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Research on Text Sentiment Analysis Based on Attention Mechanism Fusing LSTM and CNN Models

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Abstract

Text sentiment analysis is an important branch in the field of natural language processing, widely used in public opinion analysis and other aspects, and is a hot research direction in recent years. In this paper, an LSTM and CNN model are fused to build a fusion model for sentiment analysis based on the attention mechanism, and trained on comment datasets crawled from several social media sites such as Facebook, Twitter, Instagram and WhatsApp. Through experimental comparison studies, it is found that the sentiment analysis fusion model proposed in this paper can better extract the features of text data, thus effectively improving the effect of text sentiment analysis.

Keywords

NLP; Sentiment Analysis; Attentional Mechanisms.

1. Introduction

With the rapid development of information technology, the Internet has become inseparable from our daily lives, while information has begun to explode. Along with the growth in the number of internet users, more and more information is appearing online. Internet users can post their views on various events and express their emotional attitudes on public platforms such as Twitter. In this environment, the web has produced textual big data generated by large-scale web users, which originates from their real feelings, is on the emotional side, and is characterised by a huge amount of data, a variety of expressions and a deep mutual influence. In particular, these massive amounts of text data are also rich in social and commercial value and have received widespread attention from industry, academia and government. It is the main task of text sentiment analysis technology to uncover the sentiment value hidden in these massive amounts of text data.

Text sentiment analysis, also known as opinion mining, refers to the analysis of subjective texts with emotional overtones to uncover the emotional tendencies embedded in them and to classify emotional attitudes. Text sentiment analysis techniques is a general term for theories, methods and techniques for analysing, processing, generalising and reasoning about texts with emotional overtones. The use of text sentiment analysis technology to analyse the textual big data widely dispersed on the Internet can provide a scientific basis for government departments to understand social and public opinion and manage public opinion at an early stage, thus providing a scientific basis for decision making to improve the way the government works on social governance;It also enables enterprises (e.g. e-commerce platforms) to be informed more quickly of users' attitudes towards product quality, service and corporate reputation, and to carry out timely product innovation, precision marketing and reputation PR based on the analysis results, providing strong technical support for enterprise development;It can also provide the average consumer with similar subjective attitudes to the products they are buying and provide accurate recommendations to help them buy the products they want.

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It is therefore that the development of text sentiment analysis techniques has contributed significantly to the progress of modern society. Its broad application prospects provide solid research implications for the study.

2. Related Research

Text sentiment analysis is an important branch in the field of natural language processing and can be divided into three main types of text sentiment analysis methods, depending on the method of implementation used——Sentiment analysis based on sentiment dictionaries, sentiment analysis based on traditional machine learning and sentiment analysis based on deep learning.

The sentiment analysis method based on sentiment dictionaries refers to the division of sentiment polarity under different granularity based on the sentiment polarity of sentiment words provided by different sentiment dictionaries, Words of different types and degrees of sentiment dictionary are put into the model for training, and finally the sentiment types are output according to sentiment polarity judgement. (a) Cai Y et al. [1] address the problem of the existence of multiple meanings of emotive words by constructing a domain-specific sentiment dictionary; (a) Rao Y et al. [2] used three pruning strategies to automatically build a lexical-level affective lexicon for social-emotional detection, and also proposed a topic-based modelling approach to construct a topic-level dictionary. (a) Wu L et al. [3] used web resources to build the first slang dictionary sentiment word tool to effectively analyse the sentiment polarity of slang's social media content; (a) Xu et al. [4] constructed an extended sentiment dictionary containing basic sentiment words, domain sentiment words and polysemantic sentiment words, and used the extended sentiment dictionary and designed sentiment scoring rules to achieve sentiment classification of texts.However, with the rapid development of online resources, new words are being updated at an increasingly rapid rate and existing dictionaries need to be constantly updated to meet the needs of classification, which is time and resource intensive, and often fails to take into account the semantic relationships between contexts when using sentiment dictionaries for sentiment classification. As a result, sentiment analysis based on machine learning methods has received a lot of attention from scholars.

Machine learning-based classification methods fall into three main categories: supervised, semi-supervised and unsupervised methods. A multi-label maximum entropy based model for short text sentiment classification was proposed by (a)Li J et al. [5], (a)Xue J et al. [6] used the machine learning method LDA (latent Dilley-Clay distribution) to implement topic and sentiment recognition. (a) Liu L et al. [7] used supervised and semi-supervised machine learning methods to implement stance detection for microblog users, significant results were obtained through experimental comparisons on different classifiers such as SVM, Parsimonious Bayes and Random Forest. (a) Yu Z et al. [8] proposed a semi-supervised machine learning-based method for tweet sentiment classification, with experimental results showing a recall of about 60%; (a) Jiang F et al. [9] proposed a semi-supervised emotion classification method based on the emotion space model ESM (emotion space model) of emojis, which uses word vectors constructed from data where emojis are still unlabeled and works better compared to the baseline method.

Traditional machine learning-based sentiment classification methods mainly focus on the extraction of sentiment features and the combination of classifiers, and the combination of different classifiers has a certain impact on the results of sentiment analysis, however, the sentiment features extracted by traditional machine learning models are not sufficient, which greatly affects the effectiveness of classification. At the same time, with the development of technology, deep learning methods are receiving more and more attention from scholars.

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(a) Jelodar et al. [10] classified the sentiment of COVID-19 reviews by using LSTM methods, and the findings have implications for guidance and decision-making on issues related to COVID-19. (a) Lai Y et al. [11] proposed a grammar-based GCN model to enhance the understanding of grammatical structural diversity for fine-grained sentiment classification studies. (a) Yang C et al. [12] first proposed a collaborative attention mechanism that models alternating target-level attention and contextual-level attention, enabling aspect-level sentiment analysis by transferring the target to a contextual representation of the keyword. (a) Murtadha Ahmed et al. [13] put forward an attention-based LSTM model to solve a dictionary-based aspect-level sentiment analysis task. (a) Ning Liu et al. [14]proposed a model, named Attention-based AS-Reasoner, to alleviate the problem of how to capture precise affective expressions for reasoning in ABSA.

In this paper, extensive research has been carried out in terms of improving the classification model, and a sentiment analysis model that introduces an attention mechanism and fuses LSTM and CNN is proposed to further improve the classification results.

3. Related theories and models

3.1. Attentional Mechanisms

The attention mechanism is essentially a way of simplifying the complexities of information by assigning weights. The most relevant information for our current job is assigned a higher weight, and the irrelevant information is suppressed. Through the attention mechanism, information that is relevant to the current task and has stronger semantic features can be extracted from the large amount of information.

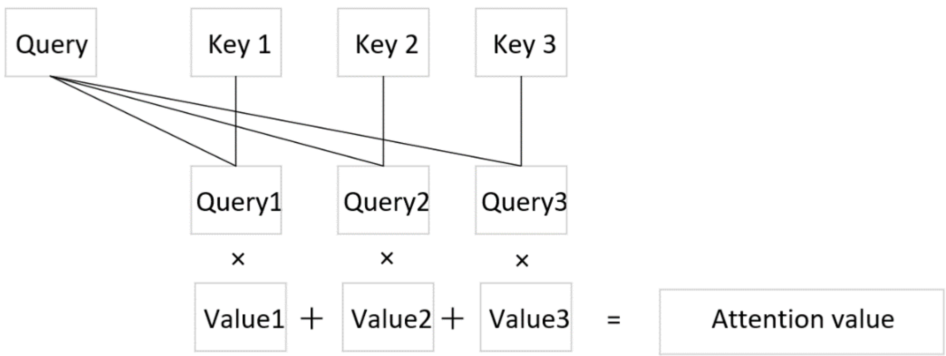

Figure 1. Schematic Diagram of the Attentional Mechanism

A typical Attention consists of three parts: Query, Key, Value. Query is the input information, Key and Value are the existing information, generally existing text information, source language, etc. Key and Value occur in groups.The correlation between Q and K is calculated by equation (1), which gives the importance of different K to the output, and then multiplied and summed with the corresponding V to obtain the output of Q.

$$\text{Attention(Query,Source)} = \sum_{i=1}^{L_x} \text{Similarity}\left(\text{Query}, \text{Key}_i\right) * \text{Value}_i \tag{1}$$

3.2. Long Short-Term Memory

The Long Short Term Memory (LSTM) network is a type of special recurrent neural network that was designed to solve the problem of vanishing and exploding gradients during the training of long sequences.LSTM is a gating algorithm where the core component is the cell , and the data in the information cell is recorded and updated by using three gate structures, the input

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gate, the forgetting gate, and the output gate, effectively improving the gradient instability and long distance dependence situation.

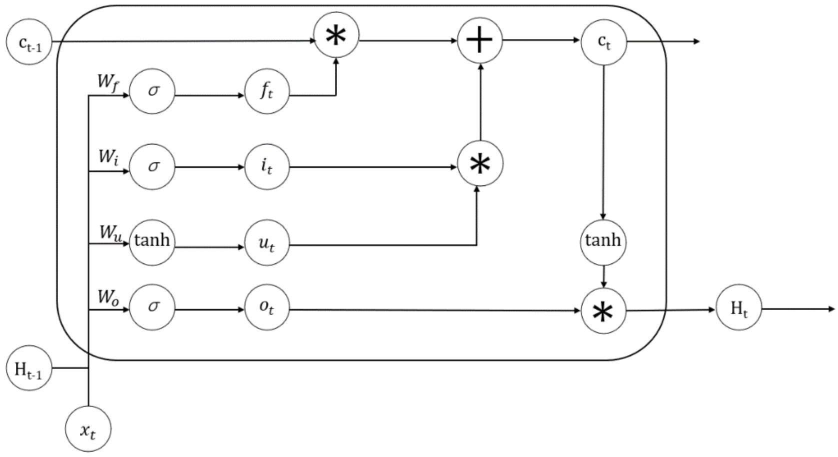

Figure 2. Long Short-Term Memory

The equations for the states of the forgetting gate, input gate and output gate at moment are as follows:

$$f_t = \sigma\left(W_f \cdot [H_{t-1}, x_t] + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i \cdot [H_{t-1}, x_t] + b_i) \tag{3}$$

$$o_t = \sigma(W_o[H_{t-1}, x_t] + b_o) \tag{4}$$

In the above equation, σ denotes the activation function Sigmoid, the Sigmoid function can return a value between [0,1] and can therefore be used as a gate control information outflow ratio.Another activation function, tanh, which controls the direction of increase or decrease of the message and locks the value within [-1,1]. The parameters of the forgetting, input and output gates are different but calculated in the same way, and the parameters can be shared at all time steps.

3.3. Convolutional Neural Networks

Kim's research [15] shows that the CNN performs well in sentiment classification tasks. Such models utilize a distributed representation of words, first converting a vector containing each sentence to form a matrix as the input CNN, and he proposes a straightforward single-layer CNN architecture consisting of a convolution layer, a pooling layer and a fully connected layer.

The convolutional layer uses multiple convolutional kernels of different sizes to extract local features from the text, The n-gram correlation features of the original text are extracted after the convolution layer, the max-pooling method is used at the pooling layer, which serves to reduce the dimension and prevent over-fitting, that is, to select the most significant word or phrase in the sentence as the result of the next layer, after the convolution and pooling layers, we obtain a feature vector representing the text, and then a fully-connected plus SoftMax layer gives us a probability vector representing the different classes to which it belongs, which completes the classification process.

3.4. Model Framework

In order to improve the performance of the sentiment analysis model by better extracting features from text data, this paper fuses LSTM and CNN models based on the attention mechanism to build a sentiment analysis fusion model. The model structure is shown in the following diagram:

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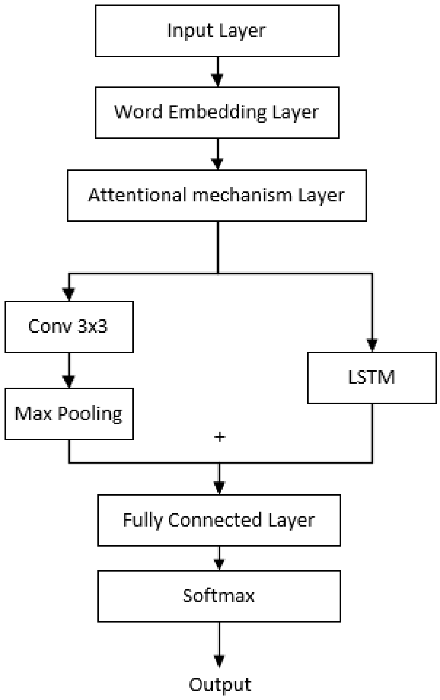

Figure 3. Fusion Model

As can be seen from the model structure diagram, the model, as a deep learning fusion model, consists of several modules:

(1) The first layer is the word embedding layer, which maps the input text data into word vectors for representation.

(2) The second layer is the attention mechanism layer, which imports an attention mechanism to weight the input text data. The attention mechanism enhances the learning of subsequent models by giving greater weight to data with greater contribution to highlight the important information in the text data and diminish the influence of useless information.

(3) The third layer is a feature learning layer, with a convolutional layer on the left, which is used to extract different local features of words in a sentence. The maximum pooling layer is then used to filter redundant features and finally generate a feature vector.

(4) The third layer on the right-hand side is the LSTM channel. The advantage of the LSTM model is that it can handle sequence data better. It captures both sequential and contextual information of sentences and filters the information through a unique gate structure as a means of global feature extraction of text data and capturing the longer distance dependence of sequential information. Finally we fuse the features obtained from the two part structure of the third layer to achieve the fusion of the CNN model and the LSTM model to obtain the local and global features in the text data.

(5) The final layer is the sentiment classification layer. The features obtained from the fusion model are used as input to the fully connected layer, with Relu as the activation function, and a Dropout mechanism is added to prevent over-fitting of the model training. Finally, the output of the fully connected layer is fed into the SoftMax classifier to obtain the classification results. The formula is as follows:

$$P(S_i) = \frac{e^{g_i}}{\sum_k^n e^{g_{ki}}} \tag{5}$$

Where k ∈ (0,n], n denotes the number of classifications, i denotes a classification in k, and gi denotes the value of that classification.

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4. Experiments

4.1. Experimental Data

The dataset in this paper is derived from a dataset of real user comments on the twitter website, which contains a total of 342,120 comments. The dataset divides the comments into a more fine-grained set of six emotions: disgust, surprise, anger, fear, happiness, and sad. Using this dataset allows the model to perform fine-grained sentiment segmentation, which helps the model to identify a wide range of emotions, and in practice the model can identify more diverse emotions of the user. The content composition of the dataset is shown in the figure below:

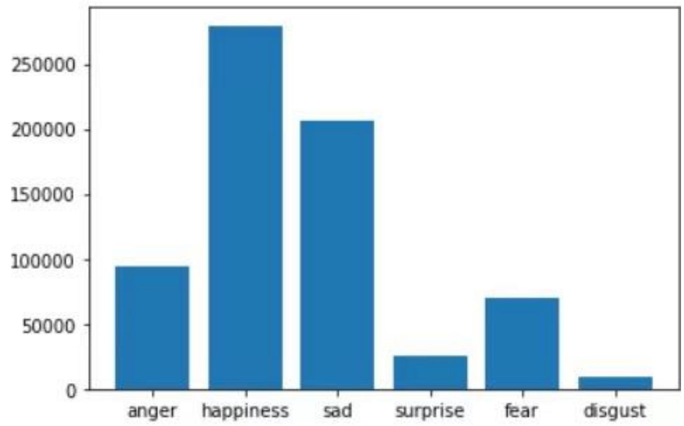

Figure 4. Data Set Content Composition

4.2. Experimental Results

In order to verify the validity of the fusion model proposed in this paper, Precision is used as a validation metric for the model performance. The SVM, CNN, Text-CNN, LSTM and CNN and LSTM fusion models were used as the comparison models, and from the Precision curve plots of each model shown in Figure 5, it can be seen that the CNN and LSTM fusion model based on the attention mechanism proposed in this paper works best.

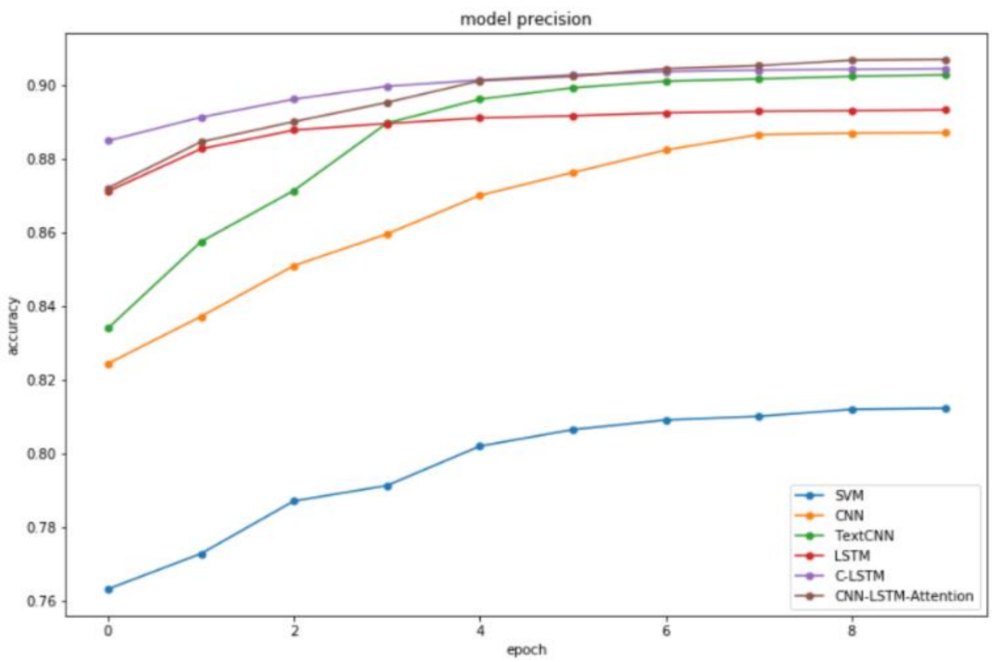

Figure 5. Experimental Results

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Table 1 shows the specific values for the Precision comparison of each model. It can be seen that although the fusion model proposed in this paper has improved the classification results compared to the other models, the degree of improvement is average. After analysis, the reason is that the dataset used in this paper suffers from the problem of unbalanced data classes, which easily leads to poor training of the model. In practical applications, means such as oversampling can be considered to supplement the dataset and improve the upper limit of performance of the sentiment analysis model.

Table 1. Comparison of Experimental Results

Number	Model	Precision%
1	SVM	81.23
2	CNN	88.71
3	TextCNN	90.28
4	LSTM	89.33
5	CNN-LSTM- Attention	90.70

5. Conclusions and Recommendations

In this paper, CNN and LSTM models are fused based on the attention mechanism, and fine-grained sentiment analysis experiments are conducted on a dataset of real user comments from the twitter website. Through experimental comparison, it is found that the proposed fusion model Precision is the highest and the model classification performance is the best.

However, the analysis reveals that there are still some shortcomings in this paper and there is still room for improvement. It is hoped that more attempts can be made in future studies, as follows:

1. Selecting a better quality dataset or addressing class imbalance in the dataset during the data processing stage improves the learning of the fusion model.

2. Improving model selection allows the use of a multi-channel CNN model to extract richer local features of words in a sentence. A bi-directional LSTM model is used to enhance the collection of discourse order and contextual association information.

3. Optimizing the model network structure, the fusion model in this paper does not make changes to the underlying structure within the network, and subsequent work could consider reconstructing the underlying network structure to enhance the classification performance of the model.

Finally, the research presented in this paper theoretically provides new ideas and technical routes for model fusion in text sentiment analysis research, and in practical applications fine-grained sentiment analysis can be applied to more scenarios and provide more fine-grained sentiment classification results. The improvement of the shortcomings in the article will be the main direction of subsequent research.

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