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Text sentiment analysis and classification based on bidirectional long and short term memory networks

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Abstract. In this study, we explored the method of text sentiment analysis and classification using bi-directional long and short-term memory networks, which brings new ideas to the field of sentiment classification. In the text pre-processing stage, we processed chat phrases, non-alphanumeric characters, deactivated words, numbers, special characters, blanks, and addresses to convert the raw text data into numerical data that can be processed by the model. Subsequently, word frequency statistics were conducted for texts of different mood types to analyse the frequency of occurrence of different words in texts of different mood types. By introducing a bi-directional long and short-term memory network model for training, we observed the accuracy and loss value performance on the training and validation sets. The accuracy of the training set increases from the initial 94.6% to 99.5%, and the accuracy of the validation set gradually grows to 99.4%; at the same time, the loss value of the training set decreases from the initial value of 0.2075 to 0.0194, and the loss value of the validation set gradually increases from the initial value of 0.0538 to 0.0372. This indicates that the bi-directional long short-term memory network achieves a significant and stable performance improvement. The confusion matrix results for the test set show that our model achieves more than 99% prediction accuracy on the test set. This implies that our proposed method can efficiently classify textual sentiment with high prediction accuracy. This research result helps to improve the effectiveness of the application of sentiment analysis techniques in the fields of social media opinion monitoring and product review analysis, and provides a useful reference for further deepening the research on text sentiment analysis. In conclusion, this study achieves the optimisation of the text sentiment classification task by means of a bidirectional long and short-term memory network model, and achieves satisfactory results. In the future, the model performance and generalisation ability can be further improved by combining more corpus and optimising the model structure, so as to be better applied in real-world scenarios.

Keywords: Text Sentiment Analysis, Bidirectional Long and Short Term Memory Networks, Accuracy.

1. Introduction

Text sentiment analysis and classification is an important research direction in the field of natural language processing, aiming at analysing text content and identifying the sentiment tendency or emotional state embedded in it through computer technology [1]. With the generation and dissemination of a large amount of text data such as social media and online comments, sentiment analysis and

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classification are of great significance in the areas of public opinion monitoring, product recommendation, and public opinion orientation.

Models such as Recurrent Neural Networks (RNN) [2] and Long Short-Term Memory Networks (LSTM) [3] in deep learning algorithms can effectively capture contextual information in text sequences, helping the models to better understand the correlations between words in a sentence or paragraph. This ability allows deep learning models to perform better when processing longer texts and to achieve more accurate results in sentiment analysis tasks.

Convolutional neural network (CNN) has been introduced to the text processing field after its great success in the image processing field and has shown good performance in sentiment analysis and classification tasks [4].CNN can extract feature representations at different levels and scales through multi-layer convolutional operations, so as to efficiently capture semantic information in the text, and combined with pooling operations to reduce the feature dimensions, which further improves the model's efficiency and generalisation ability [5].

Deep learning algorithms play a crucial role in the field of text sentiment analysis and classification. This paper analyses and classifies text sentiment based on bi-directional long and short-term memory networks, which provides a new method for sentiment classification in this paper. With the continuous progress and development of technology, it is believed that deep learning algorithms will continue to promote the continuous improvement of the technical level of sentiment analysis and classification in the future, and bring new opportunities and challenges for us to better understand and make use of massive text data.

2. Data set sources and data analysis

The data contains multiple texts and their corresponding labels, and the labels include 13 emotions such as hate, neutrality, anger, love, worry, relief, happiness, fun, emptiness, passion, sadness, surprise, and boredom, etc., and the dataset contains a total of 839,555 pieces of textual information as shown in Table 1, as well as their corresponding emotional labels.

Table 1. Selected data sets.

Text	Emotion
I feel delighted because it seems that i can n...	neutral
I strongly feel that every abortion is the tak...	neutral
I was feeling so inadequate	neutral
I feel as if people really dont believe that i...	sadness
I’m feeling adventurous i will also chuck in nu...	neutral
I feel like i havent had a ramble in a while a...	neutral

3. Text Preprocessing

3.1. Choice of words

The steps for removing chat terms include identifying common chat terms, acronyms, and internet terms, creating corresponding replacement rules or dictionaries, and replacing these terms with their formal written forms. Doing so helps to unify the format of text data, improve the training of machine learning models, and avoid misinterpretation or erroneous results due to chat terms [6].

3.2. Non-alphanumeric characters

The step of removing non-alphanumeric characters involves identifying and removing non-alphanumeric characters such as punctuation marks, special symbols, spaces, line breaks, etc. from the text, which is achieved through regular expressions. This helps to reduce data noise and improve the efficiency and accuracy of model training, while making the text more regularised and easier to understand.

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3.3. Stop words

The steps of removing stop words include firstly constructing a stop word list containing common words that need to be filtered out; then removing or replacing the words that appear in the stop word list with specific symbols in the text data; and finally obtaining clean text data after stop word processing. This step can improve the model's ability to capture and understand key information, while reducing computational complexity and storage space consumption.

3.4. Numbers

The step of removing numbers involves identifying numeric characters in the text and matching them by regular expressions; then removing or replacing these numeric characters from the text with symbols such as spaces. This helps to reduce data noise and avoid the impact of numbers on natural language processing tasks such as sentiment analysis and topic modelling, as well as simplifying the structure of the text data and improving the efficiency and accuracy of subsequent processing.

3.5. Special characters, whitespace and URLs

The steps for removing special characters, whitespace and URLs include firstly identifying and filtering special characters in the text, such as punctuation marks, emoji, etc., which is implemented using regular expressions; secondly removing whitespace characters in the text, including spaces, tabs, line breaks, etc.; and finally identifying and removing URL links in the text to avoid the URLs from interfering with the text analysis task. These steps help to improve data quality and accuracy, simplify the text structure, and make the subsequent natural language processing tasks more precise and effective.

4. Text Sentiment Analysis

After counting the sentiment labels of the text with text preprocessing, we obtained clean text data, frequency counts of the number of words in each type of sentiment, ranked the number of times a word appeared in frequency, and plotted a histogram, and the word frequency histogram for neutral is shown in Figure 1.

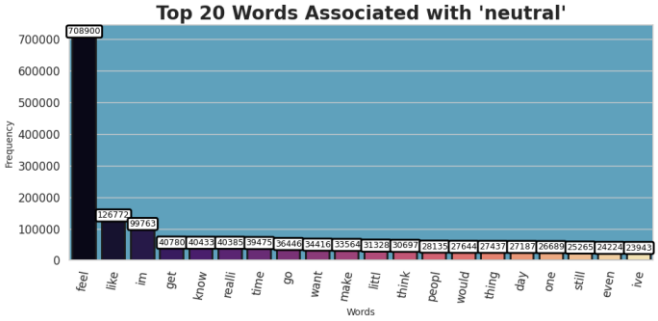


Figure 1. The word frequency histogram.
(Photo credit: Original)

As can be seen in Figure 1, the text of neutral has the highest frequency of feel, which appeared 708,900 times, followed by like, which appeared 126,772 times, and other words appeared relatively less frequently.

In addition, the frequency of the text of hate is then summarised to obtain the bar chart results shown in Figure 2.

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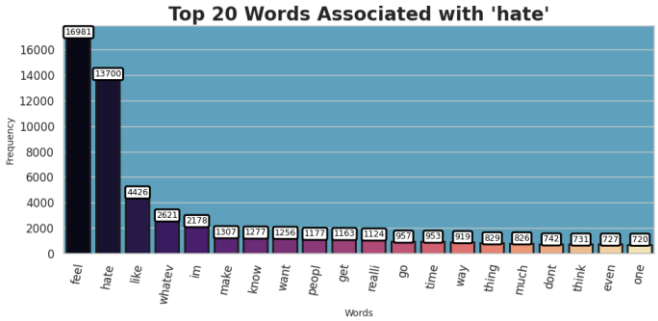


Figure 2. The word frequency histogram.
(Photo credit: Original)

As can be seen in Figure 2, the word feel still has the highest frequency of occurrence, with a total of 16,981 occurrences; followed by the word hate with 15,700 occurrences, and the high frequency of hate also directly indicates the emotional label to which this text belongs.

Bidirectional Long Short-Term Memory (BiLSTM) is a deep learning model that combines the properties of Long Short-Term Memory Networks (LSTMs) and Bidirectional Recurrent Neural Networks (BRNNs), aiming to better capture long-term dependencies in sequence data.BiLSTM is used in the natural language processing, speech recognition, time series analysis, and other fields with remarkable results.

5. Method

BiLSTM contains hidden layers in two directions for learning feature representations from the beginning and the end of the sequence, respectively. The hidden layer in each direction consists of multiple LSTM units that have mechanisms such as forgetting gates, input gates, and output gates to effectively control the flow of information [7]. During forward propagation, the input data is gradually passed from the beginning to the end of the sequence while the hidden state is updated at each time step, while in reverse propagation, on the contrary, the hidden state is updated starting from the end of the sequence [8].

This approach can make full use of the information before and after the current moment in the sequence data to help the model better understand the contextual relationship [9]. In addition, during the training process, BiLSTM continuously adjusts the parameter weights through the error back propagation algorithm to maximise the prediction accuracy. BiLSTM effectively captures long-term dependencies in sequential data by combining forward and backward information flow, and is a powerful and flexible deep learning model with prospects for a wide range of applications in a variety of fields [10].

6. Result

In the division of the data set, the training set is 80% of the data, where 20% of the data in the training set is divided to be used as the validation set, the test set is 20%, the random state is set to 42, the learning rate is set to 0.0001, the python 3.10 is used in this experiment, the CPU of the machine is 32G, the epoch is set to 10.

The variations of accuracy, loss, val accuracy and val loss during the output training process are shown in Table 2, and the line graphs of each of the four parameters are plotted as shown in Fig. 3.

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Table 2. Modelling evaluation.

Epoch	Accuracy	Loss	Val accuracy	Val loss
1	0.9465	0.2075	0.9836	0.0538
2	0.9817	0.0591	0.9845	0.0461
3	0.985	0.0463	0.9879	0.0369
4	0.9882	0.0376	0.9892	0.0396
5	0.9905	0.0315	0.9887	0.0316
6	0.992	0.0275	0.9918	0.0302
7	0.9932	0.0245	0.9928	0.03
8	0.9941	0.0209	0.9926	0.0362
9	0.9947	0.0195	0.9935	0.0345
10	0.995	0.0194	0.9941	0.0372

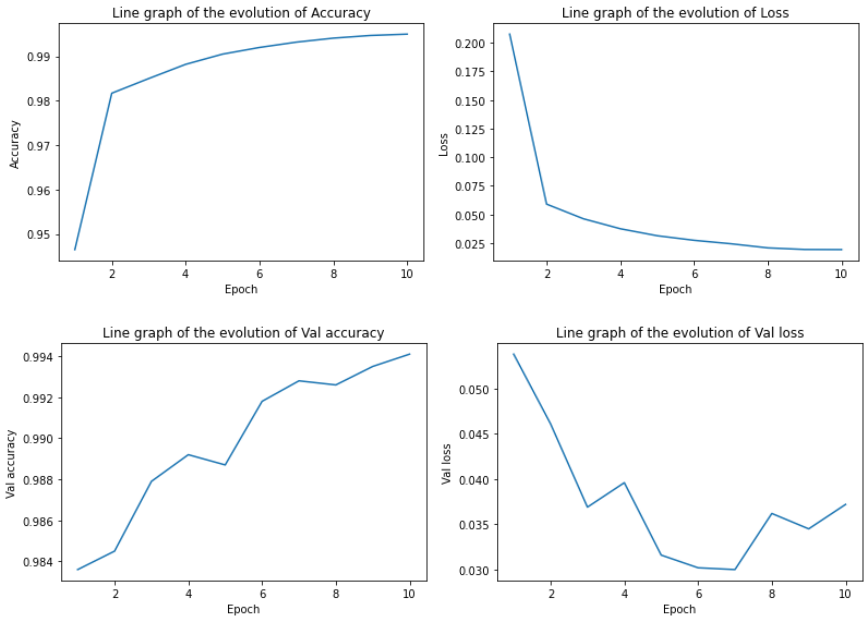


Figure 3. The line graphs of each of the four parameters.
(Photo credit : Original)

From the accuracy and loss of the training and validation sets, it can be seen that the accuracy of the training set increases from the initial 94.6% to 99.5%, and the accuracy of the validation set gradually grows from the initial 98.3% to 99.4%; the loss of the training set decreases from the initial 0.2075 to 0.0194, and the loss of the validation set gradually grows from the initial 0.0538 to 0.0372.The bidirectional long- and short-term memory network used in this paper can classify textual emotions well and achieve high prediction accuracy.

The model is tested using the test set and the confusion matrix predicted by the test set is output and the results are shown in Fig. 4, which shows that the prediction accuracy of the model's test set is more than 99% as shown by the results of the confusion matrix.

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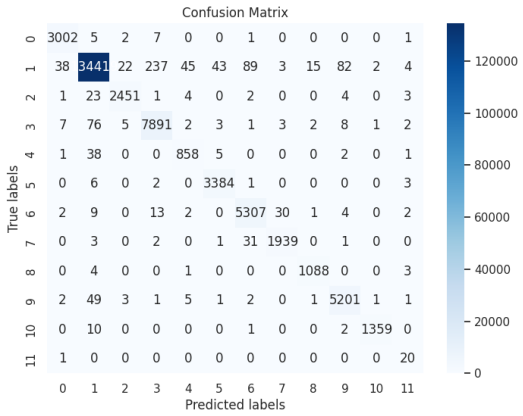


Figure 4. Confusion matrix.
(Photo credit : Original)

7. Conclusion

In this study, we explored a novel method for text sentiment classification by deeply analysing and processing the text using Bidirectional Long Short-Term Memory Network (BiLSTM) as a sentiment classification model. Firstly, in the text pre-processing stage, we effectively processed chat phrases, non-alphanumeric characters, stop words, numbers, special characters, blanks and addresses, and transformed the raw textual data into numerical data that can be used for machine learning model training. Secondly, we performed word frequency statistics on texts of different sentiment types to understand the frequency of occurrence of individual words in different sentiment categories.

Subsequently, we introduced the BiLSTM model for training and optimised it by means of supervised learning. After repeated validation of the training and validation sets, we observed that the accuracy of the training set increased from the initial 94.6% to 99.5%, and the accuracy of the validation set gradually grew from 98.3% to 99.4%. Meanwhile, the loss value of the training set decreases from the initial 0.2075 to 0.0194, while the loss value of the validation set gradually increases from 0.0538 to 0.0372.These results indicate that the adopted BiLSTM model performs well on the sentiment classification task and achieves high prediction accuracy.

In conclusion, this study successfully achieves efficient and accurate classification of textual sentiment by deeply mining textual data and combining it with the BiLSTM model for training. In the future, we can further explore how to optimise the model structure, expand the data size and apply it to a wider range of domains to improve the effectiveness and application scope of the emotion classification task. This research result brings new ideas to the field of natural language processing and provides useful reference and inspiration for research in related fields.

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