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LSTM-Based Emotion analysis of Power System Fault Maintenance Effect

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Abstract: The power industry facing the general users demandsemotion analysis on users'various natural language comments and subjective experiences in order to improve service quality and user satisfaction. In this paper, emotion analysis was made on the maintenance result records from power system fault maintenance data using deep learning-based natural language processing method. Processing was made using long-term and short-term memory neural network LSTM to overcome the shortcomings of current shallow learning in failure to extract features and autonomous abstraction whichtherefore leads to limitedcapacity to handle complex things and poor generalization capacity. Then, comparison was made with RNN, CNN (convolution neural network) and RBF neural network to prove that the LSTM-based emotion analysis model has higher accuracy and better effect.

Keywords:LSTM; power failure; maintenance;emotion analysis; natural language processing

1. INTRODUCTION

Human beingsbasically havesubjectivity indescriptions of things, which results in emotional coloring. Text emotion analysis constitutes an important part of Natural Language Processing (NLP), which is the process of analyzing, summarizing and processing texts with subjective emotions [1]. In the field of text emotion analysis, texts can be divided into three categories: positive, negative and neutral types. There are two main methods for natural language processing NLP to make text emotion analysis. One is to make judgment based on calculation ofpriori information incompleteemotional lexicon or dictionary. In fact, text is composed of words. Such method mainly judges emotional words in the emotional lexicon present inthe text and weighs the emotional polarity of the text.Quantification is made based onthe number of positive and negative emotional vocabulary words, so thatemotional score of the overall text can be comprehensively calculated [2]. The other adopts machine learning approach. Characterized by multiple feature modeling capabilities, it translates emotion analysis into dual- or multi-class problems in machine learning. Of course, to allow computer processing, it's necessary to first vectorize the text or vocabulary, and then classify the text using neural network, support vector machine, Adaboost or even deep learning [3, 4, 5, 6].

The power industry is not only a production industry, but also a service industry which also needs to pursue quality service and good user experience. Therefore, it is of important significance to acquire user's attitude towards the power industry service and subjective evaluation of service results, and make emotion analysis or public opinion analysis so that industry service can be improved andbusiness level can be elevated. Deep learning representsa development of Artificial Neural

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Network (AN), but traditional neural network is merely a shallow model for extracting data or text, while deep learning can simulate the human brain and automatically extract features of complex data or text. As a deep model, it can learn knowledge independently, so autonomous and efficient problem solution is possible. Deep learning has now been successfully applied to the field of natural language processing, with good results achieved [7, 8, 9]. Deep learning can automatically access high-dimensional abstract features by using unlabeled or partially labeled training samples or corpora, and then classify the text accurately based on these abstract features, which thus gives rise to deep learning-based emotion analysis method.

2. LSTM-based emotion analysis

2.1 LSTM model

By introducing feedback, Hopfield neural network realizes the connection between network nodes in the same layer. Recurrent neural network (RNN) represents a great progress of Hopfield neural network, but it still has the problem of short memory term. In view of this issue, Hochreiter et al. proposed LSTM neural network model, which can maintain vocabulary memory for a long time by adding input gate, output gate and forget gate.

LSTM updates the state of neuronal cells by adding and deleting information through "gate". "Gate" can selectively pass informationbased on Sigmoid layer and bitwise multiplication operation [21]. LSTM model first decides to discard certain information from interneuron cells through the Forget Gate; then determineswhich new information to be stored depending on the current candidate vector of the cells throughthe Input Gate. Then,the cell state is updated accordingly and output viatanh layer subject to the decision and adjustment of the output gate (Figure 1).

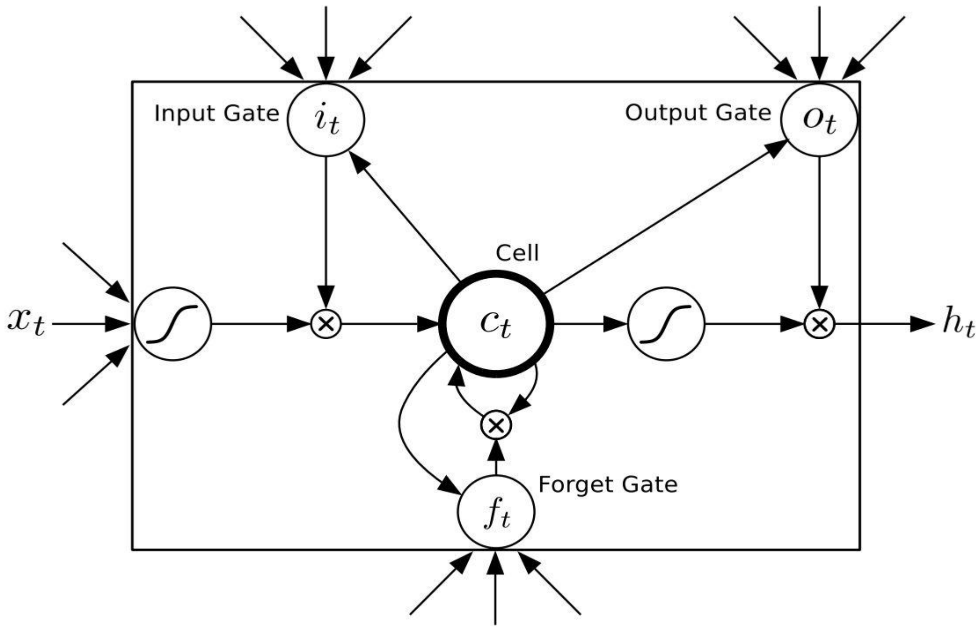

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Figure1LSTM (Long-term and Short-term Memory Neural Network) Model Structure

LSTM is a variant and improvement of the recurrent neural network RNN, both of which have a feedback loop enabling memory of sequence information. Both are suitable for processing natural language texts, but RNN has no long-term memory capability, and there is a potential of gradient explosion and disappearance. Therefore, LSTM neural network has an advantage in long-sequence memory since all its hidden layerssupport memory functions. At the same time, LSTM has forgetgate, which allows it to selectively forget some irrelevant information and process natural language sequences with unfixed length, soflexibility is high. The input gate, forget gate and output gate of each neuron cell in the LSTM neural network performnonlinear transformation usingSigmoid activation function.When the LSTM neural network is input, there is need tocalculate the activation value $i_t$of the input gate.At this time (t moment),the input transformation $\tilde{C}$of the cell state requires consideration.

$$i_t = \sigma W_i x_t + U_i h_{t-1} + b_i \quad (1)$$

$$\widetilde{C_t} = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (2)$$

Here,$x_t$is the input vector,$h_t$is the hidden layer vector,W_is the forget gate loop weight, U_i is the input weight, $b_i$is the offsetand Sigmoid activation function is:$\delta(x) = \frac{1}{1+e^{-x}}$.

Then, the activation value of the Forget Gate is determined as follows:

$$f_t = \sigma W_f x_t + U_f h_{t-1} + b_f \quad (3)$$

Here,W_f is the forget gate loop weight,b_f is the offset, and $U_f$is the input weight.

At this time, with activation value i_t and $f_t$of input gate, forget gate, as well as the input transformation candidate vector$\widetilde{C_t}$, state can be updated and the state update vector can be calculated according to the following formula:

$$C_t = i_t * \widetilde{C_t} + f_t * C_{t-1} \quad (4)$$

Following state update of the neuronal cell, based on the following formula,

$$O_t = \sigma W_O x_t + U_O h_{t-1} + b_O \quad (5)$$

$$h_t = O_t * \tanh(C_t) \quad (6)$$

It is possible to solve the output gate activation value O_t, and the output $h_t$after nonlinear transformation of the tanh layer. Here, the offset is b_O , the output weight isU_O , the forget gate loop weight isW_O. $h_t$as the output actually integrates the output of all neuron cells of the LSTM.

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2.2 Algorithm Steps

LSTM-based emotion analysis has the following algorithm steps:

(1) The text corpus data is divided into two parts, one for training and the other for testing. First, the training corpus is labeled as negative, neutral, positive according to the emotional coloring;

(2) Then, the vocabulary is separated from sentences of the training corpus by jieba and vectorized by Word2vec;

(3) These word vectors are input into LSTM to form a sequence of words, thus generating a sentence vector. Then, these sentence vectors are learned according to the already labeled emotional coloringtypes, so that the features therein can be abstracted for classifier training;

(4) The trained classifier is then verified using the test data, and then the corpus demanding emotion analysis is analyzed using the classifier to obtain the result.

3 Experimental verification

Here, we used Keras as the model framework for deep learning, and the optimization function of the hyperparameter was set as Adagrad.The learning rate was set at 0.5 in the first 12 times, which was reduced by 0.02 at each iteration.After it has been reduced to 0.1, reduce by 0.002 each time. The number of iterations was set to 40 times; the loss function was set to msle. Here, the maintenance data of Yunnan Power Grid was divided into training objects and test objects using 6-fold method for cross-training test. Then, verification was performed using test set, and generalization capacitywas tested. The accuracy and loss rates of the training model adopting 6-fold method are shown in Figure 2 and Figure 3. It can be seen that the accuracy rate of LSTM model has reached 97.1%, and the loss rate has reached 0.09%, which is close to zero loss. Then, emotion analysis was made on the remaining 30,000 pieces of maintenance datausing the trained model to test generalization capacity. The accuracy rate also reached 92.3%, indicating better result.

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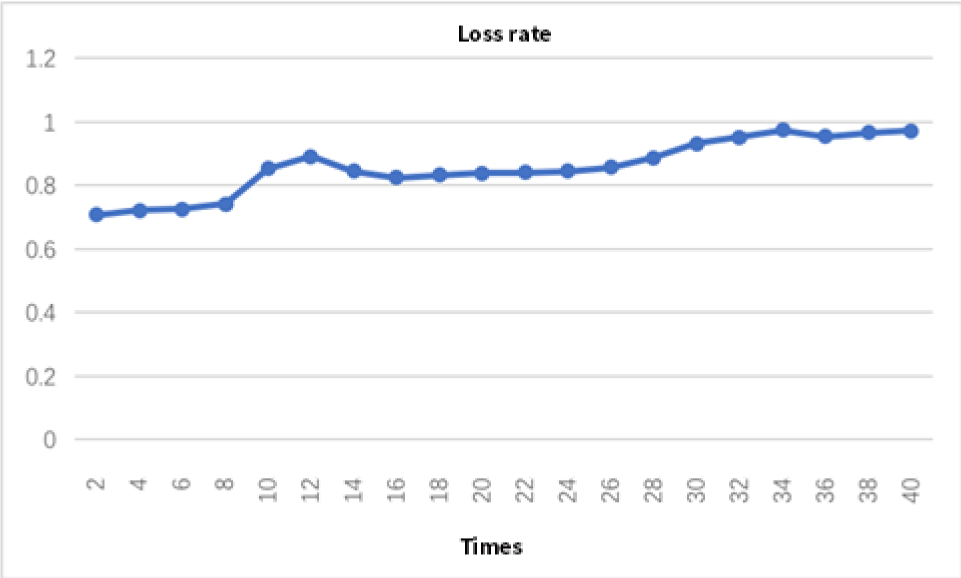

Figure1 The accuracy of LSTM model

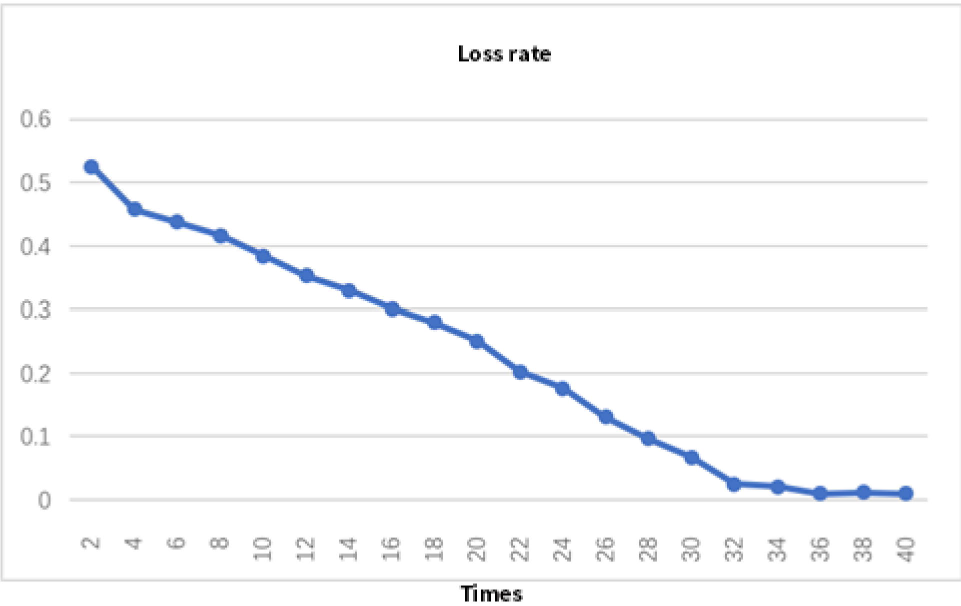

Figure2 The loss rates of LSTM model

Then, comparison was made among LSTM model, RBF neural network, convolutional neural network CNN, recurrent neural network RNN, etc. based on power maintenance data set. The experimental results are shown in Figure 3. It can be seen that the model adopted herein has the optimal accuracy.

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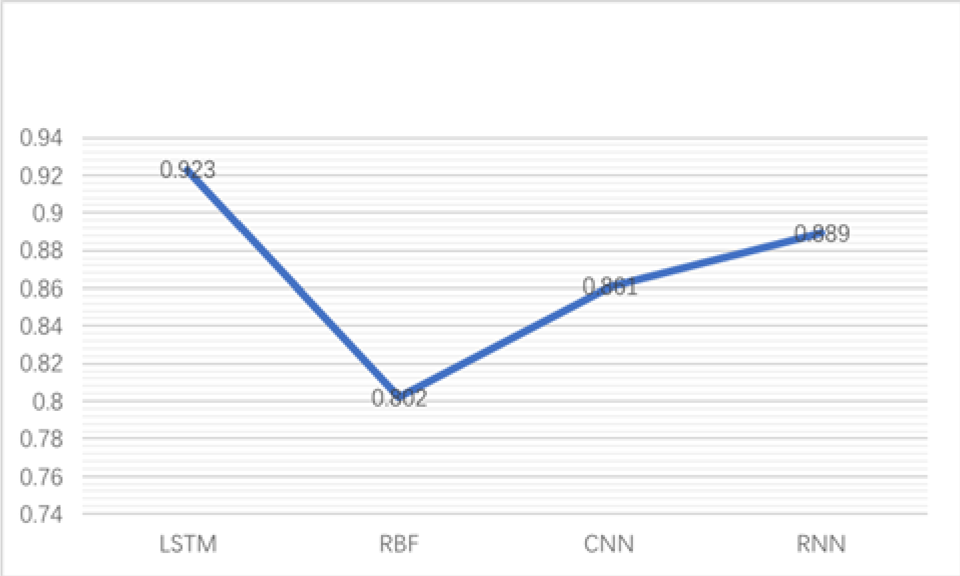

Figure3 The comparisons of different models

4. Conclusion

Deep learning is capable of self-learning, autonomous feature extraction and autonomous abstraction. It can well perform various analyses in natural language processing, including emotion analysis. This paper adopts deep learning Word2vec to vectorize the maintenance results described by natural language in the power fault maintenance data, and then extracts features independently using LSTM (long-term and short-term memory neural network) so that natural language text data can be classified. Its good autonomous abstraction and memory capability enables it to avoid over-fitting of machine learning, while achieving high accuracy and good effect.

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Author Introduction

Xin He, a master of Data Science, Southwest Forestry University, research directions: data analysis.