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BERT Model with Fuzzy Logic Optimization on Multivariate Sentiment Analysis Tasks

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Abstract. With the development of natural language processing techniques, sentiment analysis techniques are constantly updated. However, most of the sentiment analysis techniques are limited to handling binary sentiment analysis and perform poorly on multivariate sentiment analysis tasks. This paper explores the optimization in the field of sentiment analysis by using the BERT model combined with fuzzy logic to improve the performance of the model on multivariate sentiment classification tasks. The study uses the Twitter comments dataset and aims to gain insights into the challenges and optimization strategies of sentiment analysis models when dealing with multivariate sentiment. First, a single BERT model is experimentally demonstrated to perform better in binary classification tasks compared to multivariate classification tasks, highlighting its adaptability for simple sentiment classification and providing a basis for comparative experiments for multivariate classification experiments. To further improve the performance in multivariate sentiment analysis, fuzzy logic is introduced in this paper, and through the integration of this fuzzy logic, the accuracy of the BERT model on the multivariate sentiment classification task is successfully improved. The results of the study not only reveal the superiority of a single BERT model in binary classification but also emphasize the importance of incorporating fuzzy logic when facing multivariate sentiment analysis.

Keywords: component; BERT; fuzzy logic; sentiment analysis; multivariate classification.

1. Introduction

In the digital age, a large amount of user-generated text data, especially movie reviews, provides valuable information for understanding the public's perception of movies. However, in the face of huge review data, it becomes a challenge to efficiently and accurately judge the quality of a movie. Sentiment analysis emerged precisely to capture the opinions or feelings of others [1]. Sentiment analysis is a task that has been widely focused on and researched by scholars this year, and in particular, it is very important as well as challenging to analyze the sentiment of the comments on Internet platforms. Because the comments will be influenced by the author's literacy level, standard of living, etc., and the writing style varies from person to person[2-4]. Traditional sentiment analysis methods have limitations in dealing with complex and ambiguous sentiment expressions, and in general sentiment analysis methods tend to treat the sentiment classification task only as a binary classification task while ignoring more complex sentiments, which suggests that sentiment analysis has the potential for multivariate classification.

Unlike classical logic systems, Fuzzy logic can handle virtually any proposition expressed in natural language, and it is centered on modeling imprecise patterns of reasoning [5]. Such reasoning patterns play an important role in the remarkable human ability to make rational decisions in uncertain and imprecise environments [6]. Therefore, the introduction of fuzzy logic to understand and analyze emotions in movie reviews more comprehensively and flexibly becomes a potential method to improve the accuracy of movie evaluations.

Current research in the field of Natural Language Processing (NLP) has made significant progress, especially in the area of sentiment analysis. In existing sentiment analysis models for text, the outputs are usually set to positive and negative [7], which often leads to analysis results limited by binary logic, making it difficult to capture ambiguities and uncertainties in comments. Based on traditional NLP models, the introduction of fuzzy logic provides a possibility to solve this problem, which can better deal with the fuzzy emotions and subjective evaluations expressed by users in the reviews, making the movie reviews closer to the actual feelings.

The purpose of this paper is to explore the performance of traditional sentiment analysis methods in multivariate sentiment classification tasks and the application of fuzzy logic in the direction of NLP sentiment analysis, taking movie reviews as a case study, and constructing a more accurate movie evaluation model by analyzing the fuzzy language and uncertainty sentiment in the reviews. This experiment will take advantage of fuzzy logic to improve the ability to understand the emotion of movie reviews and make the evaluation more targeted and detailed. The goal of this experiment is to verify the practicality and effect of the optimized combination of sentiment analysis model and fuzzy logic in movie evaluation, and to provide practical cases and experiences for the application of fuzzy logic in the direction of NLP sentiment analysis. Through this study, this paper expects to provide a more comprehensive and intelligent analysis method for reviewing text, promote the development of the NLP field in sentiment analysis and review mining, and provide users with more accurate recommendation and evaluation services. By deeply mining the fuzzy information in the comments, this experiment pursues to provide the industry with more accurate and close to the users' needs feedback.

2. Method and data

2.1. Dataset

To balance the two tasks of commenting and sentiment analysis, this paper selects the Twitter Sentiment Analysis Dataset, which is a publicly available data resource widely used in sentiment analysis research. Since Twitter is a widely used social media platform, the comment data in it is extremely large and covers a large number of sentiment tendencies expressed by users in their tweets, including positive, negative and neutral sentiments. The collection of the dataset covers a wide range of topics and events, which gives the training data of this paper a strong breadth and generalization.

The dataset contains a large number of comment texts, each of which is labeled with positive, negative, or neutral sentiment. Such labeling allows the researcher to perform in-depth analysis for different sentiment categories, thus providing a more comprehensive understanding of users' sentiment expressions on Twitter. In addition, the presence of noise, abbreviations, and spelling errors in the text in the dataset makes the task of sentiment analysis more challenging.

2.2. Data Preprocessing

Before model training, this study performed data preprocessing on Twitter Sentiment Analysis Dataset. The main goal of the preprocessing step is to clean the data and convert it into a format acceptable to the model.

For text data, it is very effective to perform text cleaning, which involves removing special characters, URLs, punctuation marks, and other noise from the tweets. This helps to improve the model's processing of the text and reduces the impact of distractions. The cleaned data can perform the next step of tokenization and embedding processing. The tweets are segmented into words and each word is mapped into a dense vector representation by the embedding technique. This helps to preserve the semantic information between words and improves the model's understanding of the textual context.

In terms of data annotation, the sentiment labels existing in the dataset are mapped to numeric representations that are understandable to the model. For example, positive sentiment can be mapped as 1, negative sentiment as -1, and neutral sentiment as 0. Such label mapping helps to train the model to predict the sentiment tendency of tweets.

2.3. Method

This research aims to build an integrated hybrid model that combines Transformer, BERT, and fuzzy logic for sentiment analysis on Twitter Sentiment Analysis Dataset. The study integrates these three components into a unified framework to improve the performance of the model in capturing complex sentiment and handling ambiguity [8,9,10].

2.3.1. Transformer Encoder

The study first introduces the Transformer encoder as the basis of our model (Figure 1).Transformer is the core module of BERT, and the attention mechanism is the most crucial part of Transformer [4].Transformer's self-attention mechanism can effectively capture the contextual information of the input text, enabling the model to better understand the semantics of the tweets and sentiment in the tweets.

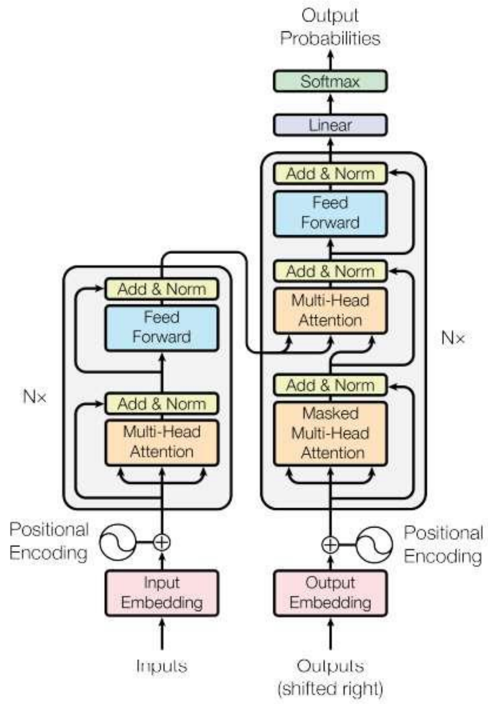

Figure 1. Transformer architecture [11]

The paper uses multiple Transformer encoder layers to encode the input, ensuring that the model captures different levels of semantic information.

2.3.2. BERT Model

To enhance the effective utilization of linguistic representations acquired from an extensive corpus, this investigation introduces a BERT pre-trained model fine-tuned on the Twitter Sentiment Analysis Dataset (Figure 2). The BERT encoder is composed of the summation of vectors processed by three embedding layers [8]. The experimental phase initiates by formulating a BERT model, incorporating a prediction parameter that anticipates the sentiment category of the input. The fundamental principle of the model involves training the language model using a bidirectional converter encoder, enabling the model to comprehend contextual information more effectively and consequently perform downstream tasks with greater efficacy for diverse purposes. Additionally, the model takes into account preceding and following phrases to offer context-driven sentence embedding. This permits the model to predict words with comprehensive contextual information, thereby facilitating a more nuanced understanding of contextual cues for the successful execution of downstream tasks tailored to various objectives. Given that the model lacks knowledge about the accuracy of words in corresponding positions [9], this approach fosters a more comprehensive understanding of semantics, resulting in an enhanced model performance [10].

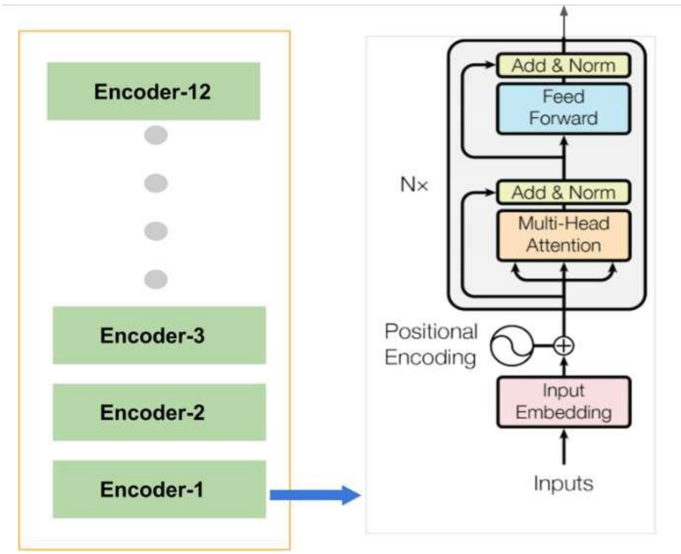

Figure 2. BERT model based on Transformer [11]

The BERT model is trained on the dataset to get a set of training parameters and saved, then the experiment uses a new model to import the BERT model parameters, receives the text comment data and performs the sentiment prediction, and finally gets the prediction results. However, the prediction result obtained by the BERT model is not the final result, the prediction result will enter the fuzzy logic layer for redefinition to complete the final prediction classification.

2.3.3. Training and Optimization

The cross-entropy loss function will be used as the objective function during the BERT model training process and the model parameters will be optimized by gradient descent algorithm. Some regularization techniques will be used to mitigate the overfitting problem and ensure better generalization performance of the model on the test data.

2.3.4. Fuzzy Logic Layer

The experiment ends with a fuzzy logic optimization layer, which uses fuzzy logic to further analyze the text to improve accuracy. The basic logic of a fuzzy control system consists of transforming inputs into fuzzy sets through fuzzification, fuzzy reasoning using a rule base, generating fuzzy outputs, and finally mapping the outputs to actual control signals through defuzzification. Such systems can effectively deal with fuzzy, uncertainty and complexity in complex systems.

In the fuzzy logic layer of this experiment, the first step is fuzzification. The paper converts the predictive labels of BERT to the degree of affiliation of each classification set. Different categories of emotions have different probabilities in the judgment of fuzzy logic. Fuzzy inference determines the results given by each fuzzy rule and combines them through these different rules.

The last step is defuzzification and this experiment uses the center of mass method to achieve defuzzification (Figure 3). After defuzzification, the fuzzy control system gives a number to indicate the probability of each emotion category. These outputs can be used to achieve the reclassification of labels.

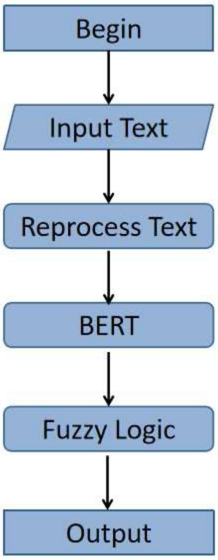

Figure 3. Flowchart of framework(Photo/Picture credit : Original)

3. Result

Sentiment analysis is a popular method for text analysis, also defined as opinion mining [8]. Most Transformer experiments have focused on binary categorization problems in sentiment analysis datasets, but in reality sentiment analysis is not just a binary categorization problem, but a multivariate categorization problem. The results of this experiment show how the Transformer-BERT model with the addition of fuzzy logic performs and compares with the performance of the Transformer-BERT model in dealing with the sentiment task of multivariate categorization.

3.1. Dataset Analysis

As shown in Figure 4, Twitter Sentiment Analysis Dataset contains a large amount of textual information, and the 69,492 comments cover different information from several domains, such as Amazon shopping reviews, B-game reviews, and so on, which ensures the complexity of the dataset.

Figure 4. Tweets Message Type(Photo/Picture credit : Original)

In order to investigate the model's problem in multivariate classification, the data feature "sentiment" with four different sentiment labels are selected for this experiment, the four sentiments are "Negative", " Positive", "Neutral" and "Irrelevant".

The statistics of the number of the four sentiments of Sentiment are shown in Figure 5, which shows that the number of comments of the four sentiments is not the same, but also relatively balanced, which ensures the stability of the model training.

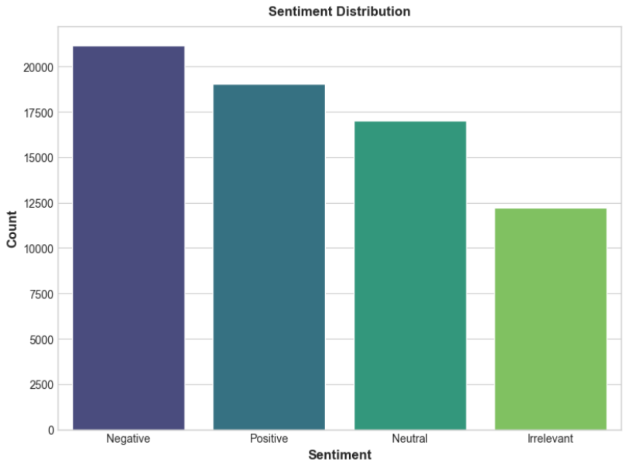

Figure 5. Number of Four Comments(Photo/Picture credit : Original)

3.2. Experimental Result

This experiment contains two comparative experiments, the first comparative experiment is the comparison of the performance of a single BERT model in handling binary classification tasks and in handling multiple classification tasks. The accuracy and Loss of this experiment are shown in Table I. The accuracy of the single BERT model in processing binary classification tasks is higher than the accuracy in processing multi-classification task, which indicates that the single BERT model lacks in processing multi-classification tasks.

Table 1. Performance of BERT for two tasks

	Accuracy	**Loss**
BERT for Binary Classification	0.6917	0.5314
BERT for Multi-Classification	0.5317	0.7056

The second comparison experiment is the performance of the BERT model on the multi-classification task before and after adding Fuzzy Logic. As shown in Figure 6, the accuracy of the BERT model with the addition of Fuzzy Logic is improved by 4% on average in 10 iterations, which indicates that the addition of Fuzzy Logic can make up for the shortcomings of a single BERT model on the multi-classification task

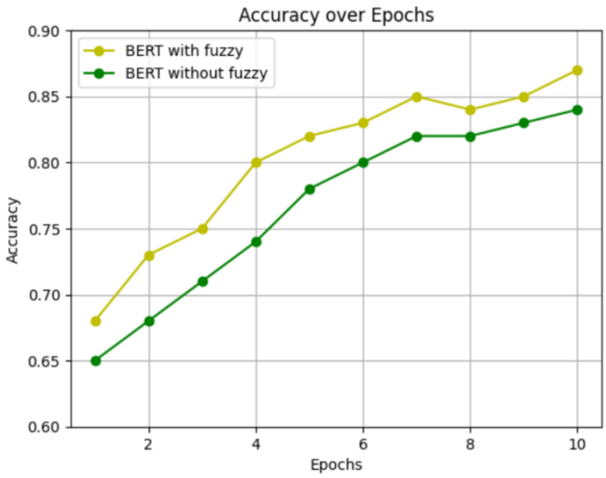

Figure 6. The Effect of Fuzzy Logic on the Accuracy of BERT Models(Photo/Picture credit : Original)

3.3. Analysis and Discussion of Results

This experiment investigates the effectiveness of the BERT model and fuzzy logic techniques on a multivariate sentiment analysis task, but again the experiment has limitations. In terms of the dataset, the Twitter comments dataset used may have some bias as language styles and topics on social media may differ from other domains. This may limit the model's ability to generalize to broader domains. In addition, the BERT model may be limited when dealing with long texts, whereas social media comments are usually short texts, which may pose a challenge for more complex sentiment expressions in real-world applications. In terms of model structure, both the BERT model and Fuzzy logic optimization have their limitations, for example, the BERT model does not perform well when dealing with multiple meanings at a time, and also the use of fuzzy logic requires the design of appropriate fuzzy rules and affiliation functions for the problem, etc.

In terms of dataset improvement, one could consider introducing more domains of data into the experiment rather than a single comment type of data to ensure the generalization of the model. In addition, for the challenge of dealing with long texts, model structure adjustments or the introduction of other techniques can be explored to enhance its ability to deal with long texts.

In future research, the extension of this experiment to more emotion-related tasks, such as emotion generation and emotion transfer, can be considered to deepen the understanding of the applicability of the model in different emotion application scenarios. In addition, besides the innovative addition of the fuzzy logic technique, other new techniques of natural language processing, such as transfer learning, self-supervised learning, etc., can be added to improve the performance of the sentiment analysis model.

4. Conclusion

In this study, the effectiveness of handling multivariate sentiment categorization tasks in the field of sentiment analysis is investigated by using a BERT model combined with fuzzy logic. The superior performance of a single BERT model on a binary classification task is emphasized to provide a reliable comparative experimental benchmark for sentiment analysis tasks. Subsequently, the performance of the BERT model on a multivariate sentiment categorization task is successfully enhanced by introducing fuzzy logic, which further validates the effectiveness of the approach for handling complex sentiment.

To summarize the research in this paper, it is found that the single BERT model performs better in binary classification, while the BERT model with the addition of fuzzy logic achieves higher accuracy on the multivariate sentiment classification task. This not only provides strong support for practical applications but also provides new insights for research in the field of sentiment analysis. In future research directions, more ways of combining fuzzy logic and deep learning models can be explored to further improve the performance of the model in complex sentiment scenarios.

This study holds paramount importance as it introduces a groundbreaking approach to address the challenges of multivariate sentiment analysis, elevating the precision of deep learning models in tackling multifaceted classification issues. A secondary focal point underscores the promising synergy between fuzzy logic and deep learning. By extending the study's scope, a more nuanced comprehension of the interplay between model performance and optimization techniques can be garnered, thereby presenting pragmatic methodologies for real-world applications. The outlined research framework positively contributes to the advancement of sentiment analysis, the enhancement of sentiment intelligence processing, and the diversification of research methodologies in other domains of natural language processing.

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