies are often dynamic (Revathy et al., 2023).

Several studies have examined the current state-of-the-art in music emotion detection and classification.; nevertheless, to the best of the authors' knowledge, seldom of them had integrated enough linguistic perspectives and machine learning approaches to classify the emotion of music. In contrast, this study combines deep learning models and handcrafted linguistic features to investigate the issue. Besides, even with the existing related research, the Mandarin Chinese music classification tasks were not only less than English ones but also conducted with relatively simple linguistic features. As a result, this research aims to incorporate a deep learning-based model with lyric-based features for classifying emotions of Mandarin song lyrics to reveal more linguistic characteristics of lyrics. It is anticipated that with the assistance of linguistic perspectives, a more robust emotional classification of Mandarin songs may be fulfilled.

The rest of this paper is organized as follows: Section 2 introduces related works on the sentiment analysis of music. Section 3 describes main methods, models and handcrafted features used in the paper, including BiLSTM and RNN-GRU. Experimental settings and results are discussed in Section 4. Finally, Section 5 summarizes this paper and potential future work.

2. Related Work

Discussing sentiment analysis on music, it is unavoidable to mention that audio-based analysis, lyrics-oriented analysis, and analysis that combined both are three dominant approaches. For instance, earlier studies primarily focused on analyzing the audio aspects such as timbral texture, rhythmic content, beats, and pitch content to classify various music genres or moods (Tzanetakis & Cook, 2002; Ujlambkar & Attar, 2012). When it comes to lyrics-oriented sentiment classification research, most existing reports tend to concentrate on analyzing emotional polarity, a relatively simple classification, valence, and arousal, and six, eight, or other self-selected emotions classification (An et al., 2017; Edmonds & Sedoc, 2021). Two main approaches have been employed to analyze music emotion: constructing emotional words lexicon (JIANG et al., 2014; Sharma et al., 2016) and in recent years, machine learning techniques are dominant. Additionally, some studies proposed multimodal approaches that combine both audio and lyrics (Houjeij et al., 2012; Malheiro et al., 2013; Zhong et al., 2012). Since this paper is also lyric-based analysis, traditional machine learning and deep learning approaches used to conduct sentiment analysis of music will be further reviewed below. Furthermore, the role of linguistic perspectives in these works will also be presented.

2.1 Traditional Machine Learning-based Song Lyrics Emotion Classification

The approaches used for classifying emotions in song lyrics can vary, ranging from traditional machine learning techniques to neural network-based approaches. Music emotion classification has become a prominent and growing research topic with applications not only in song recommendation systems but also in the field of music therapy. For instance, Furuya et al. (2015)'s study used clustering-based approach to classify music emotion for supporting music therapy. Apart from that, Devi and Saharia (2020)'s research conducted LDA-based model for exploiting topic modeling for classifying sentiment of lyrics. Others such as An et al. (2017)'s study used Naïve Bayes to classify music emotions into positive and negative that used four different datasets reaching accuracies ranging from approximately 60% to 70%.

Nevertheless, it is worth noting that most of these studies have primarily focused on

English song lyrics rather than Mandarin song lyrics. Moreover, the existing models used for Mandarin song lyrics emotion classification predominantly employ traditional machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), Maximum Entropy, and Random Forest (An et al., 2017; He et al., 2008; 駱昱岑, 2019). Furthermore, in these prior studies, the linguistic features employed are relatively basic. Common examples include term frequency, TF-IDF, bag of words (BOW), and n-grams. To sum up, while various approaches have been explored for music emotion classification in song lyrics, there is a noticeable gap in research focusing on Mandarin song lyrics that are not predominantly relied on traditional machine learning algorithms and with deep linguistic features.

2.2 Deep Learning-based Song Lyrics Emotion Classification

In the past few years, the development of deep learning models has improved a lot so sentiment analysis in diverse fields also have been employed. For example, posts on social media platforms (Tu et al., 2016) or products and services reviews (Paredes-Valverde et al., 2017). Therefore, it is without a doubt that there are more and more song lyrics emotion classification tasks utilizing deep learning models. Wang and Yang (2019) used a CNN-based model combined with pre-trained word embeddings, which leveraged a substantial corpus of over 160,000 lyrics to train, researchers have successfully extracted the emotional features distribution from Chinese lyrics. The result of this research demonstrates that by using this approach, it achieved a significant improvement of at least 15 percentage points compared to traditional machine learning methods such as TF-IDF+SVM and LIWC+SVM. Agrawal et al. (2021) claims that while using the transformer-based approach, the model outperforms existing methods used on multiple English datasets; thus, a robust model is created. Liao et al. (2021) asserts that BERT pre-trained model with transfer learning, deep neural networks can be improved for the emotion classification in Chinese song lyrics. Lately, Revathy et al. (2023) also stated that employing BERT with in-domain transfer learning, the accuracy of English song lyrics emotion classification will increase.

Although it seems that overall, the current deep learning models can achieve fine performances, it is worth noticing that as far as authors' knowledge, seldom of the deep learning models consider handcrafted linguistic features. Thus, this paper aims to address this limitation, which will incorporate handcrafted linguistic features and in-domain word embeddings while training deep learning models.

2.3 Characteristics of Song Lyrics

Observing the aforementioned emotion-classification-related investigations, it can be found that some linguistic features were seen as significant element while conducting sentiment analysis. Namely, positive, negative, and many sentiment-related lexicon, lexical diversity, and subjectivity. Therefore, the following subsections will explore more about these elements.

2.3.1 Sentiment-related Lexicon

In view of extracting positive and negative words, many studies leveraged LIWC (Linguistic Inquiry and Word Count) to achieve this goal (An et al., 2017; Wang & Yang, 2019). LIWC is utilized for the analysis and categorization of words. It enables the calculation of the proportion of different types of words, such as causal words, emotional words, cognitive words, and other psychological words, within a given text. Therefore, among many traditional machine learning models with emotional words extracted from LIWC, the improvement of the emotion classification is proved.

2.3.2 Lexical Diversity

It is proved that lexical diversity may signify the sentiment of song lyrics. Kamalnathan et al. (2019) investigated the progression of five distinct music genres (Hip-Hop, Rock, Pop, Country, and Metal) throughout the past five decades. Parameters such as frequently used words, word length, lexical diversity, and lyrics length were explored to predict genres by various traditional classification models. The results found that these lexical features of lyrics changed in different genres. Besides, entropy, a feature that belongs to lexical diversity is also used in sentiment classification tasks. Take Yu et al. (2013)'s study as an example, when conducting sentiment analysis on stock market news to identify positive and negative news articles, the performance of the model was improved by the contextual entropy features.

2.3.3 Subjectivity

Subjectivity refers to the expression of personal feelings, opinions, attitudes, and preferences. It represents the individual stance or viewpoint towards a particular subject. Moreover, subjectivity is closely linked to the affective aspects of language, encompassing emotions, intentions, and attitudes of the speakers or writers (沈家煊, 2001). Studies have demonstrated that sentiment analysis plays a valuable role in the annotation process by distinguishing between subjective and objective instances (Hatzivassiloglou & McKeown, 1997; Wilson et al., 2005).

3. Methodology

This section introduces the dataset and method used in the current study. Moreover, the features used to classify the lyric emotions, the embeddings, and the models are introduced, too.

3.1 Dataset

Lyrics of 4020 Mandarin songs were randomly sampled from Mojim.com (魔鏡歌詞網) to complete this study. However, the classification of song language on this website is based on the singers' identity, so some of the sampled songs did not match our requirement of Mandarin songs. Therefore, Taiwanese lyrics, Cantonese lyrics, and lyrics that are more than half written in English were removed from the data. This resulted to a total of 3550 songs in our dataset. Finally, the dataset was devided into 8:2 on training set and test set.

3.2 Emotion Class Annotation

We followed the definition of six basic emotions proposed by Ekman (1992) to label the lyrics instead of Plutchik's (1980) eight emotions since eight kinds of emotion may be too complicated for small dataset of ours and make it harder for the model to learn. Moreover, since *surprise* merely appears to be the main emotion of a song, we removed it from the labels. On the other hand, we found it hard to distinguish between *angry* and *disgust* because *disgust* can be alternated by *angry* or trigger the emotion of anger quite frequently. Thus, we merge *disgust* into *angry*. This brings about the five categories of emotion listed in Table 1.

Table 1
Five emotion labels

Emotion	Songs labeled
non	795
happy	855
sad	1418
angry	372
fear	110

3.3 Word Embeddings

To optimize the performance of our model, pretrained Chinese GloVe (Chen & Ma, 2018) proposed by the Chinese Knowledge and Information Processing Lab (CKIP Lab) was chosen as the embeddings of the study. Since this pretrained embeddings was based on general texts that include all kinds of genre, it may not perform well on task of specific genre such as song lyrics. Hence, we applied embeddings trained on 115636 Mandarin song lyrics to check which can perform better, too.

3.4 Feature Extraction

Following the three characteristics proposed in past studies, we extracted the meta information and linguistic information from the lyrics to examine whether linguistic information may be helpful for Mandarin lyric sentiment analysis. The extracted handcrafted features are listed in Table 2.

First, for sentiment lexicon, we extracted the positive and negative sentiment words listed in the Traditional Chinese LIWC dictionary (Huang et al., 2012). Moreover, to make it easier for the model to recognize lyrics labeled as *fear*, we added *hypothesize_word* and *escape_word* as features since people may start to hypothesize something or feeling the desire to escape when they are afraid of something.

Second, we calculated the entropy of each song to represent their lexical diversity. Moreover, since code switching to English is a common feature in Mandarin songs (刘一洁 & 杨蓓蕾, 2011; 李满亮 & 杜红原, 2010), we count the frequency of it in the songs as a sign of lexical diversity, too.

Finally, pronouns were extracted as the feature of subjectivity.

3.5 Model Training

Since song lyrics are short texts, we chose to apply Gated Recurrent Unit (GRU) as the model rather than LSTM in this study. Moreover, parts of lyrics are often repeated more than once in the song, so we considered bidirectional models not to be that useful in our task. Therefore, GRUs trained by CKIP Glove and our lyric embeddings are the baseline model in the study. The handcrafted features mentioned above are then input to the models to examine the usefulness of linguistic information in emotion classification of Mandarin song lyrics.[1]

[1] Full code link of this paper:
https://github.com/Kassia13by/Emotion_Classification_of_Chinese_Song_Lyrics

Table 2

Handcrafted features

category	characteristic	feature
Meta Information		*length*
Linguistic Information	sentiment lexicon	*positive*
		negative
		hypothesize_word
		escape_word
	lexical diversity	*entropy*
		code_switch
	subjectivity	*first_single_pronoun*
		first_plural_pronoun
		second_single_pronoun
		second_plural_pronoun
		third_single_pronoun
		third_plural_pronoun

4. Results and Discussion

The performance metrics of the models are shown in Table 3. As Table 3 shows, both baseline models performed better after the handcrafted linguistic features are added. Furthermore, we tried some different combinations of handcrafted features to get rid of those that may be not useful for the classification. After that, it was found that the model can perform best (accuracy: 0.52, loss: 1.25) getting rid of *first_single_pronoun*, *second_single_pronoun*, and *second_plural_pronoun* with CKIP GloVe as the embeddings.

Table 3

Performance metrics of the GRU models

Embeddings	**Feature**	**Accuracy**	**Loss**
CKIP GloVe	non	0.41	1.40
	all features	0.47	1.27
	selected features	**0.52**	**1.25**
lyric embeddings	non	0.41	1.40
	all features	0.49	1.26
	selected features	0.51	1.27

One thing worth mentioning is that both embeddings are not useful enough for the model to deal with the unbalanced data. If we take a look at Figure 1, we can find that both baseline model turned out to classify every song as *sad*. Nevertheless, the models started to discriminate among different emotions after the handcrafted features were added to train them (Figure 2).

Figure 1

Confusion Matrix for both baseline models

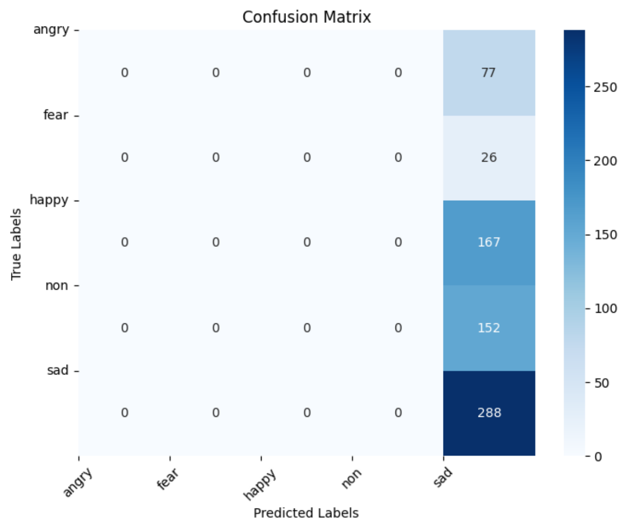
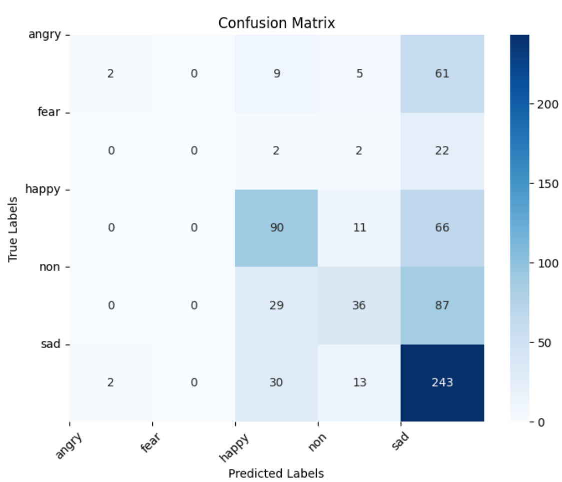
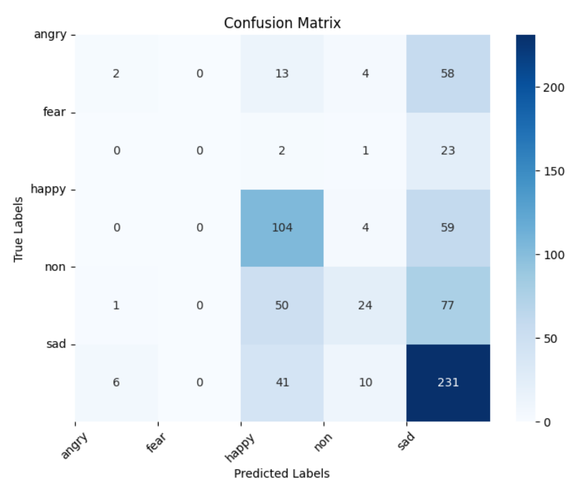


Figure 2

Confusion Matrix for models with selected features



(a) CKIP GloVe



(b) Lyric embeddings

However, it can also be observed in Figure 2 that the models perform not good enough on labeling angry songs and fear songs. There may be two reasons for this. First, the unbalanced dataset did not offer enough information for the models. Second, the linguistic features were not helpful for the models to recognize the two labels.

Finally, comparing the models which used different embeddings, it can be seen that no big difference is shown between them. Although the model trained with CKIP GloVe performed slightly better than the model trained with lyric embeddings at the end, we can still see possibility for lyric embeddings to be more useful in the future since we only made use of roughly 100000 songs, which is quite small number comparing to the data GloVe made use of.

To sum up, the linguistic features are helpful for the models to classify Mandarin lyrics with various emotions no matter with pretrained embedding or lyric-trained embeddings.

5. Conclusion

This research aims to label Mandarin song lyrics into five different emotion types, *non*, *happy*, *sad*, *angry*, *fear*, with the assistance of linguistic features. With GRU trained by pretrained embeddings and lyric-trained embeddings as the baseline model, our linguistic features about sentiment lexicon, lexical diversity, and subjectivity helped the GRU models perform better on the classification task. *first_single_pronoun*, *second_single_pronoun*, and *second_plural_pronoun* were found better to be got rid of for better performance. Despite so, the other handcrafted features showed great performance working together. However, the models performed poor on recognizing angry songs and fear songs, which are minority labels in the dataset. Therefore, it is suggested that a future study oversampling the data be done in the future to try higher the accuracy of the model labeling the these two emotion types. Moreover, we observed that the embeddings trained by small dataset of lyrics only can perform similarly with pretrained embeddings (CKIP GloVe). Therefore, it may be worth to try if a word embeddings trained by bigger lyric dataset can perform better than the general pretrain embeddings. To conclude, although having some restrictions on the study, we took a step forward in Mandarin lyric sentiment analysis by applying linguistic features in machine learning and offered a possibility for linguistic features to be utilized in this field.

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