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Recurrent Neural Networks for Sentiment Classification and Recognition

Shuhua Xu*

Dongtai Hospital of Traditional Chinese Medicine, China

jssdtsxsh@163.com

**corresponding author*

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Abstract: Website based sentiment analysis aims to reveal the potential emotional value of non-constructive text data, which is very valuable to governments, enterprises and individuals. The purpose of this paper is to study emotion classification based on reverse neural network. In the experiment, we systematically describe the design and implementation of text emotion classification using long memory, short memory and recursive element models. In this paper, a synthesis method based on surface features and deep knowledge is proposed. In addition, LSTM recruitment neural network model is used to improve the classification accuracy to 88%, which is 18% higher than the traditional vector support method based on shallow features.

1. Introduction

With the rapid development and maturity of Internet technology worldwide, the number of people using the Internet is increasing year on year. The various forums, blogs, microblogs and comment sections on the Internet are a platform for people to share information and interact with each other. Through these social media, people are free to write or share their feelings about the products they buy, reviews of new movies, personal opinions on recent events and current news, etc [1-2]. These meaningful comments often contain a large number of personal emotions and attitudes such as happiness, anger, sadness, joy, agreement, disagreement and neutrality [3]. Deep learning is an unsupervised approach that abandons the disadvantage of models requiring text annotation and maps text data into an abstract expression by constructing multiple processing units. During the training of a deep learning model, the model automatically analyses the features of the text data to obtain the sentiment tendencies of the text data [4-5].

Facial expression recognition (FER) is a necessary process for the next generation of human-computer interaction (HMI) clinical practice and behavioural description [6]. Jain N proposed a combined recurrent neural network method to obtain FER images The proposed hybrid model was evaluated based on two sets of public data and the results were more accurate than the latest method [7]. Kshirsagar P proposed a new method based on depth learning to resist the negative impact of illumination changes on face recognition. The initial photographic processing was used to improve the negative effect of strong light on facial images. LBP functions in images are extracted with Gabor Log filters, and Gabor Log functions of different sizes and directions are obtained Then, these texture functions are studied in the DBN network for classification and recognition [8]. Emotional Speech Recognition (ESR) is considered as an active field of computer interface (HCI) research Albadr M uses chalk reflection coefficient (MFCC) to extract features from speech This paper shows the significance of classification components in the ESR system, thus improving the performance of ESR, thus improving the accuracy [9]. In this context, it becomes important to efficiently extract information from this massive amount of data that can help in analysis and to analyse the information accurately.

We propose a GRU-based sentiment analysis model, based on the current LSTM sentiment analysis model, by constructing a sentiment word vector with the premise of identifying novel words. The specific steps are: to identify the new vocabulary in the dataset, to perform the word separation process; to integrate the sentiment information in the construction of the word vector, to build the sentiment word vector; and finally to study the sentiment of the web text, and to derive the sentiment classification and analyse the sentiment polarity of the user.

2. A Study on the Application of Recurrent Neural Networks in Sentiment Classification Recognition

2.1. Recurrent Neural Networks

(1) Recurrent Neural Network RNN

The computational characteristics of RNNs make them suitable for processing sequential information, such as language, stock market information, etc. The internal "memory" of RNNs means that each element of the input sequence is computed with reference to the results of previous computations, as if the network could remember the information it has processed so far [10-11].

The neural network uses different parameters at each level, while RNA has the same parameters. This means that they perform the same function at each stage, but with different inputs. This greatly reduces the total number of parameters required for network learning. In theory, RNNs can handle sequence information of arbitrary length, but in practice there are limits to the length of sequences that a typical RNN can handle due to gradient fading or bursting [12-13].

2.2. Recurrent Neural Networks in Sentiment Analysis Tasks

In the emotion analysis task, we can use the recursive function of the syntax tree to represent the repetitive neural network [14-15].

At the input level, we represent words in sentences as decentralized representations of word vectors (here we use Google's word vector 2vec), and still calculate the entire node layer by layer based on the combination of two or two nodes in the text syntax tree, as shown in Formula (1) and Formula (2).

$$P_1 = f(W(b,c)+B) \tag{1}$$

$$P_2 = f(W(a,p_1)+B) \tag{2}$$

Where W in the equation is the weight matrix to hold the weight information of the neural network edges after training, and B is the bias parameter of the neural network, both of which are randomly assigned during the initial process of the network [16]. It has the same number as the word vector, so the dimension of the W matrix storing weight information should be set to $W \in R^{d*2d}$. On each node of the syntax tree, we use the softmax function layer to define the feature distribution of the senses and calculate the formula, as shown in Formula (3).

$$y^i = soft\max(W_s x_i) \tag{3}$$

Where xi is the d-dimensional feature vector of the node, yi is the c-dimensional sentiment output vector of the node, representing the c levels of sentiment, ws is the feature to sentiment mapping matrix, c is the number of sentiment levels we have defined, and d is the dimensionality of the vector features of each node. The function returns a vector that measures the emotional level used to soften the output, so that each element of the vector corresponds to a probability feature, that is, the mathematical form specified in equation (4).

$$soft\max(Z_m) = \frac{e^{zm}}{\sum e^{zk}} \tag{4}$$

With the help of recurrent neural networks, we can see the emotional information in words (hidden in the attributes of word vectors, and extended through the Softmax layer), improve or reject inversion through syntax tree structure, hierarchical propagation and fusion, and finally put the emotional information on the top of the grammar to complete the emotional tendency degree in the whole sentence [17].

2.3. A Recurrent Neural Network Model Based on an Improved LSTM

LSTM enhanced recurrent neural network model is an RNA variant, in which amnesia in LSTM structure is defined as ϕ; The entrance door is marked ω; The memory unit is represented by C, and the storage unit is represented by C [18]. These three gates are controlled by the sigmoid function marked by the factory, and the memory activation function is represented by G.

The entrance of the front door includes three aspects: the exit of the entrance layer, the exit of the hidden layer at a certain time and the information stored in the storage unit. In the equation, at t time, the ATT input and BTT output of the entrance door are as follows (5) and (6):

$$a_t^t = \sum_{i=1}^{I} w_{it} x_t^t + \sum_{h=1}^{H} w_{ht} b_h^{t-1} + \sum_{c=1}^{C} w_{ct} s_c^{t-1} \tag{5}$$

$$b_t^t = f(a_t^t) \tag{6}$$

The LSTM-based recurrent neural network model and each hidden layer contains 256 activation units.

3. A Survey and Study on the Application of Recurrent Neural Networks in Sentiment Classification Recognition

3.1. Introduction to Experimental Tools

The experiments in this paper are written in python language, including the pre-processing of text, extraction of fusion features, and implementation of classification algorithms. Among them, the word separation in preprocessing is done with the NLPIR word separation system, also known as ICTCLAS, which can perform word separation and lexical annotation for Chinese, and supports user-defined dictionaries to meet the different needs of different tasks. Deep learning features are extracted with the help of the word2vec tool. In addition, the recurrent neural network model is based on theano's python framework keras.

3.2. Data Sources

The hotel review corpus was collected from www.ctrip.com by researchers at the University of M. During the collection process, they removed the html tags and parsed the elements inside, treating reviews with a score of 4.5 or higher (including 4.5) as positive affective tendency data, and reviews with a score of 2.0 and below as negative affective tendency data. The data in the middle were discarded. This resulted in approximately 13,522 positive and 12,312 negative samples, followed by 3,000 randomly collected samples for the training set and 2,000 for the test set.

3.3. General Framework of Text Sentiment Polarity Classification

In order to classify the sentiment polarity of text, this paper firstly performs pre-processing operations such as word separation on subjective text; then, shallow and deep learning features are extracted from it, where shallow learning features include unigram, POS and dict, and deep learning features are the feature vectors extracted from word2vec; then, the shallow and deep learning features are fused; Finally, the text training set is used to train an RNN model based on LSTM improvement, and the test set is used to evaluate the sentiment polarity classification results. The general framework of the specific text sentiment polarity classification is shown in Figure 2.

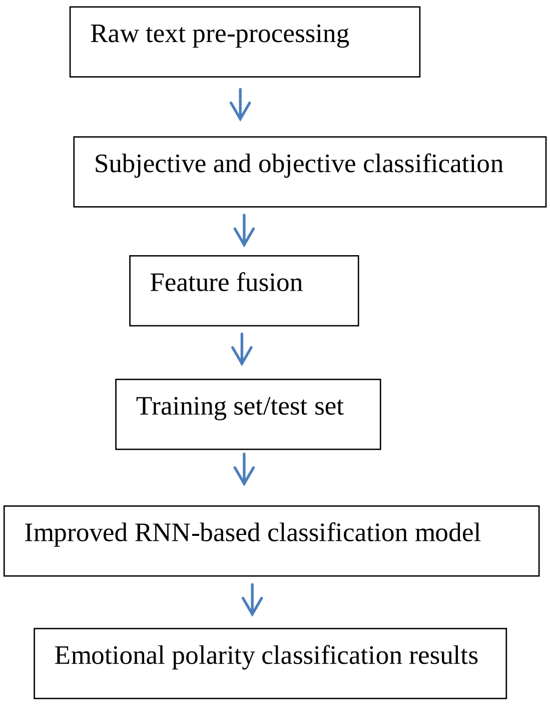

Figure 1. General framework of text sentiment polarity classification

4. Analysis and Research on the Application of Recurrent Neural Networks in Sentiment Classification Recognition

4.1. Emotional Polarity Classification Based on a Recurrent Neural Network Model with LSTM Improvement

The network model used in this experiment is a three-layer hidden layer structure, and each layer contains 256 activation units, where the optimization function uses the SGD algorithm and the objective function uses cross-entropy. The specific experimental results are shown in Table 1.

Table 1. Effectiveness of recurrent neural network model based on LSTM improvement for sentiment polarity classification

Emotional classification	Accuracy (%)	Recall rate (%)	F1 value (%)
Positive	88	89	89
Negative	90	88	85

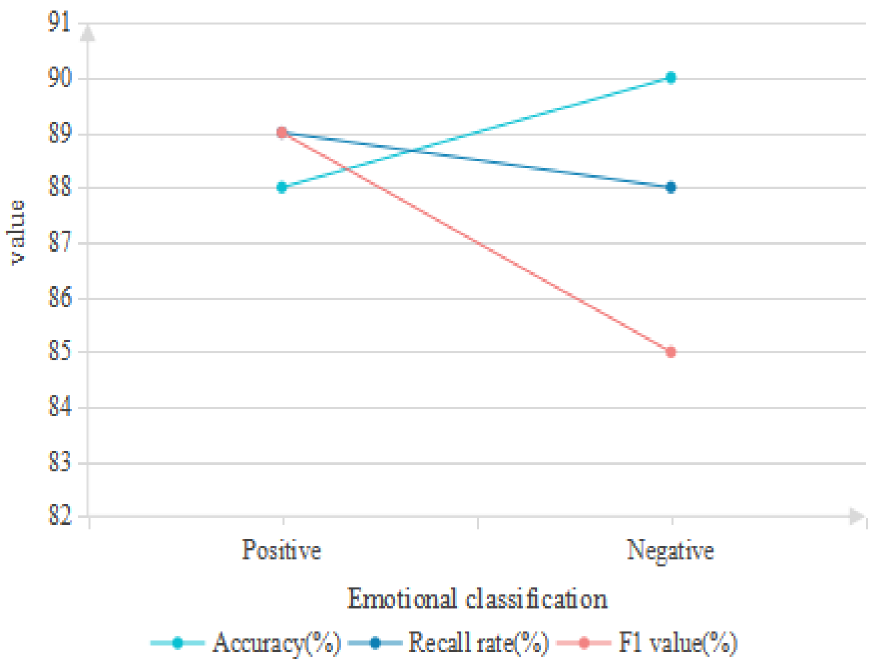

Figure 2. Experimental results

From the experimental results, it can be seen that the improved recurrent neural network model based on LSTM performs well in text sentiment polarity classification, with high accuracy, recall and F1 values, as shown in Figure 3.

4.2. Comparing the Effectiveness of Different Models for Sentiment Polarity Classification

This experiment compares three models, namely support vector machine, reverse neural network and improved neural network based on LSTM. For better comparison, RNN and the improved recursive neural network model based on LSTM adopt a three-layer hidden layer structure, with 256 activation units in each layer, as shown in Table 2.

Table 2. Comparison of experimental results for different models

Classification models	Accuracy
SVM1	70%
SVM2	76%
RNN	82%
Model for this paper	88%

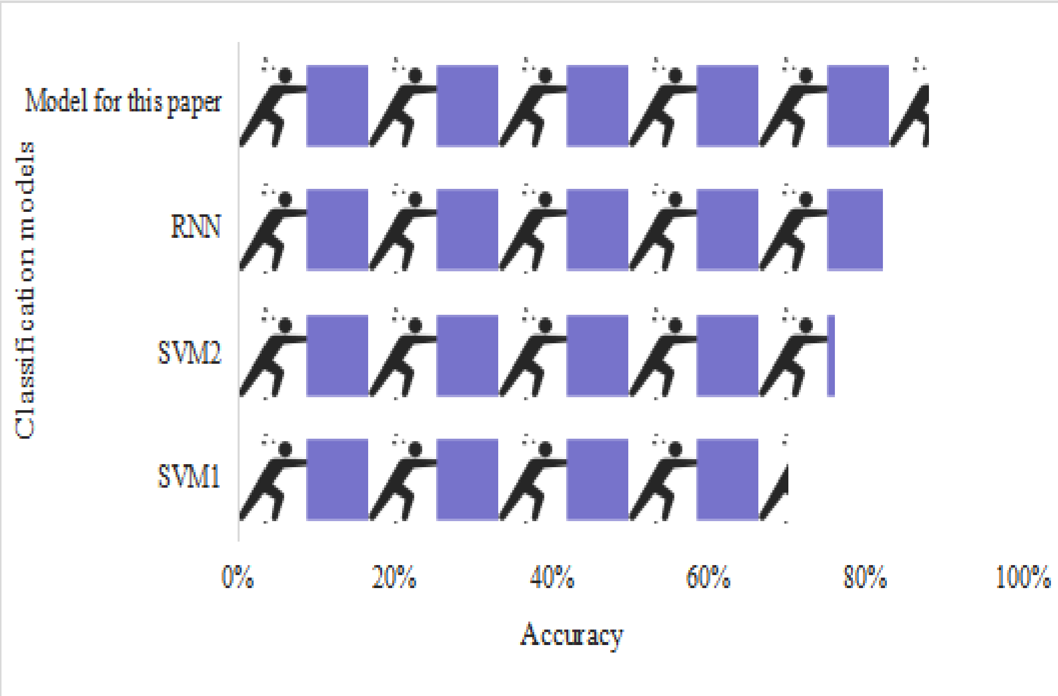

Figure 3. Emotional polarity classification accuracy of different models

As shown in Figure 3, SVM1 is a support vector machine device that uses plane learning opportunities, and SVM2 is a support vector machine device with integration function. The above figure shows that SVM2 is superior to SVMI, indicating that the integrated features used can improve the classification accuracy to a certain extent. In addition, more accurate RNA classification based on advanced LSTM recurrent neural network shows that the internal correlation of text sequences is also an important basis for emotion pole classification. In addition, the improved recursive neural network based on LSTM performs best in the above models.

5. Conclusion

With the rapid growth of the web population and the web application market, the scale of text data on the Internet is increasing day by day, showing a geometric growth trend. In the face of such a large amount of text data, the traditional means of manually discovering textual sentiment information is no longer suitable for the current environment, and how to use machines to automatically identify the sentiment tendency of large amounts of text is a hot topic of research in the field of natural language processing today, and there are also cross-applications with machine learning, pattern recognition and other fields. In this paper, we have conducted some research on document-level sentiment polarity discrimination and aspect-level sentiment polarity discrimination respectively, but we have not gone far enough, and there are some areas for improvement and further research: for example, using the advantages of each method to complement each other to further improve the accuracy of sentiment discrimination.

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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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