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Research on the Emotional Classification Model of Online Public Opinion Based on Complex Contexts

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Abstract

Under the backdrop of the information explosion and the accelerated pace of globalization, online public opinion has become an important channel for reflecting social dynamics and public attitudes. With its huge volume of information, rapid dissemination, diverse viewpoints and ambiguous correlations, it is difficult for traditional sentiment analysis methods to cope with it. This paper aims to construct a sentiment analysis model for online public opinion that can adapt to complex contexts. By means of the Scrapy crawler framework, the public opinion data about the "problematic vaccines" on Sina Weibo is collected. A convolutional neural network situational awareness classification model that combines spatial features and word vectors is proposed. Firstly, preprocessing is carried out based on the spatial distribution characteristics of words in the text. Then, word vectors are constructed based on sentiment features. Finally, the model is constructed and trained. Through comparison with models such as Linear SVM and CNN+Skip-gram, the results show that this model has a certain improvement in both accuracy and recall rate. This paper provides more effective decision-making support and theoretical reference for the analysis of online public opinion, and realizes the improvement of the sentiment classification model in complex contexts.

Keywords: Online Public Opinion, Complex Context, Sentiment Classification, Convolutional Neural Network, Word Vector

1. Introduction

Public opinion, in brief, refers to the basically consistent opinions or attitudes publicly expressed by the public regarding specific social public affairs. Sociological studies hold that public opinion has a powerful social control function, which can exert a strong influence on the emotions and cognitions of individuals and groups, and further affect their social psychology and social behaviors.

With the rapid development of Internet technology and the widespread popularization of smart devices, online media such as news websites, Weibo, WeChat, forums, Tieba, Douyin, Kuaishou, etc. have become common channels for the public to share, accept information, and express themselves freely. The collective participation of a huge number of users has made the Internet a converging platform that contains multimodal online public opinion data such as texts, pictures, videos, and audios.

Online public opinion refers to the online viewpoints of different opinions on social issues that are popular on the Internet, and it is a form of manifestation of social viewpoints. As the power of these viewpoints continues to grow, some sensitive online public opinions on the Internet are extremely likely to attract widespread attention from people, and have a great instigating effect on the people who are unaware of the truth. There is a high possibility that it will develop into a major and malignant real-world event.

The more significant an public opinion incident is, the more likely it is to be filled with some veiled comments, or even those containing satire, metaphors and allusions. Different from the consistent emotional tendency of multimodal information in a normal context, the information of various modalities in such comments presents a complex context with a strong inconsistency or even mutual contradiction in emotional expression. It is precisely the comments in complex contexts that are the key factors for triggering public opinion crises and determining the trend of public opinion. How to avoid being swept along by the torrent of massive real-time data and losing the initiative in decision-making, and how to obtain the public opinion situation that can reflect the current real situation based on the accurate emotional analysis of a large number of individual micro users is the key for emotional analysis to move towards practical application. Therefore, it is urgent and necessary to study the emotional analysis of micro users that can adapt to complex contexts based on massive multimodal data.

Early research on emotional classification in situation awareness mainly adopted research methods based on dictionaries and statistical knowledge. Such method models formulate judgment rules according to grammar and sentence structures, obtain features by statistically analyzing a large amount of textual data, compile dictionaries and templates using artificial knowledge, and complete the analysis of the emotional tendency of texts. These methods are usually relatively simple to operate and have a fast processing speed, but they have the disadvantage of low recognition accuracy and are usually applied to simple application scenarios with a large amount of data.

Zhu et al. (2006) extracted basic emotional words from the currently widely recognized emotional dictionaries, calculated the similarity between the words in the text and the extracted emotional words to obtain new emotional words, and then carried out emotional tendency classification after expanding the emotional words into the emotional dictionary. Li et al. (2018) applied syntactic division and syntactic rules to extract simple word combinations in Chinese texts, and used the word features in the word combinations to make similarity judgments to achieve text emotional classification.

With the rise of deep learning technology in the field of natural language processing, more and more researchers have achieved breakthrough improvements in text emotional classification through deep learning models. Among them, what has attracted much attention is that Kim (2014) used a convolutional neural network for English emotional classification, achieving a breakthrough improvement compared with previous researchers. In Chinese text classification, Song and Yan (2020) proposed an emotional classification method based on the convolutional neural network (CNN) and recurrent neural network (RNN) models in deep learning models, which is used to extract the local features of texts and the long-distance features of texts.

2. Public Opinion Data Collection

This paper collects public opinion information on “Sina Weibo” by adopting the Scrapy crawler framework. The crawler takes the “Weibo Hot Search List” page as the starting point, obtains the URL addresses of various popular topics, and uses the depth-first search strategy to crawl the web pages of each popular topic one by one. In terms of crawler maintenance, in order to achieve stable data crawling, it is necessary to promptly check and update the proxy IP addresses in use and the Cookies information of the login accounts.

The crawled data is stored by dividing it into three types of entities: personal information, user relationships, and Weibo information. These three types of entities and their included attributes are defined in the items class of the crawler. Among the various crawled Weibo hot topic data, the information collection and data mining results of the Weibo hot topic “Problematic Vaccines” are selected, and the specific contents are as follows:

The Weibo posts related to the “Problematic Vaccines” incident were crawled within the time range from July 15, 2018, to July 29, 2018, and a total of 5,668,087 pieces of Weibo information were crawled. Based on the publication time, the number of comments, and the number of reposts in the Weibo information (corresponding to the “PubTime”, “Comment”, and “Transfer” attributes in the “Weibo Information” category respectively), the total number of comments and reposts of the Weibo posts published each day was counted as an indicator to measure the degree of attention of Weibo users to the “Problematic Vaccines” incident. The obtained event trend chart is shown in Figure 1. Among them, on July 23, the number of reposts and comments by Weibo users reached the highest, which was 1.52 million.

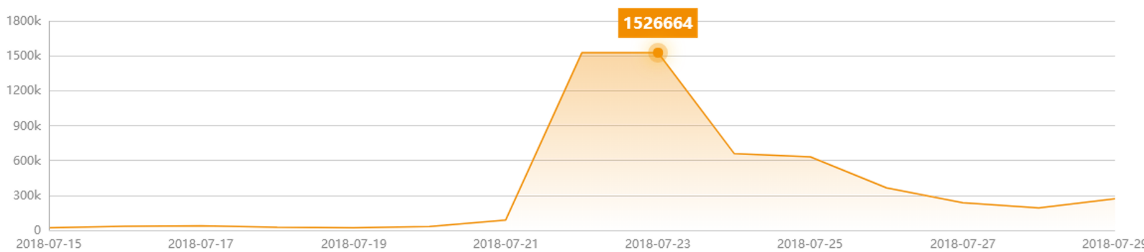

Figure 1: “Problem Vaccine” Incident Microblog Trend Chart.

In addition, the “Location Coordinates” attribute of the “Weibo Information” category in the database was also counted, and a geographical distribution map of the Weibo posts about the “Problematic Vaccines” incident was drawn, as shown in Figure 2. At the same time, based on the preprocessing algorithm of spatial features, the weight value of each word was calculated, and according to the weight values, a keyword cloud as shown in Figure 3 was obtained.

3. Emotional Classification Model Based on Convolutional Neural Network

Emotional classification models play a crucial role in uncovering users’ perspectives and stances within public opinion events, thereby determining the performance of opinion - mining systems (Liu et al., 2024). In terms of methods, emotional classification research can be categorized into two types: traditional machine - learning - based and deep - learning - based. In recent research, diverse deep - learning - based models have witnessed remarkable breakthroughs in classification performance. Nevertheless, most of these deep - learning - based approaches typically overlook both the spatial features inherent in the text and the unique characteristics of individual words. Additionally, the classification outcomes are highly contingent upon the training samples.

This paper proposes a convolutional neural network situation awareness classification model that combines spatial features and word vectors in a complex context. Firstly, preprocessing is carried out based on the spatial distribution features of words in the text. Then, words are abstractly represented and vectors are constructed based on the word annotation features. Finally, a convolutional neural network is constructed and trained to achieve the judgment of the emotional polarity of the text.

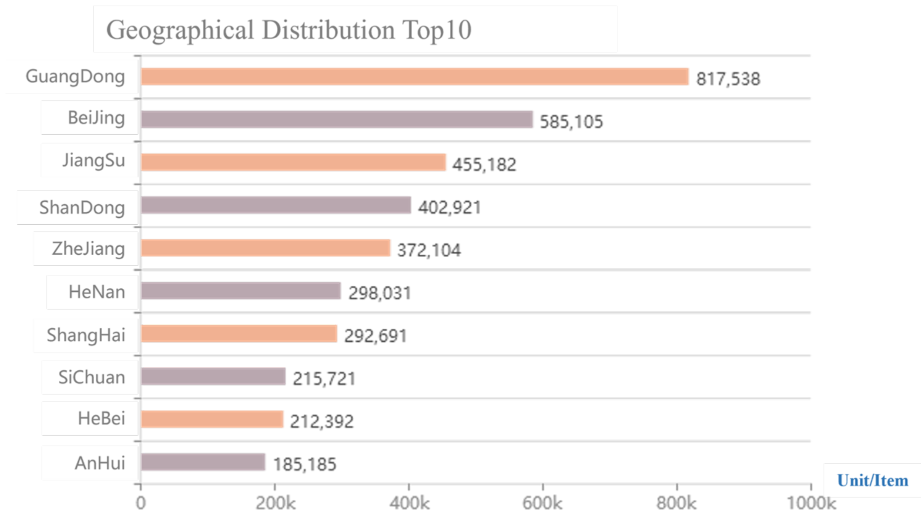

Figure 2: Microblog Regional Distribution Map of the "Problem Vaccine" Incident.

Figure 3: Microblog Keyword Cloud Map of the "Problematic Vaccine" Incident.

3.1. Conduct Preprocessing in Accordance with the Spatial Distribution Characteristics of Words

Texts on the Internet usually have characteristics such as trivial language descriptions and scattered thematic contents. If the words in the texts are directly segmented, word vectors are constructed, and these are used as the input for the convolutional neural network model, the result of emotional classification will be unsatisfactory due to the sparsity of features (Dai et al., 2021). This paper introduces a vector space model, combines the word distribution and frequency in the article, calculates the importance of each word, and conducts screening and filtering. Figure 4 shows in detail the preprocessing process based on the distribution characteristics of words in the space.

First, the ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) of the Chinese Academy of Sciences is adopted to carry out word segmentation processing on all texts. Take the text set $D = \{d_1, d_2, d_3 \dots d_n\}$ to be classified as the space, simplify each text dj into a vector in the space, and map each word ti in the text to each numerical value Wi in the vector in order. Each text vector di is expressed as:

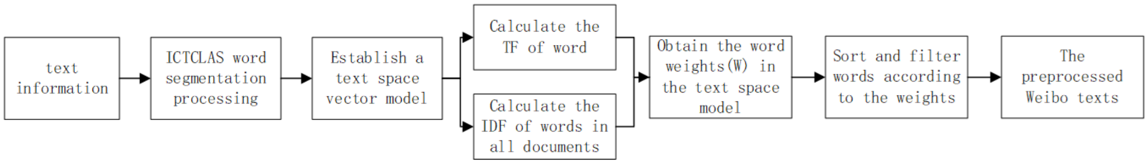

Figure 4: The preprocessing process based on spatial features.

$$d_{\mathrm{j}} = \{(t_1, w_1), (t_2, w_2), (t_3, w_3)...(t_i, w_i)...(t_n, w_n)\} \tag{1}$$

Among them, n represents the total number of characteristic words in the text d_{j}, $t_i(1 \leq i \leq n)$ represents the term in the text, and $W_i(1 \leq i \leq n)$ represents the value corresponding to the term t_i in the text vector. Therefore, the text d_{j} can be briefly recorded as the following vector:

$$d_{\mathrm{j}} = \{w_1, w_2, w_3...w_i, w_n\} \tag{2}$$

It can be seen from Formula (2) that the value corresponding to each term in the vector space model within the vector reflects its importance to the text to which it belongs.

Next, based on the established spatial model, the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm is used to calculate the numerical value W_i corresponding to each term t_i in the text set within the vector space. The TF-IDF algorithm consists of two parts: term frequency calculation (TF) and inverse document frequency calculation (IDF). The formula for calculating the term frequency is shown in Formula (3). Among them, $t_{i,j}$ represents the number of times the word t_i appears in the text d_{j}, $\sum\limits_k t_{k,j}$ represents the sum of the number of times all words appear in the text d_{j}, that is, the total number of words in the text d_{j}, and $\mathrm{tf}_{i,j}$ represents the frequency of the word t_i appearing in the corresponding text d_{j}. The higher the frequency of a word, the more densely it is distributed in the corresponding text:

$$\mathrm{tf}_{i,j} = \frac{\mathrm{t}_{i,j}}{\sum_k \mathrm{t}_{k,j}} \tag{3}$$

Under normal circumstances, the term frequency values corresponding to words that are close to the text theme will be relatively high. However, not all words with high term frequency values are close to the text theme (He et al., 2022). For example, words such as "is", "are", and "were" have high term frequencies in various types of texts, but their importance should be lower than that of words such as "vaccine", "child", "listing", and "medicine". The word cloud diagram obtained based on the term frequency ranking is shown in Figure 5.

In order to accurately measure the degree of closeness between words and the text theme, it is necessary to further calculate using the inverse document frequency value IDF. The word cloud diagram obtained according to the term value IDF is shown in Figure 6.

By comparing Figure 5 and Figure 6, it can be seen that the preprocessing based on spatial features can filter out many words with trivial descriptions and scattered thematic contents. The processed text word segmentation can better reflect the Weibo theme, playing a fundamental role in the research on the emotional tendency of Weibo texts with high precision.

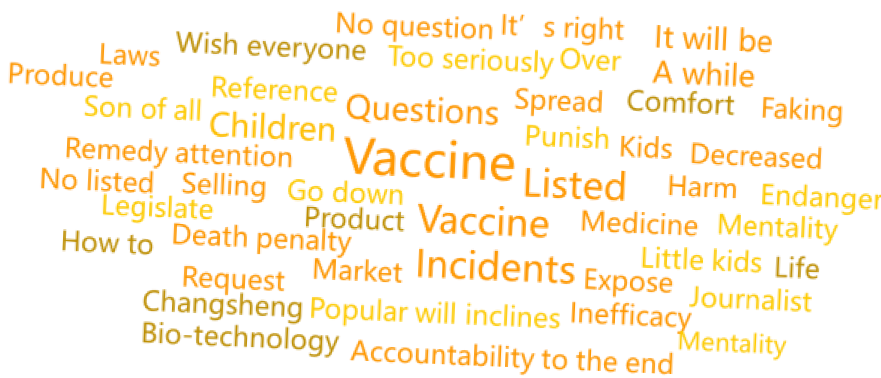

Figure 5: Word cloud chart based on the word frequency algorithm.

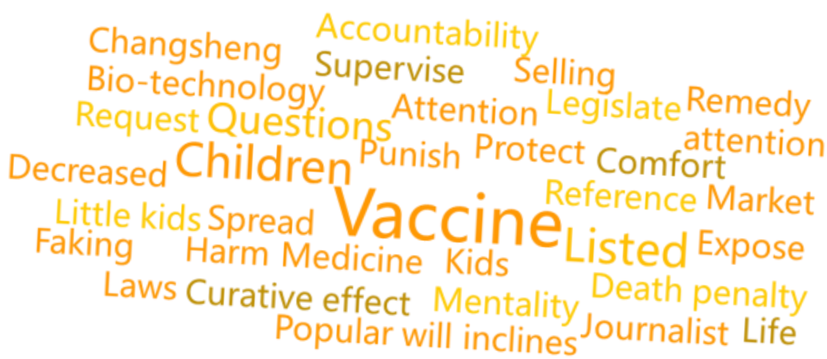

Figure 6: Word cloud chart based on the term values.

3.2. Construction of Word Vectors

When establishing an emotional analysis model, it is necessary to transform the text in natural language into information that can be recognized by a computer. As the most basic component of a text, words are represented in the form of vectors in the research, which promotes the computer’s ability to analyze and process natural language. In the task of emotional analysis, the characteristic information such as the word polarity and part of speech in the original data greatly affects the emotional expression of the text. If the part of speech and the distribution characteristics in the text can be effectively utilized when constructing an emotional classification model, better results can be achieved.

The Skip-gram model (Li et al., 2016; Yu, 2016) maps each word into a k-dimensional real-valued vector. After representing words using word vectors, it is convenient to calculate the similarity between words through vectors. Then, further judgments can be made on the word categories according to the magnitude of the similarity values.

This paper uses the Skip-gram model to train the preprocessed text dataset. For a group of words $W_1, W_2, W_3 \cdots W_n$, the probability $p(W_{\mathrm{i}} \mid W_t)$ of the occurrence of the following words is predicted according to the word W_t, and the objective formula (4) is maximized. Among them, the window size c represents the number of adjacent words before and after. The larger its value is, the better the model training effect will be, but it will also increase the training time.

$$E_{Skip-gram}=\frac{1}{N}\sum_{n=1}^{N}\sum_{-c\leq i\leq c}\log p(W_{\text{t+i}}|W_t) \tag{4}$$

Set the dimension k of the word vector to 300 dimensions, and set the last two digits of the word vector as the emotional polarity of the word. Add annotations according to the emotional dictionary, where "11" represents a positive emotion, "00" represents a negative emotion, and "10" or "01" represents a neutral emotion.

During the training process, it was discovered that the value of the window size c has an impact on both the training effect and the training time. After the word vectors have been well-trained, it is necessary to represent the text as a two-dimensional matrix of $m \times k$ by combining word vectors, which serves as the input for the neural network. Here, m represents the number of word vectors contained in the longest text within the preprocessed text set (in the experiment of this paper, m is set to 260). For texts with the number of word vectors less than m, padding processing is carried out. The dimension of the word vector $k = 300$. Eventually, each text is represented as a two-dimensional matrix of 260×300 and used as the input.

3.3. Construction of the Sentiment Classification Model Based on Convolutional Neural Network

The research on the emotional tendency of situation awareness judges the emotional tendency contained in the text content by analyzing the text. Therefore, a better model method has higher accuracy in the classification results (Wang et al., 2021). Traditional machine learning methods require a large amount of data mining and analysis to extract the surface features of the text. With the increase in the amount of data, the entire process becomes more time-consuming and labor-intensive (Wang and Tang, 2023). Although deep learning-based methods are efficient and fast, their effects depend heavily on the training of the model, the selection of features, and the tuning of parameters. Moreover, only a sufficiently deep model can extract features that can better reflect the semantic information of the text.

3.3.1. MODEL CONSTRUCTION

In 2014, Yoon Kim proposed the TextCNN, a convolutional neural network model for text classification. By applying the convolutional neural network to natural language processing tasks, especially text classification, it can effectively capture the local features in the text and achieve efficient classification. The core of it lies in extracting local features through the convolutional layer and the pooling layer, and finally conducting classification. The model structure is divided into the following parts:

The input layer converts the text into a word vector matrix. It first segments the words and converts them into an index sequence, and then maps the indexes into a word vector matrix.

The convolutional layer extracts local features through multiple convolutional kernels (such as kernels corresponding to 2, 3, or 4 words), and captures the correlations between word sequences.

The pooling layer reduces the dimension through the max pooling operation and extracts the most important global features. The fully connected layer connects the results of the pooling layer and outputs the classification results.

This paper makes improvements based on the TextCNN established by Kim:

Input layer: Use the above-mentioned two-dimensional text matrix of 260×300 as the input of the neural network.

Convolutional layer: In order to study the local features of text at different granularities, feature maps are extracted using windows with sizes $h = 4$, $h = 5$, and $h = 6$ respectively. When the window sizes h are 4, 5, and 6, and the stride is 1, the dimensions of the obtained local feature maps are 257×1, 256×1, and 255×1 respectively. The convolution kernel scans the entire word vector matrix. Each convolution operation is equivalent to extracting the feature vector of that window. Different parameters within the convolution kernel define different windows, ensuring that distinct and high - density feature vectors are extracted.

Pooling layer: A max-pooling operation is used. In sentiment analysis, local words and phrases with strong sentiment in the text can usually reflect the sentiment polarity of the text (Wang et al., 2024; Zhao et al., 2024). The pooling layer samples the feature maps based on local correlations, retaining the features with obvious sentiment polarity while reducing the amount of data.

Fully connected layer: Map to the two outputs of the last layer to achieve sentiment classification.

3.3.2. MODEL VALIDATION

The stochastic gradient descent method is adopted for training. There are a total of 3,600 samples in the training dataset. Among them, the "10 - fold cross - validation method" is used, and all the training samples in the dataset D are evenly divided into 10 subsets. During training, 9 subsets are used as the training set each time, and the remaining subset is used as the test set.

During training, the dropout in the fully - connected layer is set to 0.5, which means that half of the parameters are randomly discarded in each iteration. Ten groups of training are carried out in each round to analyze the training effect of the model.

4. Analysis of Model Validation Results

The experimental data is from the annotated COAE2014 dataset. 3,600 samples (mainly divided into positive and negative samples) are selected from this dataset, and 10 - fold cross - validation is used to evaluate the prediction accuracy of the model.

After the dataset is divided, pre - processing based on spatial features, construction of word vectors based on emotional features, and input processing of the convolutional neural network model are carried out in sequence to obtain a 260×300 two - dimensional text matrix. The convolutional neural network model uses the above matrix as the input of the neural network, effectively combining the word vectors and the spatial features of the text.

To verify the effectiveness of this model in emotional classification, it is compared with two models, namely Linear SVM and CNN + Skip - graml:

(1) Linear SVM: The linear support vector machine (Linear SVM) model, which is commonly used in traditional machine learning, has been widely applied in various natural language processing research. By adopting the Linear SVM model, features can be constructed relatively directly based on the text representation, and the problem of emotional tendency can be addressed. It is characterized by a short training time and high efficiency (Chauhan et al., 2019).

(2) CNN + Skip - gram: The word vectors generated by the Skip-gram model are used to transform the text into a matrix and input it into the convolutional neural network for training (Wu, 2024). Through the comparison with the Linear SVM in the experiment, the differences in efficiency and accuracy between the traditional machine learning model and the convolutional neural network model are analyzed.

(3) CNN + Vector Space Feature (VSF) + Skip - gram: The model designed in this paper pre-processes the text based on spatial features, then combines emotional features to train word vectors to form a 260×300 two - dimensional data matrix, and inputs it into the convolutional neural network for training. In the experiment, by comparing with the CNN + Skip - gram model, the influence of the pre - processing based on spatial features and the word vectors retrained based on emotional features on the classification performance is verified.

According to the above design, experiments are conducted on the three well-trained models in sequence (using the "10-fold cross-validation" method). The experimental results are shown in Table 1 and Figure 7:

Table 1: Comparison of the experimental performance of the three models

Model	Precision+ Precision-	Recall+ Recall-	F-Score+ F-Score-
Linear SVM	0.7175 0.7536	0.8273 0.6185	0.7685 0.6794
CNN+Skip-gram	0.7870 0.8438	0.8864 0.7190	0.8337 0.7764
CNN+VSF+Skip-gram	0.7953 0.8506	0.8803 0.7295	0.8356 0.7854

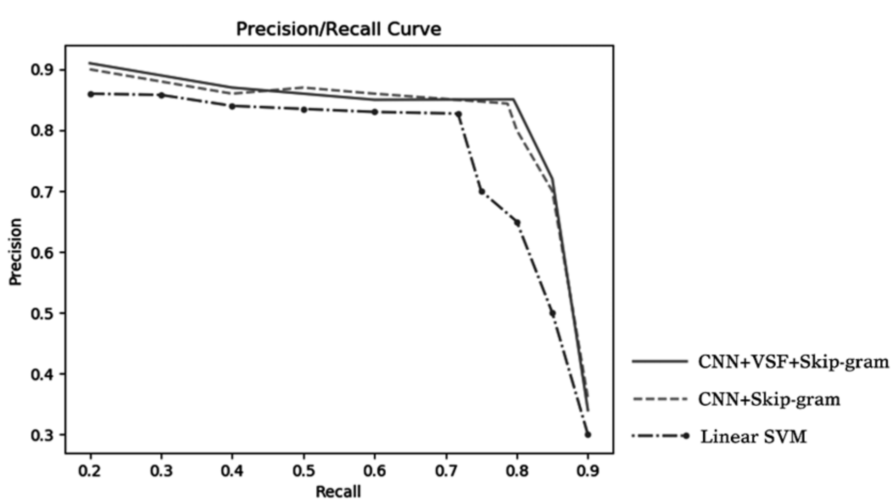

Figure 7: Comparison chart of the precision/recall curves of the three models.

Although the precision of the Linear SVM model in the emotional classification problem has achieved certain results, there is still a large gap compared with the CNN + Skip-gram model combined with word vectors. Through the experimental comparison, it can be analyzed that: word vectors can extract the feature distribution of the input text at the level of abstract connections between words; in addition, the convolutional neural network can better extract local features, thus achieving better results in text classification.

Compared with the CNN + Skip-Gram model, the CNN + VSF + Skip-gram model proposed in this project fully combines the preprocessing of spatial features and the retraining of word vectors, resulting in a slight increase in both the accuracy and recall rate. On the one hand, the preprocessing based on spatial features can extract the distribution features of words, filter out some words irrelevant to the text theme, and reduce the noise and interference during word vector training. On the other hand, compared with general word vector training, the word vector training based on emotional features can grasp the emotional connections of words in the text while extracting the abstract features of the text. With the help of the prior knowledge of the emotional dictionary resources during training, an input matrix that is more beneficial for the convolutional neural network to perform emotional classification can be obtained.

5. Conclusion

This paper takes the text information in the complex context of social networking sites as the processing object. The information collection of social networking sites is completed through a distributed web crawler. Judging from the collection results, the required collection of Weibo text information can be achieved. However, what needs to be improved is that the collected text content still needs to be filtered for URLs, tags, and special symbols.

Then, by analyzing the emotional classification model methods of different situation awareness, the convolutional neural network model is improved in two aspects: preprocessing based on spatial features and constructing text feature inputs from word vectors. Finally, a convolutional neural network model that combines spatial features and word vectors is constructed. From the comparison results, the accuracy of emotional classification in situation awareness has been improved, achieving the purpose of model improvement.

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