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Sentiment analysis and implementation in film evaluation utilizing BERT

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Abstract: This study explores the use of the dmsc_v2 dataset, which is a rich collection of over 2 million ratings and commentary data from over 700,000 users on 28 films, to train the BERT model for sentiment analysis. This expansive dataset, drawn from the popular Chinese movie-rating website, Douban, has been meticulously curated for this research. In the context of the methodology, it is comprehensive and involves multiple stages. Initially, data preprocessing is conducted to refine and format the dataset suitably for model training. Subsequently, the BERT model is trained using the prepared data. Following the training process, the model's performance is critically evaluated to validate its efficacy and accuracy. The resulting model is adept at performing sentiment classification on comments pertaining to films across various social media platforms such as Weibo, Xiaohongshu, and more. This is particularly beneficial as it enables a nuanced analysis of user opinions and trending topics, offering invaluable insights for businesses, movie producers, or marketers. The findings of this study demonstrate that the BERT sentiment analysis model, developed with the dmsc_v2 dataset, exhibits impressive performance and has expansive potential for application within the sphere of social media commentary analysis. The successful development and validation of this model underscore its potential to transform the way sentiment analysis is conducted, especially in the context of entertainment and social media discussions.

Keywords: sentiment analysis, implementation, BERT.

1. Introduction

Users across the globe are increasingly voicing their thoughts, emotions, and perspectives on numerous social media platforms. The comments and user-generated content found on these platforms are brimming with emotional information that holds significant value for understanding user attitudes, market trends, and social public opinion. Consequently, sentiment analysis has emerged as a crucial field of study. Sentiment analysis, initially proposed by Nasukawa and colleagues in 2002 [1], has garnered considerable interest in research circles. The discipline is focused on the automatic identification and classification of emotional information within text, with the intention of facilitating a deeper understanding and analysis of emotional tendencies and states within large-scale text data. Its applications extend to social media monitoring, public opinion analysis, brand management, market research, and other areas.

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Presently, sentiment analysis methodologies can be broadly categorized into three core approaches: those that rely on emotion dictionaries, machine learning-based ones, and those built on deep learning techniques. Of these, the deep learning approach has seen a significant surge in popularity. The emotion dictionary method necessitates the creation of a sentiment dictionary [2], which is then utilized for sentiment calculation. Conversely, machine learning-based methods [3-6] involve manual feature extraction initially, followed by the sentiment classification of microblog texts using machine learning algorithms.

The approach founded on deep learning [7-9], like its machine learning counterpart, involves initial manual feature extraction. However, instead of employing traditional machine learning algorithms, sentiment classification of microblog texts is executed using deep learning techniques.

The attention mechanism [10] has been incorporated into various natural language processing (NLP) tasks by numerous researchers. This was aimed at resolving the issue of deep learning models overlooking the significant role of key words when extracting semantic information, thus making it challenging to consider all text information. Vanswani and others proposed the Transformer model in 2017, which leverages the Self-Attention mechanism to comprehensively take into account the role of each word in the overall context. The BERT model (Bidirectional Encoder Representations from Transformers), which is predicated on the Transformer model, was introduced by Devlin and others in 2018 [11]. Since then, there has been an increase in studies investigating sentiment analysis methods based on this model [12].

2. Related works

This study first classifies the datasets of reviews of movies by the rating of movies that rated by the users from Douban. In this study, the dmsc_v2 data set was selected as the training data, and the BERT model was used for sentiment analysis research. Through this research, this study explores how to effectively conduct sentiment analysis on social media comments about movies. This will provide new methods and insights for sentiment analysis of social media comments, which will help to deeply understand user attitudes and market trends.

2.1. Data sources

The assessment of this model's performance leverages film reviews, supplemented by a data set comprising comments crawled from various platforms for specific movies.The first component of the data set is the dmsc_v2, derived from Douban Movies, a renowned website. This data set includes feedback on 28 movies (refer to Table 1, Table 2), contributed by over 700,000 users, and aggregates over 2 million rating/comment data points. This rich repository of information has found wide application in the creation of recommender systems, as well as in sentiment/opinion/comment tendency analysis [13,14].

Table 1. Field description.

Field of the dataset	introduction
movieid	Movie ids (starting at 0, consecutively numbered)
title	English name
title_cn	Chinese name

Table 2. 7 of 28 movies.

movieId	title	title_cn
0	Avengers Age of Ultron	复仇者联盟 2
1	Big Fish and Begonia	大鱼海棠
2	Captain America Civil War	美国队长 3
3	Chinese Zodiac	十二生肖

Table 2. (continued).

4	Chronicles of the Ghostly Tribe	九层妖塔
5	CUG King of Heroes	大圣归来
6	Forever Young	栀子花开

The second portion of the data collection focuses on accumulating comments pertaining to various movies from Weibo [15] and Xiaohongshu [16]. Weibo operates as a microblogging platform, where users can readily post or retrieve news online. This is facilitated through diverse media such as text, images, and short videos. Owing to its ease and speed, Weibo has garnered a vast user base, cementing its position as one of the key channels through which the public, notably Chinese netizens, share online comments, express opinions, and communicate demands. Meanwhile, the primary feature of Xiaohongshu centers on "notes", where users document and share personal experiences spanning life, shopping, travel, and beauty. It provides an avenue for users to recount their life, travel, shopping, and other experiences, serving as a reference for others. Gaining increasing popularity among the public, Xiaohongshu has become a platform where many engage in movie discussions.

Therefore, a model trained on movie reviews will be employed to scrutinize reviews posted on Weibo and Xiaohongshu. This will allow for a prediction of movie reputation and facilitate an analysis of the unique attributes of movie reviews across different platforms.

2.2. BERT

BERT, as proposed by Devlin et al. from Google in 2018, is a language model constructed upon a bidirectional Transformer architecture. This model leverages three input vectors: the word vector, the segment vector, and the position vector. The word vector serves as an encoding of the current word, the segment vector provides an encoding of the word's position within the sentence, and the position vector pertains to the positional encoding of the current word. The encoding of sentence position is denoted by special tokens, with CLS marking the beginning and ESP indicating the end.

BERT has exhibited high performance in numerous tasks within the field of Natural Language Processing (NLP), including emotion classification and question answering systems. Sentiment analysis utilizing the BERT model [17-19] is considered a downstream task of BERT. In general, it is crucial to utilize the pre-trained BERT model to generate a vector representation of the text, followed by implementing the relevant classification algorithm for sentiment analysis. Given that this research targets Chinese movie reviews on platforms such as Weibo and Xiaohongshu, the bert-base-chinese model is employed for training. This model is a pre-trained iteration, trained on Transformers, based on a Chinese corpus.

2.3. Sentiment analysis

In recent years, the field of natural language processing has witnessed extraordinary advancements thanks to deep learning technologies. Pre-trained language models such as BERT [11] have been particularly noteworthy, demonstrating effective performance in sentiment analysis tasks. Through training on expansive corpora, BERT models acquire a rich understanding of semantics and context, which positions them as potent tools for sentiment analysis.

While existing research on sentiment analysis predominantly concentrates on datasets in general domains [20-22], the investigation into sentiment analysis for specific domains and social media commentary remains comparatively limited. As such, there exists a compelling need to undertake sentiment analysis of social media comments. Utilizing sentiment analysis models in practical contexts, such as assessing user opinions, evaluating market trends, and monitoring public sentiment, is indeed an area of interest warranting further exploration.

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3. Methodology

This study selected the dmsc_v2 dataset as the training data, and used the BERT-Base-Chinese model for sentiment analysis research. Through this research, we explore how to effectively conduct sentiment analysis on social media comments about movies, and evaluate the application performance of the model on different domains and platforms. As shown in Figure 1.

3.1. Dataset introduction

The dmsc_v2 dataset contains 700,000 Douban comments and ratings about movies. This dataset contains rich text of movie reviews, including positive reviews (5-star movie reviews) and negative reviews (1-star movie reviews).

Before performing sentiment analysis, some preprocessing steps are required on the dmsc_v2 dataset. First, the dataset is tokenized to split sentences into lexical units. Next, stop words such as common nonsense words and punctuation are removed. Then, the data is tokenized, mapping each term to its index in the BERT vocabulary. Finally, convert the data to the input format of the BERT model, such as adding special markers and padding sequences to maintain a uniform length.

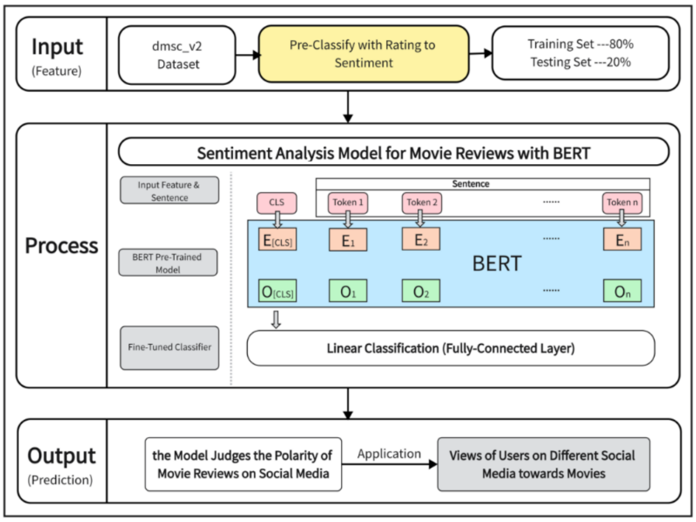

Figure 1. Overall research framework (Photo/Picture credit: Original).

3.2. Model selection and pre-training

In this experiment, BERT-Base-Chinese was selected as the pre-training model. BERT-Base-Chinese is a Chinese pre-trained language model that can be trained on large-scale Chinese text data and has strong semantic understanding and representation capabilities.

The goal of this experiment is to use BERT-Base-Chinese for sentiment analysis and classify Douban comment texts into positive and negative comments. Positive reviews correspond to 5-star movie reviews, and negative reviews correspond to 1-star movie reviews.

3.3. Model training

Data division: Partition the dmsc_v2 dataset into two subsets, which is the training set, and the test set. Model training: During training, we use the BERT-Base-Chinese model to perform end-to-end fine-tuning on the training set. By training with the cross-entropy loss function and the Adam optimizer, the model is able to gradually adjust the weights to minimize the loss. In addition, we also adopted learning rate decay and early stopping strategies to improve the training effect and prevent overfitting. Parameter setting: Specify the hyperparameters for training, such as the learning rate, batch size, and number of training iterations. In this experiment, the learning rate is chosen as 0.0001, the batch size is set to 32, and the training is performed for 5 rounds. These parameter values have been determined through a process of empirical and experimental tuning to ensure optimal performance during the training phase.

3.4. Model evaluation

The following indicators serve to evaluate the model's performance in the emotion classification task: Comment Analysis on Weibo and Xiaohongshu: Leveraging the trained sentiment analysis model, a sentiment analysis is conducted on the comments about movies on Weibo and Xiaohongshu. This approach helps predict the emotional tendencies in the comments, thereby enabling the analysis of the movie's word-of-mouth reputation. Analysis of Platform-specific Film Review Characteristics: A comparative analysis is performed on movie reviews from Weibo and Xiaohongshu. This provides insights into the evaluation and discussion patterns of users across different platforms. Examination of aspects such as comment length distribution, sentimental tendencies, common keywords, and phrases, reveal the distinctive differences and characteristics between platforms.

By employing the above methodological steps, the dmsc_v2 dataset can be used to train the BERT-Base-Chinese model for sentiment analysis. This results in a model highly capable of analyzing movie reviews. Further, this model is used to conduct sentiment analysis on movie reviews from Weibo and Xiaohongshu. It helps predict the word-of-mouth reputation of the movie and analyze the distinctive features of movie reviews across different platforms.

4. Experiment results

4.1. Dataset processing and division

The preview of the data set fields is shown in the Table 3. The comment with the rating field of 1 is reserved as a negative movie review, the target is marked as 0, the comment with the rating field of 5 is reserved as a negative movie review, and the target is marked as 1. The preprocessed dmsc_v2 dataset is set according to 80% is divided into training set and 20% into test set. Such division ensures the evaluation of the generalization performance of the model on different datasets.

Table 3. Samples of dmsc_v2 dataset information.

	userId	movieId	rating	timestamp	comment	like
1763779	130888	24	5	1474560000	原著的剧本不是这样的,而是最后只有那个自私鬼活了下来。孕妇中枪,小孩中枪的时候哭出了声音,...	1
1608147	23695	22	2	1377360000	郭敬明真的要为中国产生如此大规模的青少年脑残群体负一定责任 = =	0
1735498	323858	24	3	1473696000	三分不能再多。其中一分给壮汉大叔,帅过男主。	0
2093623	232598	27	5	1474560000	比之前大热的冰雪奇缘好太多,一部全家人都可以坐在一起看的电影。	0
1112590	495975	16	4	1336838400	浩克抖包袱……	0

4.2. Model training and evaluation

4.2.1. Model training process. After setting the parameters of the BERT-Base-Chinese model, the experiment carried out 5 rounds of training, and the effect of each round of training is shown in the Table 4.

Word-level classification from Masked Language Model (Mask-LM) and sentence-level classification. This enables BERT to effectively handle both token-level and sentence-level aspects in its learned representation. Loss function is shown in Eq. (1)

$$\mathrm{L}(\theta, \theta_1, \theta_2) = \mathrm{L}_1(\theta, \theta_1) + \mathrm{L}_2(\theta, \theta_2) \tag{1}$$

Eq. (2) presents the negative log-likelihood function utilized in the first part of the loss function, where M represents the set of words to be masked. This function is applied due to the multi-classification nature concerning the dictionary size |V|, and its optimization is aimed at minimizing the loss, ultimately maximizing the log-likelihood function for improved valence.

$$\mathrm{L}_1(\theta, \theta_1) = -\sum_{\mathrm{i}=1}^{\mathrm{M}} \log\ \mathrm{p}\,(\mathrm{m} = \mathrm{m_i}|\theta, \theta_1), \mathrm{m_i} \in [1,2, \dots, |\mathrm{V}|] \tag{2}$$

Eq. (3) represents the loss function utilized in the second part of the loss function, focusing on the sentence prediction task. Similar to the first part, this loss function is also designed for classification problems. The objective is to effectively handle the sentence-level classification task, where the model aims to minimize the loss and maximize the classification accuracy for predicting the correct sentence labels.

$$\mathrm{L}_2(\theta, \theta_2) = -\sum_{\mathrm{j}=1}^{\mathrm{N}} \log\ \mathrm{p}\,(\mathrm{n} = \mathrm{n_i}|\theta, \theta_2), \mathrm{n}_1 \in [0,1] \tag{3}$$

Eq. (4) illustrates the loss function employed for the joint learning of the two tasks.

$$\mathrm{L}(\theta, \theta_1, \theta_2) = -\sum_{i=1}^{M} \log\ p\,(m = m_i|\theta, \theta_1) - \sum_{J=1}^{N} \log\ p\,(n = n_i|\theta, \theta_2) \tag{4}$$

Table 4. 5 epoch of loss of training model on movie comments.

EPOCH	LOSS
1	0.46917349630493227
2	0.2596859005674467
3	0.13875321946027924
4	0.0504978570724064
5	0.05295303091012194

4.2.2. Model evaluation. During the evaluation of the sentiment classification task on the test set, we assess several performance metrics to gauge the model's effectiveness. The accuracy rate is determined by calculating the ratio of correctly classified samples to the total number of samples, as shown in Eq. (5). The F1 value is a comprehensive metric that takes both precision and recall into account, as shown in Eqs. (6), (7), and (8), respectively.

Comparing the results of the BERT model with the trained bert-base-chinese model, we can ascertain the model's performance and determine how it fares in sentiment classification. As shown in Table 5.

$$\mathrm{Accuracy} = \frac{\mathrm{True\ prediction}}{\mathrm{True\ prediction + False\ prediction}} \tag{5}$$

$$\mathrm{Precision} = \frac{\mathrm{True\ positive\ prediction}}{\mathrm{True\ and\ false\ \ positive\ prediction}} \tag{6}$$

$$\mathrm{Recall} = \frac{\mathrm{True\ positive\ prediction}}{\mathrm{True\ positive\ prediction + False\ negative\ prediction}} \tag{7}$$

$$\mathrm{F1 - score} = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision + Recall}} \tag{8}$$

Table 5. Comparison of model result in experiment.

Evaluation model	Recall	Precision	Accuracy	F1-score
BERT-Base-Chinese	0.667	0.867	0.872	0.754
Movie comment of BERT-base-Chinese	0.954	0.956	0.957	0.954

4.3. Weibo and Xiaohongshu comment analysis

4.3.1. Data collection. When conducting Weibo and Xiaohongshu review analysis, we collected related movie review datasets. Movie list is shown in table 6. Through API or crawler technology, a large number of Weibo and Xiaohongshu posts containing movie reviews were obtained.

4.3.2. Sentiment analysis and prediction. Using the trained BERT-Base-Chinese model, we perform sentiment analysis and prediction on movie reviews on Weibo and Xiaohongshu. The result of experiment is shown in table 7. Categorize reviews as positive or negative based on the sentiment bias predicted by the model. And get the final praise rate, and compare it with the Douban score. The definition of praise rate is the percentage of the number of positive comments, and the formula is shown in Eq.

$$rate = \frac{positive\ comments}{negative\ comments + positive\ comments} \tag{9}$$

4.3.3. Word-of-mouth prediction and analysis. By performing sentiment analysis on reviews, we can predict the word-of-mouth of a movie on Weibo and Xiaohongshu. By counting the ratio of positive and negative reviews, it is possible to infer the popularity of a movie on social media platforms. In addition, we will also analyze the length of comments, the distribution of emotional tendencies, common keywords and phrases, etc., to reveal the differences in the characteristics of film reviews and user discussion methods on Weibo and Xiaohongshu.

This research uses crawlers to obtain the content of different movie reviews in each social media, and then uses these reviews to draw the word cloud map of each movie review on each platform. The word cloud map is shown in Table 8. Through these word cloud maps, we can see the characteristics of different movies, as well as the characteristics of movie reviews on different platforms, and observe the emotional distribution on different social media platforms.

Table 6. Social media and collecting movie list.

SOCIAL MEDIA	MOVIE LIST	ENGLISH NAME OF MOVIE
WEIBO	人生路不熟	Godspeed
	速度与激情 10	The Fast and the Furious 10
	流浪地球 2	The Wandering Earth
	银河护卫队 3	Guardians of the Galaxy 3
XIAOHONGSHU	人生路不熟	Godspeed
	速度与激情 10	The Fast and the Furious 10
	流浪地球 2	The Wandering Earth
	银河护卫队 3	Guardians of the Galaxy 3

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Table 7. Prediction of movies and real Douban rating.

SOCIAL MEDIA	MOVIE	PRAISE RATE	DOUBAN RATING
WEIBO	Godspeed	0.905	6.3
	The Fast and the Furious 10	0.918	6.7
	The Wandering Earth	0.914	8.3
	Guardians of the Galaxy 3	0.969	8.7
XIAOHONGSHU	Godspeed	0.813	6.3
	The Fast and the Furious 10	0.872	6.7
	The Wandering Earth	0.942	8.3
	Guardians of the Galaxy 3	0.914	8.7

5. Conclusion

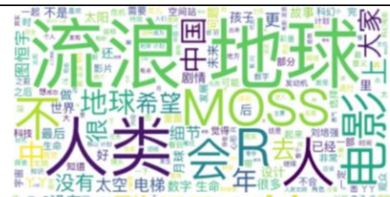
Based on experimental findings and thorough discussions, it can be concluded that BERT-Base-Chinese, when trained with the dmsc_v2 dataset, proves proficient in analyzing movie reviews. Through sentiment analysis of reviews from Weibo and Xiaohongshu, word-of-mouth predictions for movies can be made, and characteristics of movie reviews from different platforms can be discerned. These findings have significant implications for market research and promotional strategies within the film industry.

Despite the extensive collection of movie review data in the dmsc_v2 dataset, an expansion of this dataset could enhance the model's generalization capabilities. More data from Douban or diverse movie reviews from other credible sources could be harvested to enrich the training set. The experiment employed a set of default hyperparameters for training, but varying these settings could influence model performance. Hyperparameters could be systematically fine-tuned, using methods such as grid search or random search, to identify an optimal model configuration. Beyond the singular application of a BERT-Base-Chinese model, model ensemble techniques could be explored - be it through vote casting or average prediction results, or through the integration of various pre-trained models or multiple iterations of model training. With model ensembles, the performance and robustness of sentiment analysis tasks could be significantly improved. It's important to note, however, that the dmsc_v2 dataset is sourced from the Douban website, and as such, potential data biases may exist. Given the dataset's limited source, the reviews and ratings could be more reflective of specific movie types or user groups, consequently influencing the model's generalization capacity. Additionally, sentiment analysis confronts the challenge of emotional expression diversity. Users may employ metaphors, irony, or other literary rhetorical devices in their comments, making sentiment analysis a complex task. Therefore, capturing and interpreting these complex emotional expressions accurately might present a challenge to models.

Table 8. Word cloud map of movies from Weibo and Xiaohongshu.

	Weibo	Xiaohongshu
Godspeed		
The Fast and the Furious 10		

Table 8. (continued).

The Wandering Earth		
Guardians of the Galaxy 3		

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