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Emotion Analysis of Shopping Software Reviews Based on Neural Network

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Abstract: With the development of Internet technology, more and more businesses begin to open up online sales channels, which is both an opportunity and a challenge. In order to stand out from the competitive sales environment, it is a very effective means to obtain and analyze the feedback information in the product review data. Businesses can improve and publicize products through the feedback information to improve sales. This paper implements a set of fast insight system based on emotion analysis and neural network. The system can configure the collection items through the visual interface, and then use the data collection module to collect data from the e-commerce platform to build a commodity comment corpus. At the same time, it also embeds two emotion analysis models to analyze the processed comment data. The two-layer emotion tendency model is responsible for coarse-grained emotion analysis of the comment data to obtain commodity word of mouth, The comment theme model is responsible for fine-grained emotional analysis of the comment data to get the comment theme of the commodity. The analysis results can help merchants get the improvement points and promotion points of the commodity.

1. Introduction

With the development of social science and technology, Internet of things, cloud computing and other Internet technologies have also developed and popularized. While the scale of application systems in various industries has expanded, the amount of data generated has also exploded. How to collect and make good use of these data has become a common opportunity and challenge for many enterprises, for which the term "big data" has been derived [1]. "Internet +" shopping has long been integrated into our lives when major traditional industries are exploring new development paths for "Internet +".

The huge user market breeds new business opportunities. More and more businesses choose to carry out online business to provide customers with online shopping channels. Many online shopping platforms have emerged as the times require. Online shopping not only facilitates the purchase process, reduces the round-trip time, but also can clearly and simply find the items you want to buy [2]. Consumers can post their evaluation of the use of purchased goods on the online shopping platform, while other consumers can refer to the historical comments of the goods to make a choice before purchasing, avoiding the sense of shopping gap caused by the huge difference between "Buyer show" and "seller show", and improving the disadvantage that physical goods cannot be seen in online shopping [3]. Text sentiment analysis, also known as opinion mining, is a hot topic in natural language processing. Its purpose is to identify and extract subjective information in text through relevant methods [4]. Text emotion tendency analysis can effectively mine and analyze the data representing the views in the comment information, select the comment information with subjective emotions from the comment text, preprocess it, and then analyze the consumer's tendency to each dimension of the commodity through the emotion analysis algorithm. The merchant makes targeted improvements according to the analyzed results, If there are too many negative comments in some aspects, they can be found in time so that corresponding measures can be taken to save public opinion. Affective analysis is a kind of task in the field of natural language processing, also known as propensity analysis, opinion extraction, emotion mining, etc. [5]. The advantage of the dictionary based emotion analysis method in this paper is that the algorithm idea is relatively simple, and it is easy to be implemented by programs. For the emotion analysis in a specific field, only the emotion dictionary in the corresponding field needs to be constructed, and the effect of emotion classification is better. However, to achieve good results, we need to constantly maintain the corresponding emotion dictionary with the update of the information society [6].

The emotion tagging method proposed in this paper makes the original dictionary more universal in emotion analysis after automatic tagging, and is also convenient for maintenance. Neural network-based emotion analysis uses several different neural network models to train different network models for different tasks, such as considering local features and time-series features. However, neural network-based emotion analysis requires a large amount of training data for training. Theoretically, for deep neural networks, the more training data, the better the effect of emotion analysis. This paper proposes an emotion classification model that combines multiple networks. Through theoretical explanation and experiments, it proves that it is progressiveness and effective in emotion analysis.

2. Overview of Relevant Concepts

2.1. Text Processing and Presentation

Today's mainstream scientific research uses machine learning or deep learning related technologies. The first priority is how to obtain a large number of training corpora or related dictionaries. On the one hand, researchers can search the authoritative open corpus provided by some third-party websites on the Internet, such as Wikipedia, IMBA, Amazon, etc. [7]. But in fact, many research or development software systems are often applied to a specific field, and these open corpora often can not fully meet the relevant corpus needs. On the other hand, we need to use some data crawling methods ourselves, and use open crawler plug-ins to actively get the large amount of data we want from the network [8]. After data cleaning and sorting, researchers can use it as their own training set, so that they can continue their research. But now there are many anti crawler plug-ins on domestic websites, and some websites will violate relevant national laws by using some data of crawlers [9].

Emotion classification is the process of classifying the emotional text to be classified into predefined positive and negative labels. The rules of the classification system are to analyze the emotional tendency of the text to be classified and tested according to the emotional analysis rules obtained from the training process of the currently known emotional data set. Based on these emotional analysis rules, it can be used to accurately determine the category of the text to be tested [10].

2.2. Text Representation and Feature Extraction

The method in engineering is not a single method. It is almost impossible to completely solve complex problems on various data sources with a simple method or model tool. Therefore, to make good products or effects, we need to adopt a divide and conquer idea [11]. When each method is actually applied to the product, it is better to combine the vertical characteristics of the product. For example, in some financial and stock markets and automobile industries, there will be their own jargon, which has very obvious industry rules or characteristics [12].

The original features are measured or extracted according to the relevant methods, but they are generally not directly input, mainly for the following reasons: on the one hand, the original samples and features can not accurately reflect all the essential features of the object. Finally, the direct input of the original feature calculation to represent the feature needs a lot of computer space [13]. Direct input for feature recognition and classification is not only very time-consuming, but also will seriously affect the effect of feature classification, resulting in technical problems such as "dimension disaster".

2.3. Tf-Idf Features

TF indicates the frequency of the word a in the document. The main idea of IDF (reverse file frequency) is that if the document contains fewer words a, that is, the smaller the overall number of words a and the larger the IDF, it means that word a has a good ability to distinguish documents. The formula is as follows:

$$TF = \frac{\text{Number of words a in this document}}{\text{Number of all words in this document}} \tag{1}$$

$$IDF = \log\left(\frac{\text{Total number of documents in the corpus}}{\text{Number of documents containing word a} + 1}\right) \tag{2}$$

$$TF - IDF = TF * IDF \tag{3}$$

The larger the TF-IDF value, the greater the probability that this word will become a keyword, and then the keyword can be used to analyze the emotional tendency of documents [14].

2.4. Emotion Analysis of Convolutional Neural Network

The application of neural networks to emotion classification is to find out rules through continuous learning, which is a nonlinear modeling process. Generally speaking, for neural network models, the deeper the neural network training effect is, the better the concept of deep learning is. In the field of artificial intelligence, deep learning has won the favor of many researchers, and more and more researchers begin to apply deep learning technology to their own research fields [15].

Convolutional neural network (CNN) is a mechanism that simulates the human brain's collection and processing of various signals, and can quickly extract hierarchical complex features from complex original data [16]. It is characterized by using the spatial relative relationship of neurons to improve and improve the performance of model training by reducing the number of neuron parameters, which is essentially the operation of multilayer convolutional neural networks [17]. In the traditional feedforward neural network, each neuron located in the input layer has a completely corresponding output neuron connected to the next layer, which is mathematically called fully connected or symmetric affine. The convolutional neural network is built by using multiple convolution layers, pooled input layers and a fully connected output layer. At present, convolutional neural networks have made many achievements in the field of image deep learning [18].

3. Comment Emotion Analysis Based on Neural Network

3.1. Experimental Data Set

The dictionary data set used in this experiment includes positive and negative evaluation dictionaries and emotion dictionaries. This experiment aims at the word level, and 5855 words are obtained by cleaning the phrases in the data set. This experiment mainly labels HowNet's emotion dictionary, selects 1637 emotion words, and then carries out the emotion value labeling experiment.

Two data sets are used in this experiment. One is the Amazon auto comment data set collated by Amazon. The corpus includes 20473 comments. After data cleaning, there are still 20407 actually downloaded data. The second is the review dataset of Amazon musical instruments, which includes 10261 reviews. After data processing and cleaning, the first 10000 reviews were selected. For the two data sets, there are five emotion levels, which are discriminated by the artificial emotion of the text. In this paper, 1-3 grades are marked as negative, the comment label is set as 0, 4-5 grades are marked as positive, and the comment label is set as 1. The dataset contains three fields (reviewtext, labels and rate) where reviewtext is the sentence to be trained, labels is the emotional polarity label, and rate is the emotional degree value of the sentence.

3.2. Experimental Environment

Table 1. Experimental environment

Hardware environment		Software environment	
CPU	Intel(R)Core(TM) i7-6700 CPU	Development tool	Eclipse(2019)、Pycharm(2019)
Memory	16GB		
System	Windows 10 professional (64 bit)	Python version	3.7.3

4. Numerical Analysis Results

4.1. Analysis of Labeling Results

Get the screened seed word, and then get the maximum semantic similarity between the seed word and HowNet emotional word through a semantic similarity calculation method, and then multiply the emotional weight of the seed word to get the emotional annotation value of the word. Then calculate the emotional value of HowNet dictionary according to the emotional word labeling formula proposed in this chapter. The following are 10 unmarked emotional word results based on seed words listed by me:

It can be seen from table 2 that the first 20 tagging results obtained from the emotional word numerical tagging will be analyzed by calculating the emotional value below. After determining the tagless emotion dictionary numerical labeling method, let's observe the distribution trend of emotion values in bosonnlp dictionary and HowNet labeling results. The distribution trend is shown in the following figure:

Table 2. Dictionary labeling results

Words to be marked	Emotional seed words	Seed word weight	Similarity value	Value of words to be labeled
Adroitness	Integrity	5	0.66667	3.33333
Aesthetic	Satiation	1	0.23529	0.23529
Affability	Optimism	3	0.76921	2.30769
Affableness	Optimism	3	0.76923	2.30769
Affirmative	Integrity	5	0.16667	0.83333
Affluence	Satiation	1	0.61538	0.61538
Agreeability	Optimism	3	0.83333	2.5
Agreeableness	Optimism	3	0.83333	2.5
Alacrity	Optimism	3	0.46153	1.38461
Alert	Integrity	5	0.66667	3.33333

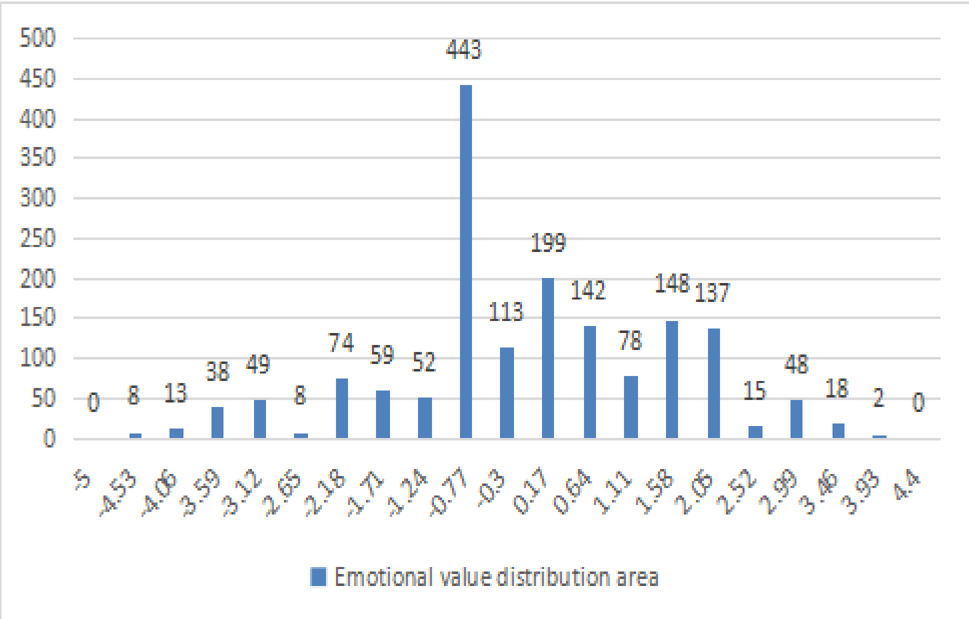

Figure 1. Emotion value distribution trend of bosonnlp dictionary

4.2. Comment Emotion Analysis Combined with Neural Network

It can be seen from the experimental data of the four models in Figure 2 and figure 3 above that various network models have achieved certain effects in different emotional comment text experiments. In general, the accuracy of textcnn is low, while the accuracy of CblA based emotion network classification model and F1 bid evaluation index are higher than the experimental results of other models. In particular, the CblA network classification model in this paper has improved the accuracy and F1 value of the Bi LSTM + atten model, which is mature in text classification, to a certain extent. Therefore, the results show that the CblA network classification model is effective and progressiveness in the application of emotion analysis.

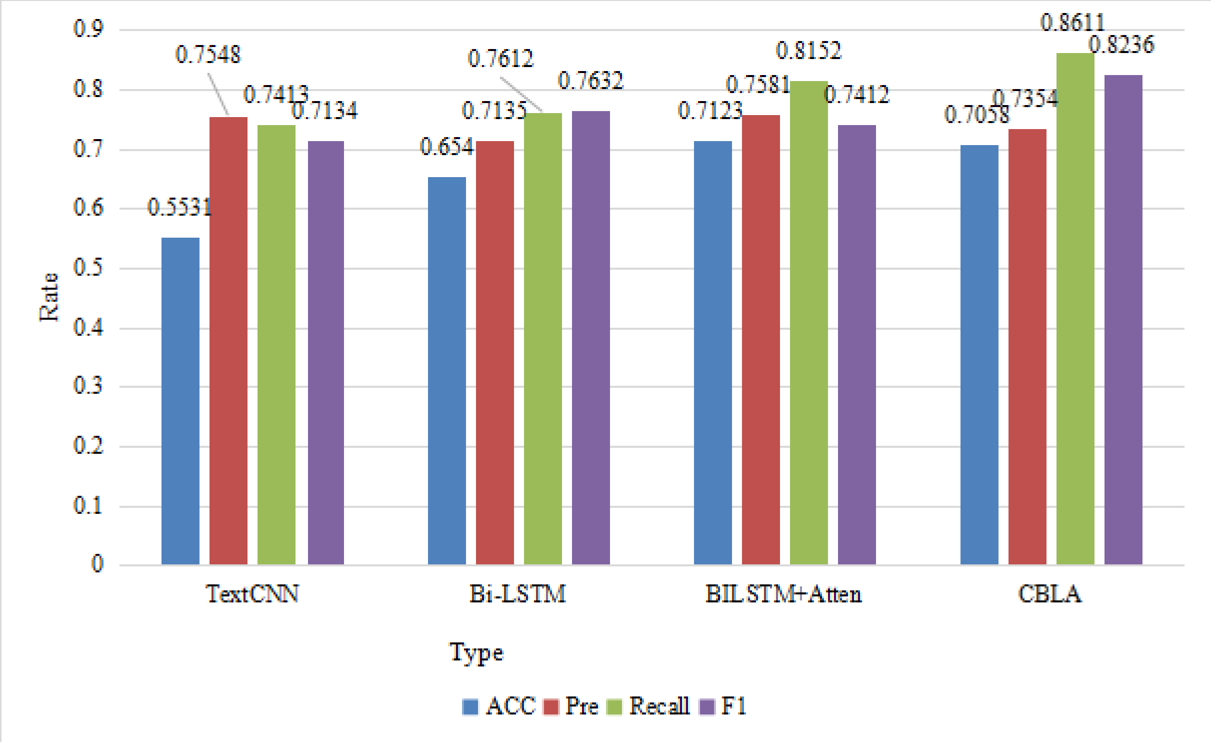

Figure 2. Results of Amazon auto review dataset on different models

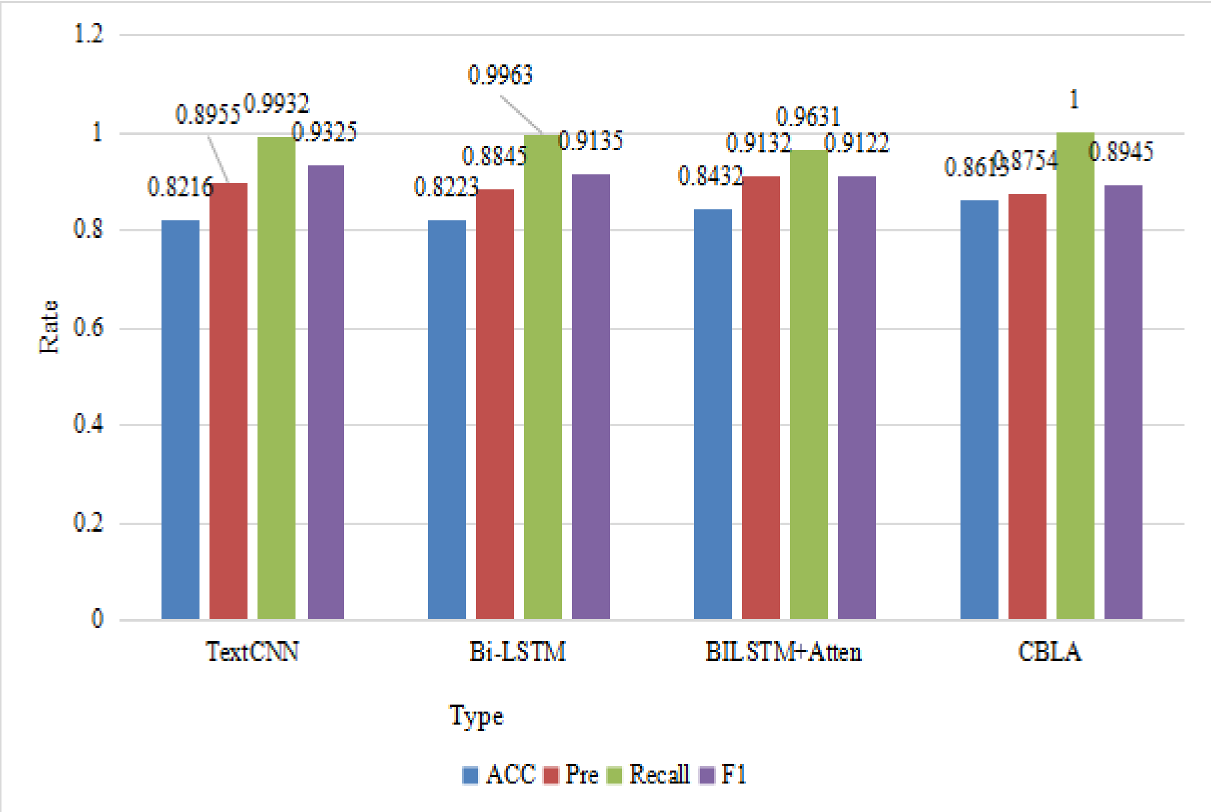

Figure 3. Results of musical instruments' review dataset on different models

5. Conclusion

At present, affective analysis based on deep learning is popular in affective analysis tasks, but many affective analysis systems at home and abroad are still based on dictionaries. Because the dictionary based emotion analysis method relies on the fineness and accuracy of the dictionary, a better dictionary can get a better classification effect, and it does not need to spend a lot of time training like neural networks to get a better classification effect. However, due to my limited understanding of natural language processing, the emotional analysis technology in this paper is still in the exploration stage, and there may be some shortcomings in the intermediate processing process, which still needs further research in the follow-up work.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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