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Long-term and short-term memory network based movie comment sentiment analysis

Ruoxue Bi

Computer Science and Technology, Beijing Normal University - Hong Kong Baptist University United International College, Zhuhai, 519000, China

q030026002@mail.uic.edu.cn

Abstract. This paper proposes an emotional analysis method of movie reviews based on Long-term and Short-term Memory(LSTM) Network model. Emotional analysis is widely used in movie recommendation system, which can recommend and judge movies by understanding the audience's emotional response to movies. However, due to the characteristics of movie text and the complexity of emotional expression, traditional methods such as machine learning have limitations and shortcomings in emotional analysis. However, the LSTM model's better memory is utilized by the method proposed in this paper and the ability to capture the long-term correlation in movie texts, which obviously improves the accuracy and reliability of emotional analysis, and demonstrates the advantages of the LSTM model in emotional analysis compared to the traditional model. Future research can further explore other deep learning models and algorithms, so as to make emotional analysis more accurate and provide users with reliable movie recommendation information.

Keywords: LSTM, word2vec, movie recommendation, emotional analysis.

1. Introduction

As a natural language processing technology, sentiment analysis can explore the emotional color of subjective texts. It is widely used in many aspects. For the movie recommendation system, emotion analysis can provide a more perfect movie recommendation algorithm by understanding the audience's emotional feedback to the movie. The traditional sentiment analysis method shows some disadvantages and deficiencies in dealing with the semantic analysis of long texts and the change of sentiment polarity. Deep learning has grown significantly in recent years, and approaches for sentiment analysis based on deep learning have been introduced gradually. Among them, Long-term and Short-term Memory Network (LSTM) can also be used in sentiment analysis because it can capture context information [1] and deal with long-term dependence. Collaborative filtering algorithm is a kind of recommendation algorithm that predicts users' liking for unknown things by analyzing the similarity of users' behaviors [2]. The aim of this paper is to combine the LSTM emotion analysis model with the collaborative filtering algorithm and apply it to the movie recommendation system to obtain more precise recommendation results.

The collaborative filtering algorithm can be combined with the LSTM model, can refer to the audience's emotional feedback and the similarity of their love for movies at the same time, and on this basis, in order to get more accurate and referential recommendation results. In a word, this paper adopts

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the LSTM emotional analysis model and collaborative filtering algorithm, and applies them to the movie recommendation system. By analyzing the audience's emotional feedback to the movie, then train a large number of movie review data to get more personal and accurate movie recommendation results.

2. Literature review

Natural language processing and artificial intelligence technology have developed quickly in recent years, movie sentiment analysis is also an important research direction. Applying sentiment analysis in movie reviews can effectively analyze the audience's preferences and provide more reference for market research and movie recommendation. Researchers use the tagged movie review data to train the machine model to complete the classification and prediction of emotional tags. More and more researchers are incorporating the deep learning model into the task of emotion analysis as deep learning technology develops, which has achieved better results in the field of emotion analysis, proved the superiority of the deep learning model, and provided strong support for effectively analyzing the audience's emotional tendency and interest similarity.

2.1. Research status of deep learning based sentiment analysis

For the application research of introducing deep learning model as emotion analysis model in movies, Socher et al. proposed recursive depth model in their paper [3], which can analyze the semantic combination of emotion tree library. By combining the tree structure with the deep learning method then achieved good results.

Kim et al. introduced convolutional neural network into the task of sentence classification, as shown in the following article [4]. Researcher captured the local features of sentences through the convolution layer, effectively realized the emotional classification of sentences, and applied this model to the emotional analysis of movie reviews. Xu et al. put forward an long-term and short-term network model based on attention mechanism [5], which is different from the previous judgment of emotional polarity of the whole sentence, but classifies the different aspects stated in the sentence, and applies this model to emotional analysis of film reviews, and obtains good results. Smith and others put forward a deep neural network [6] which can handle multi-language and cross-cultural sentiment analysis tasks. By extracting images from movie clips and mining audio features, it has been improved in feature extraction and model optimization. Liang Jun and others applied recursive neural network to Weibo's emotional analysis [7], which avoided artificial feature design for specific tasks and saved a lot of manual work.

To sum up, convolutional neural networks and LSTM are two examples of deep learning models that have been extensively used and researched for emotional analysis applications. The researchers have continuously optimized the model framework and fully explored the features, and produced positive results in the task of emotional analysis, which increased the reliability and accuracy of assessing the emotional tendencies of film reviews and gave the film industry technological assistance for growth.

2.2. Research status of collaborative filtering algorithm

In recommendation systems, collaborative filtering algorithms are frequently employed, Movie recommendation systems also frequently use it. Resnick and others discussed the architecture, function and principle of GroupLens system [8], and pointed out the problems of sparse data and cold start in the algorithm. GroupLens is a news recommendation system using collaborative filtering algorithm. Sarwar et al. introduced the similarity and prediction calculation of collaborative filtering algorithm in detail [9], and put forward a collaborative filtering algorithm based on items, and achieved better results. Kiren and others put forward a combined model [10] in the paper, which integrates the domain-based collaborative filtering model and the latent factor-based model. After testing on Netflix data, it is found that the results are better than those on the previous data set. Bell and others put forward SVD++ algorithm in the paper [11], which expanded and assisted SVD model and improved the problems of SVD's difficulty in collecting implicit feedback data and sparse data.

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To sum up, collaborative filtering algorithm has been widely used in personalized recommendation system, and it is still one of the research hotspots. The future research direction may pay more attention to better solving the problems of data sparsity, improving recommendation effect and user experience.

3. Methodology

In this section, Internet Movie Database(IMDB) data set is used, and after data cleaning and other preprocessing, feature extraction is performed.

3.1. Data preprocessing

The purpose of data processing is to remove invalid information and noise in data, such as HTML tags and special symbols, which need to be deleted and replaced by regular expressions. After data cleaning, data can be guaranteed to have higher accuracy and reliability in later modeling and analysis.

3.2. Feature extraction

After data cleaning, it is necessary to extract effective features from the data. Jieba word segmentation tool is used to deal with word segmentation processing before extraction, and then word vectors are extracted by combining Word2Vec [12] and COBW [13], and the word vectors are trained and predicted by COBW, and finally effective features are extracted. CBOW mainly infers The current word is used to determine the target vocabulary based on the context. The structure of CBOW model was shown in Figure 1.

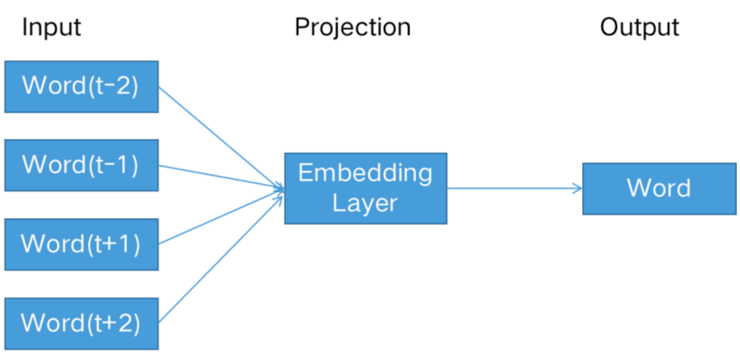

Figure 1. Schematic diagram of CBOW model structure

3.3. Emotional analysis model

The emotion analysis model proposed in this paper is long-term and short-term model, which is a deep learning network controlled by forgetting gate, input gate and output gate. The initial step is to determine the amount of information to keep from the cell state. By examining the input cells from the previous moment and the current input vector, the forgetting gate determines whether the information in the cell state needs to be saved or discarded by selectively forgetting the input cells at the previous moment. The second stage involves selectively recording new information in the cell state, that is, the principle of input gate is to judge the current cell state according to the current input quantity and the input cell at the previous moment. Removing some old information and adding new information are realized in updating the cell state. Finally, the output gate calculates the new cell state according to the current cell state, the input cell at the previous moment and the current input vector, and finally obtains the output of the current cell. In short, LSTM uses these three gates to control and calculate the state of storage cells. Figure 2 is a schematic diagram of the cell structure of LSTM model.

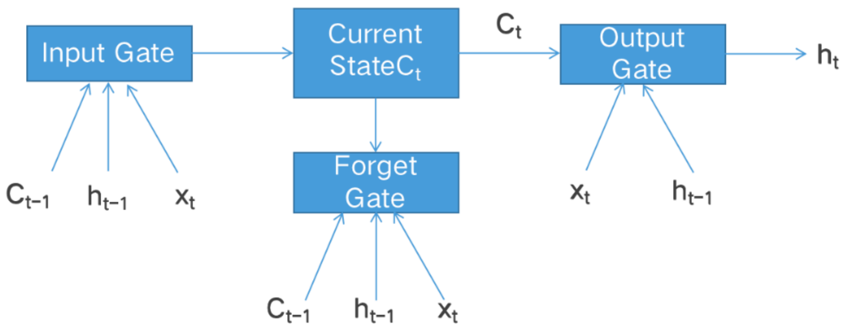

Figure 2. The LSTM unit structure is depicted in a schematic diagram

The back propagation algorithm for the LSTM model can be used to optimize the model parameters in sentiment analysis. After the LSTM model completes the text classification, a fully connected layer can be added, and the fully connected layer can map the cell state to the emotion category, and the softmax classification function [14] can be used to classify and predict the emotion category. Finally, the model is evaluated and debugged with training data and training sets marked with emotion categories.

3.4. Collaborative filtering algorithm

Movie recommendation is to recommend and screen similar products, the user-based collaborative filtering algorithm will identify other users who are similar to the current ones and recommend movies that these users like, but which haven't been watched by the current users, movie recommendation systems can also utilize it. The method of collaborative filtering algorithm [15] that is based on users was proposed in this paper. By analyzing the common interests and behavior patterns of the audience, the algorithm can discover the potential similarity and relevance between the audience, so as to provide personalized and accurate services for the audience.

There are multiple methods for calculating similarity in the user-based collaborative filtering algorithm, among which Pearson correlation coefficient and cosine similarity are the most commonly used. Compared with them, Pearson correlation coefficient is suitable for measuring the linear relationship between users, while cosine similarity is suitable for calculating the nonlinear relationship. Cosine similarity algorithm makes the calculation more efficient and gives users a better experience. The cosine similarity calculation formula is shown below.

$$\mathrm{sim}(\mathrm{u},\mathrm{v}) = \frac{\sum_{\mathrm{i}\in\mathrm{I}} \mathrm{R}_{\mathrm{ui}} \cdot \mathrm{R}_{\mathrm{vi}}}{\sqrt{\sum_{\mathrm{i}\in\mathrm{I}} \mathrm{R}_{\mathrm{ui}}^2}\sqrt{\sum_{\mathrm{i}\in\mathrm{I}} \mathrm{R}_{\mathrm{vi}}^2}} \quad (1)$$

After calculating the similarity, it is necessary to predict the target audience's rating of movies that have not been watched. This can be predicted according to the historical behavior of similar users, and the weighted average is needed to calculate. The formula for predicting the rating is as follows.

$$R_{uj} = \frac{\sum_{v\in S(u,K)} sim(u,v)\cdot R_{vj}}{\sum_{v\in S(u,K)} sim(u,v)} \quad (2)$$

In the prediction scoring formula, R_{uj} represents the prediction scores of audience u and project j, and S(u, k) represents the selection of the K audiences with the highest similarity to the remaining target audience u as a set. The selection based on a fixed threshold can be used to screen similar audiences to improve the accuracy and reliability of recommendation results and prediction scoring. User-based collaborative filtering algorithm still has the shortcomings of sparse data, and it is easy to ignore the multiple interests of the audience when calculating similar audience sets, which can be improved and studied in related aspects in future work.

4. Experiment

4.1. Experimental environment

Table 1 depicts the experimental environment.

Table 1. Lab environment.

Experimental environment	Experimental configuration
Operating system	Ubuntu22.04
Programming language	Python3.8.8
Deep learning framework	Pytroch1.1.0
Graphics card model	RTX309024GB

4.2. Data set

In this experiment, IMDB data set was selected, which contains a large number of users' comments on movies. Among them, there are 25,000 comments, including three fields: id, sentiment and review. Among them, those with emotional classification of 1 are regarded as favorable comments, while those with emotional classification of 0 are negative comments. Review represents the specific text content of the comment. The data set divides training data and test data equally, and abandons neutral comments.

4.3. Result analysis

The test results assess the performance of the model proposed in this document by its accuracy, recall and F1 value. The same data set is compared to SVM model, which is a the machine learning method. Experimental findings show that the accuracy of the SVM detection is 83.2%, while the test accuracy of the model selected in this paper is 87.2%, which has obviously improved the accuracy. After analyzing the results, SVM needs to manually extract features in the task of sentiment analysis, and may lose context information when extracting features and processing sequence data. The LSTM model is capable of addressing the problem of long-term dependence and having a stronger memory capacity, so it has more advantages than SVM model in emotional analysis tasks. This also shows the feasibility and availability of the model chosen in this paper. The application of LSTM in the movie recommendation system can help users get more accurate recommendation information, but the accuracy is still relatively low. In the future research, researchers can further improve the accuracy and test efficiency by introducing other deep learning or debugging loss functions.

5. Conclusion

In a word, this paper introduces LSTM model as an emotion analysis model through feature mining and emotion analysis of users' movie reviews, and combines it with user-based collaborative filtering algorithm to calculate the emotion tendency and interest similarity of target users and similar users for movies according to emotion tags, and provide users with more personalized and accurate movie recommendations based on this. By comparing with traditional methods, it is proved that the traditional machine learning method has improved the problem of low accuracy in emotion analysis tasks to some extent. However, there are still many improvements in this method. Firstly, despite the LSTM model's advantages over the traditional model, it may have the problem of information loss when dealing with long texts. Because of the limitation of the model structure, LSTM can not fully capture the details and context in long texts, so the generalization ability of the sentiment analysis model can be improved by improving the model structure or introducing more advanced deep learning models.

On the other hand, the movie recommendation system mainly recommends similar products, so the user-based collaborative filtering algorithm can be applied and recommended. However, the algorithm

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has the shortcomings of sparse data and cultural differences and other factors will affect the emotional analysis and expression of users. The user-based collaborative filtering algorithm will be slightly inferior in considering different types of mixed recommendations, and how to improve the accuracy and quality of mixed recommendations is also an important research direction. To sum up, the LSTM model still has great application potential in emotion analysis in the future research. By improving the depth of semantic features mining and optimizing the structure of deep learning model, using more advanced hybrid recommendation algorithm can provide more accurate and efficient movie emotion analysis and recommendation services.

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