Research and analysis of psychological data based on machine learning methods

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Abstract: The integration of psychology and computer science has become the mainstream contemporary research method on psychological data. Weibo, China's largest open platform for communication and information sharing between users, has many emotional contents hidden in its data. According to the current trend, the Weibo data are segmented by machine learning to obtain a psychological portrait of Weibo users. This design uses Long and Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) to perform sentiment classification on Weibo data. The classification results are analysed using word frequency analysis and the Latent Dirichlet Allocation (LDA) model to obtain portraits of Weibo users' sentiment and an analysis of the results. The results are displayed in the form of word clouds. According to the clustering results of the word clouds, the main factors affecting different polar emotions can be analysed.

Keywords: recurrent neural network; short-term memory network; convolutional neural network; emotion analysis; LDA.

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1 Introduction

The rapid development of the internet and information technology has promoted the revolution of information technology, provided great convenience for human life and made humanity enter the era of digital information with rich data. In the age of information technology, the ability to generate and store data has been dramatically developed, and people live in an unimaginably vast data world. With the rapid development of internet technology and software technology, people-to-people communication has appeared more on online platforms and more and more social networks have become spaces for people to express their emotions. People express their joys and sorrows through words, which contain rich psychological meanings. The research trends of applying machine learning methods to individual psychological feature vectors and analysing the results to obtain people's psychological activity are the primary means for studying psychological text data (Xue et al., 2015).

In recent years, psychology research combined with machine learning algorithms has entered the public's vision and realised some achievements. At the same time, this combination has also been featured by some psychology magazines (Yarkoni, 2012). This means that social science psychology research supported by machine learning technology has gradually become the mainstream way of studying social psychology and has played a decisive role.

We propose a method using long and short-term memory networks and convolutional neural networks to perform sentiment classification. The portraits of users are obtained to analyse their sentiment. Our paper is organised as follows. Section 2 introduces related work. Section 3 describes text pre-processing. Section 4 describes the method. Section 5 illustrates the results and presents an analysis. Finally, Section 6 concludes our paper.

2 Related work

2.1 Sentiment analysis

Text sentiment analysis is a crucial research branch of natural language processing that involves subject knowledge in various fields such as artificial intelligence. Text sentiment analysis is to first process the source and data of the text by applying computer algorithms, classifying the data; then analysing the basic semantics, emotional polarity and degree of the text; and finally, it judges the emotion of the text expresser. Emotional polarity is mainly divided into two types: positive emotions (appreciation, affirmation) and negative emotions (criticism, negation).

2.2 Research corpus

The research corpus refers to the data set that is required for use in experimental research. Weibo, short for MicroBlog, is a broadcasting and social networking platform that shares short-term and real-time information through an attention mechanism. According to the 2019 annual report, the number of monthly active users of Weibo reached 468 million. The personal data of many people are recorded on Weibo. The primary purpose of this paper is to perform sentiment analysis on text data. Therefore, more than 200,000 Weibo data are selected for the experiment, and the existing Weibo expectations are built to verify the modelling results by testing the expectations.

2.3 Mainstream research methods

In recent years, the mainstream research methods in text sentiment analysis have been as follows: The first class of methods is based on rules or unsupervised learning methods. The unsupervised learning method performs sentiment classification on the text without labelling the samples. Using unsupervised learning for emotions in text does not require the labelling of the corpus so that it can save many resources. Therefore, it has attracted the interest of a group of research scholars. Turney proposed calculating the Point-to-point Mutual Information (PMI) value between emotional phrases and seed words, used adjectival and adverbial phrases as emotional phrases, and calculated the emotional inclination value of the phrase on this basis (Turney, 2002). The method has unique advantages and originality, strong independence, a wide application range, and accessible applications. The domain relevance of emotional vocabularies is expected to be logical in this article.

The second class of methods is based on supervised learning approaches. A method based on supervised learning first needs first to convert the text document into a corresponding feature vector that a computer can understand, then train the classifier on the labelled samples and finally use the classifier to classify the new document. For supervised learning methods, there are two main methods for performing sentiment analysis tasks: one is a dictionary-based method and the other is based on machine learning. Articles and sentences are composed of different words which connected to express different emotions. Therefore, the dictionary-based method is to analyse the polarity of the article through words. The third class of methods is based on a neural network. In recent years, the frequency of applying neural networks in sentiment classification has increased rapidly.

The latest method is to use recursive methods to perform recursive operations on adverb and build a sentence representation based on these adverbs. This method is called a recursive autoencoding neural network. The recursive self-encoding neural network is composed of a tree structure dependent on the text, and each adverbs needs to be annotated before use. Convolutional Neural Networks (CNNs) are often used in sentiment analysis, which can capture the polar features of text very well in text analysis. Long Short-Term Memory (LSTM) has a memory for making decisions based on prior knowledge from the input, and it can capture the changing emotions due to context in sentiment analysis. The LSTM model is often used in the operation of learning sentences because it has strong context modelling capabilities.

3 Text pre-processing

The acquisition of text data is the first operation to start machine learning and statistical modelling. Information about the space and the uniformity of the data sample will affect the final accuracy of the algorithm. There are many ways to obtain text predictions. The most common one is to find a corpus provided by a third party on the internet for experimentation (such as a wiki corpus). However, many studies have been conducted in specific fields, and these opening corpora often cannot meet our requirements. Therefore, crawler technology to obtain the required information we want has become an important method for many researchers to obtain expectations.

The topic summary and sentiment analysis of Weibo blog posts and comments have important practical significance in network management, public opinion monitoring, and public sentiment guidance (Zukang et al., 2019). This article pre-processes more than 200,000 Weibo data. Text pre-processing is to perform word segmentation, text cleaning, standardisation (used for the English corpus, via the conventional methods of stemming or morphological normalisation), feature extraction and other operations on the text before inputting the text into the model. We first convert the relevant text into a word and vector, then use a machine learning algorithm, and finally perform multi-sentiment analysis on the text.

The acquisition of text data is the first operation of start machine learning or statistical modelling. Information such as the space of the data sample and the uniformity of the distribution of the data sample will affect the final accuracy of the algorithm. As shown in Table 1, we use the crawler technique to obtain Weibo text and data corpus. We mark the text with emotional polarity labels, where the number 0 represents positive emotions, and the number 1 represents negative emotions.

We choose 0 positive emotion such as 'Happy birthday to the motherland ~ Yeah, I'm one year older' and 1 negative emotion sentence ('I'm busy tonight~ ~ ~~ ~ I'm so annoying').

Table 1 Examples of the original corpus

label	*Weibo text*
0	Happy birthday to the motherland~ Yeah, I'm one year older
1	I'm busy tonight~ ~ ~ ~ ~ I'm so annoying

Chinese word segmentation mainly uses two principles of word segmentation. The first is dictionary word segmentation, which is an algorithm for word segmentation through string matching. The second is the use of statistics-based algorithms in the class of machine learning algorithms. The commonly used algorithms are CRF, SVM, deep learning algorithms and some other algorithms. For example, Stanford's word segmentation tool is also based on the CRF algorithm. Stuttering word segmentation is the most commonly used method for Chinese word segmentation currently. We use the algorithm of the stuttering word segmentation algorithm to segment the corpus. We divide the two sentences in Table 1 and separate the words in each sentence. The results of the word segmentation process are shown in Table 2.

Table 2 Examples of the corpus after a stuttering

label	*Weibo text*
0	Happy birthday to the motherland ~ yeah one year older
1	I'm busy tonight~ ~ ~ ~ ~ I'm so annoying

Text cleaning involves removing redundant information in the text, such as stop words and punctuation, etc. In Table 2, we deleted some words, such as 'the', 'to' and 'so'. Finally, we extracted a few key words. An example of this experiment after text cleaning is shown in Table 3.

Table 3 Example of the corpus after data cleaning

label	*Weibo text*
0	Motherland happy birthday one year old
1	Tonight annoying

Text feature extraction converts text into a language that can be read by a computer to construct, constructs, describes, and replaces text by establishing a mathematical model. There are many text feature extraction methods. The current mainstream text feature extraction methods are represented by one-hot encoding, TF-IDF and Word2vec. This article uses the Word2vec method to display the word 'happy' in the word vector after word2vec. Some results are shown in Table 4.

Table 4 Word vector display

0.47605005	*–1.2055278*	*–0.4230525*	*2.2460167*	*0.8101846*
0.0239265	–0.0239265	–0.036313493	–0.27077818	0.8660904
–0.6653266	1.2208289	1.5264819	–2.1799848	0.175549245
0.334663	–0.4184326	0.0040567326	–2.3842044	1.1461884
–0.083962694	–0.41631052	–0.083962694	–0.41631052	–1.1174165
–0.7923423	–0.1611876	–0.7923423	–0.1611876	1.8177235
–1.4161704	2.199837	–1.4161704	2.199837	0.47831795
0.7863432	1.928426	0.7863432	1.928426	0.53212035

4 Core algorithm application

4.1 Convolutional Neural Networks

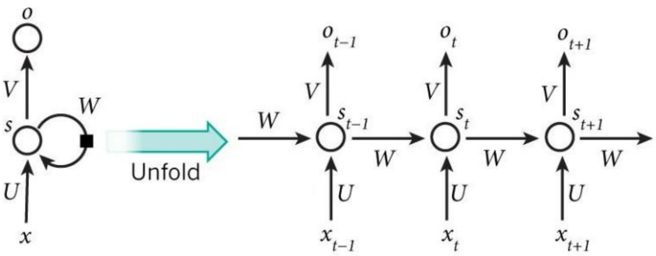
One of the representative algorithms of deep learning is the convolutional neural network (CNN), which can perform convolutional calculations and is a feedforward neural network with deep structure (Li et al., 2018). In the convolutional neural network, the convolutional layer and the subsampling layer constitute the feature extractor. Each convolutional layer in a convolutional neural network is composed of several convolutional units. In the convolutional layer, a neuron is only connected to a subset of the neighbouring neurons. These neurons form feature planes in the form of a matrix, and the feature planes are superimposed to become the most important part of the convolutional layer. The sharing of the convolution kernel by the neurons in the same feature plane is done by using sharing weights. Sharing weights can reduce the connections between the various layers of the network and the risk of overfitting. The convolution kernel is the most important part of the convolutional neural network. It uses a random decimal matrix as its initial value. During the continuous update process of the network, the convolution kernel obtains increasingly reasonable weights. Subsampling is regarded as a special form of the convolution process. It includes two forms of mean subsampling and maximum subsampling.

Convolution and subsampling greatly simplify the model complexity and reduce the number of model parameters. A fine-grained sentiment analysis method based on CNN was proposed by Hui and Yang (2019), which can be used to improve the precision of sentiment classification dramatically. This also shows that CNNs achieve excellent performance in the field of sentiment analysis.

4.2 Recurrent neural networks

The modelling of changes in time series is a problem that ordinary neural networks cannot solve. The chronological order of the samples is significant for applications such as natural language processing, speech recognition and handwriting recognition. To meet this demand, Recurrent Neural Networks (RNNs) appear in everyone's field of vision. In RNN, the output of a neuron can directly act on itself as the input of the neuron, that is, the input of the i-th neuron at time m, includes the output of the (i–1) layer neuron at that time and its own output at time (m–1). RNN can be regarded as a neural network acting on time series; its depth is the same as the length of time (Jain et al., 2015). The structure of the RNN is shown in Figure 1.

Figure 1 RNN structure



4.3 Local receptive field and weight sharing of CNNs

The receptive field is a mapping between an input layer and an element of the output of a certain layer in CNN and is one of the most important concepts in CNNs. In nature, it is believed that people's cognition of the outside world is based on local knowledge first and then on the overall picture. For an image, the distance in pixel space is inversely proportional to the correlation of the pixels. Neurons behave in the same way when performing image operations. We can obtain sufficient relevant information only by perceiving the local area, without wasting resources to perform global perception. We can also get global information by integrating local in information. Many ideas in the computer world originate in biology, as do convolutional neural networks. For example, neurons in the visual cortex receive information locally.

After the local receptive field operation is performed in the CNN, there are still too many parameters, for which we can use weight sharing. For example, when processing pictures, the parameters used in the same picture are the same, so we can use a convolution kernel. The process of sharing the same convolution kernel is called weight sharing, which can effectively reduce the excessive number of parameters used during the convolution process in the convolutional neural network. In most cases, weight sharing is not only for reducing parameters, but it is also for down-sampling.

4.4 LSTM

Long Short-Term Memory is generally called LSTM. It is a special type of RNN and can learn information in the long-term time series. LSTM was proposed by Hochreiter and Schmidhuber (1997). Despite many problems, LSTM has achieved considerable success and has been widely used. LSTM is designed to avoid long-term dependence problems. Obtaining long-term information is the default behaviour of LSTM in practice, and it is the ability to obtain without paying a great price. Both RNN and LSTM have a repetitive neural network structure. This module RNN is much simpler than LSTM. RNN is only a straightforward structure, while LSTM is more complicated. It has four different repetitive structures for a unique interaction. LSTM uses the three gates of the input gate, output gate and oblivion gate to operate. What is indispensable during the operation is the state of the cell. It is transmitted on the transmission chain.

5 Machine learning algorithm implementation and result analysis

The work of this paper is to perform sentiment analysis on Weibo texts. The data set used in the experiment comes from 200,000 texts that have been polarised on Weibo (Zhou, 2013). The first step of the experiment is to pre-process the Weibo data. The pre-processing step includes stuttering, word removal, and word vectorisation. The second part of the experiment is to input vectorised text into the LSTM + CNN network for training. The third part of the experiment uses the validation set to test the trained model until the accuracy of the validation set reaches expectations. Finally, by analysing the text in the data set, the analysis results of different polar emotions are obtained. The experimental flow chart is shown in Figure 2.

5.1 LSTM-CNN and LDA implementation

CNNs are a network originally created for image tasks and they can learn to capture specific features regardless of local features. In our case, a CNN can capture a negative phrase, such as ‘dislike’ regardless of where it occurs on Weibo. LSTM is a kind of network with a memory that remembers previous data from the input and makes decisions based on this knowledge. These networks are more directly applicable to the input of written data. On the one hand, every word in the sentence may be affected by the meaning of the surrounding words. In actual situations, LSTM may capture changing emotions in Weibo (An and Moon, 2019). For example: ‘At first I loved it, but then I ended up hating it.’ Contradictory views will eventually lead to confusion in the simple feedforward network confusion. On the other hand, the meaning expressed at the end of the sentence is more important in LSTM than the meaning expressed at the beginning.

The first model to try is the CNN-LSTM model (Jin et al., 2016). Its combination includes the initial convolutional layer. This receives word embedding (a corresponding vector for each different word in the document) as input and outputs it converged to a smaller size and then inputs it to the LSTM layer. This model is that the convolutional layer will extract local features, and the LSTM layer will be able to use the ranking of the features to understand the input text ranking. The second model tried is that the LSTM-CNN model with an initial LSTM layer, which will receive the word embedding of each token in the tweet as input. The token it outputs not only stores the information of the initial token, but also stores any previous tokens. In other words, the LSTM layer generates a new code for the original input. Then we input the output of the LSTM layer into the convolutional layer that we expect to be able to extract local features. The initial convolutional layer of CNN-LSTM seems to have lost some information about the text sequence information. If the order of the convolutional layer does not really give us any information, the LSTM layer acts only as a fully connected layer, so it cannot achieve its maximum potential. In fact, this scenario makes the model worse than the traditional LSTM model. In the LSTM-CNN model, because the initial LSTM looks like an editor, there is an output tag for each tag in the input, which not only contains the information of the original tag, but also contains the output tag and all other previous commands brand. Then, the CNN layer will use the richer representation of the original input to find local patterns, resulting in better accuracy. So, we use a combination of LSTM and CNN algorithms next.

The LSTM and CNN algorithms are used in combination. The LSTM-CNN model consists of an initial LSTM layer that receives word embeddings as input, then inputs the data containing Long Short-Term Memory into CNN, performs convolution through CNN, and finally outputs positive and negative labels. In the implementation process, we need to initialise the parameters required by the LSTM layer first, and pass the parameters such as sentence length and number of classifications to the class; then we need to define placeholders for the data input into the model. When defining placeholders, we also need to define dropout parameters to control the degree of activation of neurons. Next, we define the embedding layer. Its role is to map vocabulary indexes to low-latitude word vectors. The next step is to create the LSTM layer, which is used to maintain the long-term memory of the data. The output of LSTM is used as the input of CNN, and the final positive and negative labels are output through CNN pooling operation in CNN.

Figure 2 Experimental flow chart

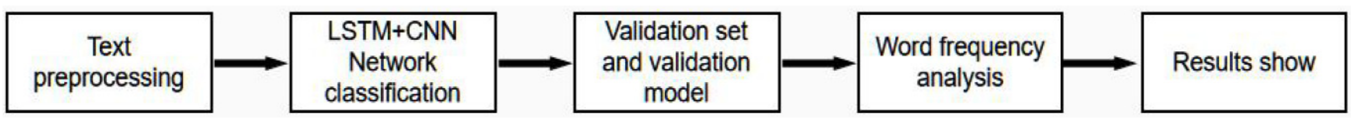


Table 5 Partial results of the accuracy rate and loss rate for the training and testing sets

global_step	*training_loss*	*training_accuracy*	*test_loss*	*test_accuracy*
100	0.14572863	0.953125	0.03690303	1.0
200	0.14308174	0.96875	0.11706975	0.96
300	0.20059854	0.953125	0.06791143	0.98
400	0.054822188	1.0	0.06865457	0.98
500	0.035053864	1.0	0.016831875	1.0
600	0.0140069295	1.0	0.064862765	0.94
700	0.0512669	1.0	0.1455506	0.96
800	0.18090038	0.921875	0.21682964	0.94
900	0.18016341	0.953125	0.015783846	1.0
1000	0.06623147	0.96875	0.081953578	0.98

The most widely used unsupervised technology for classifying text is the LDA algorithm. Its main role is to identify latent semantic topics, such as large-scale document sets or corpora. In LDA, each document is used as a vector word frequency vector. This method is called a bag of words model. The bag-of-words model allows the computer to read sentences and easily form mathematical models. Similarly, the bag-of-words model also has a drawback where it does not care about the order between words. This approach simplifies the complexity of the problem and provides researchers with the opportunity to improve the bag-of-words model. In this paper, all words of the same polarity in the data set are stored in an array. The corpora Dictionary () method is used to build a dictionary. Based on the constructed dictionary, the doc2bow () method is used to convert the words into sparse vectors to form a sparse vector matrix. The matrix is input into the LDA model. The LDA model is implemented using Gensim. Ten topics are output in the LDA model, and the output topics are stored in a text file for subsequent analysis.

5.2 Displaying the model results

This experiment analyses the polarity of sentiment in Weibo text. For the analysis of the polarity of emotions, this paper proposes a model with an algorithm of LSTM and CNN combined. That is, the data first generates a new code through LSTM, then uses the output of LSTM as the input of CNN, extracts the features through CNN and finally outputs the emotion polarity label (Lou and Yao, 2006). In the experiment, we used 58,259 positive emotion data and 58,884 negative emotion data as the training set to train LSTM_CNN, using 1000 data points for each, negative emotion and positive emotion as a test set. The classification of the model is determined by calculating the accuracy and loss rate of the training set and test set. The accuracy and loss rate of the test set and training set are shown in Table 5, where the accuracy rate is defined as followed. For a given test data set, the ratio of the number of samples correctly classified by the classifier to the total number of samples; and the loss rate is defined as, for a given test data set, the ratio of the number of samples classified incorrectly or uselessly by the classifier to the total number of samples.

It can be seen from Table 5 that the accuracy achieved by this experiment is in line with the expected value. Finally, we use the verification set to verify the experimental model. The accuracy of the verification set is shown in Table 6.

Table 6 Verification set accuracy and loss rates

Accuracy: 0.97607654										
Predicting the top 10	0	1	0	1	0	1	1	0	0	0
Determining the top 10	0	1	0	1	0	1	1	0	0	0

5.3 Analysis of the model results

Positive emotion classification results: The text data labelled as positive emotions are classified by the LDA model, and the resulting word cloud with the keyword distribution of the theme of ‘applaud’ can be seen in the word cloud. There are ‘dream’, ‘awesome’, ‘actor’, ‘movie’, ‘mighty’ and other keywords. The word clouds in Figure 3(a) below mainly focus on different forms of programs and entertainment activities. Large-scale activities and performances are some of the sources of human positive emotions.

Figure 3 Word cloud: cases 1 and 2

The text data that share the label of ‘optimistic’ are classified by the LDA model, and the resulting word cloud with the theme of ‘hee hee’ is shown. In Figure 3(b), there are ‘tourism’, ‘hotel’, ‘free’, ‘prize’, ‘winning’ and other keywords. The word cloud mainly focuses on tourism-related words and award-related words. Tourism and different award activities are also one of the sources of positive human emotions.

Figure 4 Word cloud: cases 3 and 4

a b

The text data labelled as negative emotions are classified by the LDA model, and a word cloud with keyword distribution with the theme of 'scold' is obtained. In Figure 5(a), it can be seen that 'candle', 'despise', 'weak', 'sad' and other negative words appear. We can see that the uncivilised phenomenon in life, negative news reports, etc. may also be the sources of negative human emotions.

The text data labelled as negative emotions are classified by the LDA model, and the resulting word cloud with the keyword distribution of 'sadness' as the theme can be seen in Figure 5(b), where some words such as 'disappointment', 'pitiful', 'poor' and other negatives appear. From some family-related words in Figure 5(b), it can be inferred that negative emotions often appear in daily family life.

The text data that share the label of 'optimistic' are classified by the LDA model, and the resulting word cloud with the keyword distribution of 'hee hee' as the theme can be seen in Figure 4(a), where 'happy', 'cake', 'coffee', 'cake', 'gift' and other keywords in the word cloud mainly expand on the words related to food and gifts. It can be seen that *food* and *gifts* can also make humans happy.

Negative emotion classification results: The text data labelled as negative emotions are classified by the LDA model, and a word cloud with keyword distribution with the theme of 'envy' is obtained. In Figure 4(b), 'danger' and 'pollution' can be seen. Negative words such as 'pain' and 'liar' appear. The destruction of living environments in life, physical discomfort, etc., may be the sources of negative emotions in humans.

Figure 5 Word cloud: cases 5 and 6

a b

We intercept the top three topics with the highest polarities for analysis and display. Through the data displayed in the first two sections, different forms of entertainment, entertainment, tourism, various awards, food and gifts are the main sources of people's positive emotions. One can increase entertainment activities, develop tourism projects, and share food culture and other ways to guide people's positive emotions. For negative emotions, the destruction of living environment in life, the discomfort of people's lives, uncivilised phenomena, negative news reports and daily family life trivialities are the main sources of negative emotions, so maintaining a good living environment and building a civilised city, improving the medical system and increasing the people's sense of happiness and belonging are all effective means of eliminating people's negative emotions.

6 Conclusion

Human sentiment analysis is a continuous optimisation process. With the development of society, there will be various language expressions. Therefore, the method of sentiment analysis may require continuous iteration and optimisation to maintain a good recognition effect. At present, this paper uses the research method of combining the LSTM model and the CNN model to analyse the polarity of Weibo texts. The model inputs the analysis results into the LDA model according to their different polarities for classification. Through the analysis of the LDA results, the influences on people's polar emotions are observed. In the LDA clustering results, this article selects the first three factors that affect people's emotional polarity changes for analysis. This paper only analyses polar emotions, but will continue to divide emotions such as sadness, happiness, tension, etc., in other directions in the future to conduct more detailed emotional analysis research. In text sentiment analysis, expressions of human emotions are sometimes very obscure, so in the future, we will consider using different sentiment analysis methods for experiments, such as the method of using context information and multiple methods of cross-checking for experiments.

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