This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2021.3085663, IEEE Transactions on Industrial Informatics

A Sentiment Classification Method of Web Social Media Based on Multi-dimension and Multi-level Modeling

Bingkun Wang, Donghong Shan, Aiwan Fan, Lei Liu and Jingli Gao

Abstract— **Sentiment classification of web social media faces the problem of text context semantics missing. The existing research mainly solves the problem of text context semantic missing by mining language symbol information in web social media text, seldom considering the emoticon symbols and punctuation symbols in web social media text. Similar to language symbols, emoticons symbols and punctuation symbols in web social media text also contain certain sentiment information. In order to make full use of sentiment information contained in web social media to solve the problem of text context semantics missing, we propose a sentiment classification method of web social media based on multi-dimension and multi-level modeling. By modeling web social media text from three dimensions (language symbols, emoticons symbols and punctuation symbols) and three levels (words, sentences and documents) based on deep learning framework, this paper attempts to solve text context semantics missing faced by sentiment classification of web social media, and improve the accuracy of sentiment classification of web social media. Experimental results on Sina weibo and Twitter datasets show that the average accuracy of our method is 0.9479, which achieves more than 5.86% performance compared with the existing sentiment classification methods.**

Index Terms—**deep learning, multi-dimension, multi-level, social media, sentiment classification**

I. INTRODUCTION

With the development of the Internet of things and Web2.0, web social media has become the preferred communication platform for web users. Because of the interactive nature of web social media and the social nature of people, web users prefer to express their opinions and sentiments in web social media, which results in rich sentiment information in social media [1]. For example, users of Twitter, and Sina Weibo often post a large amount of short text messages containing emoticons to share their sentiment views on things. As a result, social media with rich sentiments has become an excellent resource for the state and enterprises to understand sentiments and opinions of web users [2]. In order to effectively mine the sentiment information in web social media, sentiment classification of web social media came into being.

Compared with traditional media, web social media has many unique features [3]. These characteristics bring enormous challenges to the existing sentiment classification methods of web social media.

Firstly, the web social media has the characteristics of rich pictures and text. When expressing their sentiments in social media, web users not only use a lot of language symbols (such as “I love this film”), but also publish emoticons symbols and repeated punctuation symbols (such as “!!!”) to enhance the effect of sentiment expression.

Secondly, web social media has the features of short text length and non-standard language. In web social media, users can use a variety of language forms to express their sentiment. For example, in "Sina Weibo", users can use web new words, homophonic words, abbreviations and other non-standard language forms to express their sentiment.

Web social media has the features of short text length, non-standard language and the characteristics of picture and text. These characteristics make the sentiment classification of web social media face the problem of text context semantics missing [4].

Because web social media has the characteristics of non-standard language and short text length, it is difficult to understand the real meaning of web social media text only through the literal meaning of the text [5]. In order to truly understand the semantics of web social media texts, a lot of background knowledge and contextual information are needed. In web social media, the sentiment information expressed by language symbols and emoticons symbols released by users have strong sentiment consistency. Therefore, emotional symbol information in web social media text is very good context information of web social media text, and one of the data sources to solve the lack of context semantics of web social media text. For example, in the microblog "this software is simple [crying face], seeking Dai", if we only understand the sentence "this software is simple", we may conclude that the sentiment tendency of this microblog is positive, while after

Manuscript received Jan 4, 2020; revised April 1, 2020; accepted, June 21, 2021. (Corresponding author: Jingli Gao)

This work was supported in part by Foundation of Henan Educational Committee under Grant 21B520013, Henan Institute of Science and Technology under Grant 192400410199 and 202102210365, Doctoral Startup Foundation of Pingdingshan University under Grant PXY-BSQD-2018028 and National Natural Science Foundation of China under Grant U1536201.

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considering [crying face] and context information, the true sentiment tendency of this microblog is negative.

The existing sentiment classification methods of web social media have two problems in resolving the lack of text context semantics.

(1) Existing research mainly implements sentiment classification by mining language symbols information in web social media. Few studies consider sentiment information contained in emoticons symbols and punctuation symbols in web social media. Emoticons symbols and punctuation symbols containing sentiment information are important sources of sentiment information, and have important value in solving the lack of text context semantics.

(2) Existing research mainly extracts sentiment features and models text content from document level, but seldom consider extracting sentiment features and modeling text content from multiple levels such as words, sentences and documents. By extracting sentiment features and modeling text content from multiple levels, we can extract sentiment information from different levels better, and provide richer information for solving the lack of text context semantics in web social media.

In order to solve the problems of the existing sentiment classification methods of web social media, we propose a multi-dimension and multi-level sentiment modeling method (MDMLSM). Our main contributions are as follows.

(1) We propose a sentiment classification method of web social media based on multi-dimension and multi-level modeling. Experiments on Sina Weibo and Twitter datasets show that our method improves 5.86% more accuracy than the competitive baselines in sentiment classification.

(2) We propose a multi-dimension sentiment modeling method (MDSM) from three dimensions: language symbols, emoticons symbols and punctuation symbols. By mining multi-dimension sentiment information, we partially solve the problem of text context semantic missing in web social media.

(3) We propose a multi-level sentiment modeling method (MLSM) from the three levels of words, sentences and documents. By mining multi-level sentiment information, we have partially solved the lack of text context semantics in web social media text.

The remaining sections are arranged as follows: Section II introduces the related work. Section III gives an overview of our proposed method and describes the key content of our method. Section IV gives experimental settings. Experimental results and discussion are presented in Section V. Finally, we summarize the contents of the full text in Section VI.

II. Related Work

Since 2000, the sentiment classification of web social media has attracted more and more researchers and produced a lot of research results [6]. Existing sentiment classification methods of web social media mainly focus on supervised sentiment classification, including classical machine learning methods and deep learning methods. Different supervised sentiment classification methods differ only in text representation models and sentiment classification methods [6]. The sentiment classification methods are not very different from those used in other areas. Instead, the complexity in these approaches lies in extracting complex features from the text, filtering only relevant features, and selecting a good sentiment classifier.

The sentiment classification method based on classical machine learning usually uses the bag of words (BOW) model to represent text and uses Naive Bayesian (NB), Expectation-Maximization algorithm (EM), Random Forest and support vector machine (SVM) as classifiers [7]. In BOW, each document is represented by the bag of its constituent words. Word order is disrupted, and syntactic structures are broken. Khan *et al.* used word-based n-grams, character-based n-grams, spelling features and emoticons as BOW to represent text and used SVM for polarity classification [8]. The BOW model does not solve the problem of synonyms and polysemy in natural languages. As a result, a great deal of information from natural language is lost and the accuracy of sentiment classification is not high.

In recent years, new approaches based on deep learning have shown excellent performance in sentiment classification [9-12]. The sentiment classification method based on deep learning generally use end-to-end pattern and implement text representation and classifier based on the neural network. These algorithms do not need to be passed manually crafted features: they automatically learn new complex features. In the realm of Natural Language Processing (NLP), most of the focus is on learning fixed-length word vector representations using neural language models. These representations, also known as word embedding, can then be fed into a deep learning classifier. Many studies employed CNN and LSTM for sentiment classification and demonstrated favorable performances [9-10]. Distributed vector representation based on deep learning partially solves the problem that BOW model can't distinguish synonyms, but it can't solve the problem of polysemy.

Based on CNN and LSTM, some researches combined sentiment lexicon and different neural network architecture to propose some revised methods [11-14]. Hao *et al.* proposed a mutual-attention CNN to integrate word and character-level features [11]. Xu *et al.* present a cached long short-term memory neural network to capture the overall semantic information in long texts [12]. Yang *et al.* proposed a method combined sentiment lexicon and deep learning [13]. Ling et al proposed a hybrid neural network model which combined CNN and LSTM to deal with the polysemy phenomena of words and topic confusion with Sina Weibo [14]. Yang *et al.* proposed a hierarchical attention network for document classification to improve the performance of sentiment classification [15].

Based on the existing deep learning model, some research combined the characteristics of web social media and proposed some revised methods [16-21]. Singh *et al.* considered sentiment hash tag embedding through multi-task learning to achieve sentiment classification [16]. Wang *et al.* combined textual information and sentiment diffusion patterns to improve the performance of sentiment classification [17]. Akhtar *et al.* proposed a multi-task ensemble framework to finish emotion, sentiment and intensity prediction [18]. Majumder *et al.* argued that knowledge in sarcasm detection can also be beneficial to sentiment classification and vice versa. So, Majumder *et al.* presented a multi-task learning framework by using a deep neural network to improve the performance of sentiment classification [19]. Ji *et al.* presented a novel bi-layer multimodal hyper-graph learning towards robust sentiment prediction of multimodal tweets [20]. Abdi *et al.* used sentiment knowledge, sentiment shifter rules and multiple strategies to improve the performance of sentiment classification [21].

These revised methods try to solve problem of synonyms and polysemy from the perspective of neural network architecture and social media characteristics. However, sentiment classification method based on fixed word vector representation cannot solve the problem of polysemy fundamentally.

Recently, pre-training methods have shown their powerfulness in learning general semantic representations, and have remarkably improved most natural language processing (NLP) tasks like sentiment analysis [22-25]. These methods build unsupervised objectives at word-level, such as masking strategy, next-word prediction or permutation. Such word prediction-based objectives have shown great abilities to capture dependency between words and syntactic structures. The pre-training model partially solves the problem of synonyms and polysemy in natural language. However, as the sentiment information of a text is seldom explicitly studied, it is hard to expect such pre-trained general representations to deliver optimal results for sentiment analysis.

III. An Overview Framework Of Our Methods

The overall framework of the sentiment classification method of web social media based on multi-dimension and multi-level modeling is shown in Figure 1. In Figure 1, the red circle represents the vector representation of emoticons symbols, the blue circle represents the vector representation of linguistic symbols, and the green circle represents the vector representation of punctuation symbols.

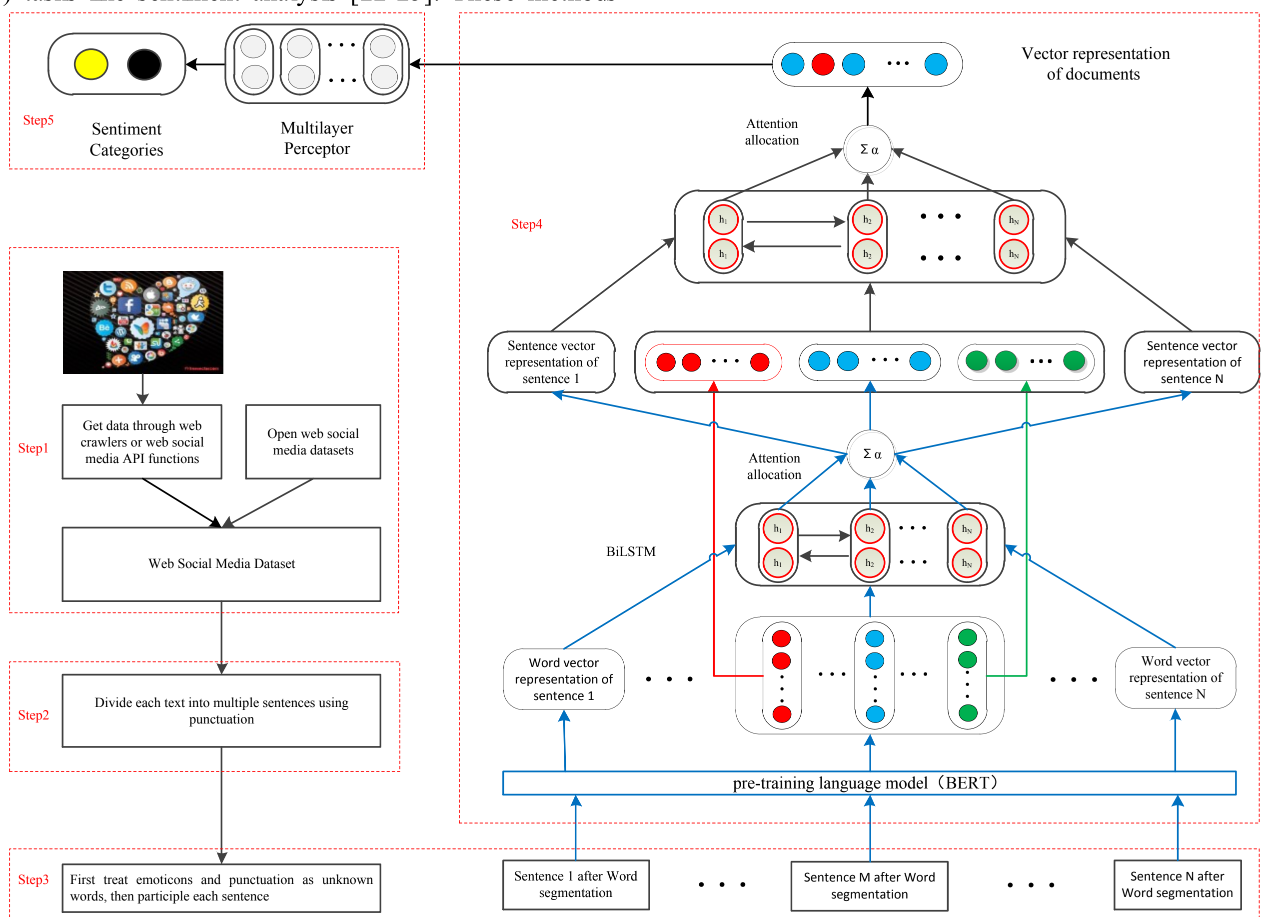

Fig. 1. The framework of sentiment classification method of web social media based on multi-dimension and multi-level modeling, the red circle represents the vector representation of emoticons symbols, the blue circle represents the vector representation of linguistic symbols, and the green circle represents the vector representation of punctuation symbol.

The sentiment classification method of web social media based on multi-dimension and multi-level modeling mainly includes the following steps.

(1) Through web crawler, web social media API and public web social media text datasets, multiple web social media text datasets are constructed.

(2) For each text in web social media dataset, the text is divided into multiple sentences using punctuation symbols.

(3) After treating emoticons symbols and punctuation symbols as unregistered words, each sentence is segmented

using the existing word segmentation tools.

(4) As a whole, we proposed a multi-level sentiment modeling method to model text content from three levels: word, sentence and document. At the word level and sentence level, we proposed a multi-dimension sentiment modeling method to model text content from three dimensions: language symbols, emoticons symbols and punctuation symbols.

(5) The results of multi-dimension and multi-level modeling are input into the multi-level perception network to get the final sentiment classification results.

MDMLSM mainly includes two key contents. One is the multi-level sentiment modeling method from the three levels: word level, sentence level and document level. The other is the multi-dimension sentiment modeling method from three dimensions: language symbols, emoticons symbols and punctuation symbols. The pseudo-code representation of the algorithm is shown in Table 1.

TABLE I

MULTI-LEVEL AND MULTI-DIMENSIONAL SENTIMENT MODELING METHOD

```
Algorithm 1: Multi-Level and multi-dimensional sentiment modeling method
input: document
output: document DocumentVector
initialize the Bert and Bi-LSTM models
document SentenceVector = []
for each sentence in document:
    for each word, emoticon, punctuation in sentence:
        WordVector = Bert(word)
        emoticon WordVector = Bert(emoticon)
        punctuation WordVector = Bert(punctuation)
    sentence WordVector = [WordVector, emoticon WordVector, punctuation WordVector]
    SentenceVector = Attention(LSTM(sentence WordVector))
    emoticon SentenceVector = emoticon WordVector
    punctuation SentenceVector = punctuation WordVector
    sentence SentenceVector = [SentenceVector, emoticon SentenceVector, punctuation SentenceVector]
    document SentenceVector += sentence SentenceVector
document DocumentVector = Attention(LSTM(document SentenceVector))
```

A. Multi-Level Sentiment Modeling Method

The existing studies mainly extract sentiment features and model text content from the document level, and seldom consider the correlation and interaction between sentences in the document, and rarely consider the correlation and interaction between words in the sentence. There are clear progressive and adversative relationships between different sentences within the text, and there are clear correlation and mutual influence between different words within the sentence. For this reason, we proposed a multi-level sentiment modeling method. By extracting sentiment features and modeling text content from multiple levels such as words, sentences and documents, we can better extract various levels of sentiment information, and provide more abundant information for solving the lack of context semantics of web social media text.

The multi-level sentiment modeling method mainly consists of three levels: word, sentence and document. At the word level, the input is the result of sentence segmentation, and the output is the word vector representation of the sentence. For details, please refer to the multi-dimension sentiment model at word level (reference B in Section III). At the sentence level, the input is the word vector representation of the sentence, and the output is the sentence vector representation of the sentence. For details, please refer to the multi-dimension sentiment model at sentence level (reference B in Section III). At the document level, the input is the sentence vector of multiple sentences, and the output is the document vector. The details in document level are as follows.

(1) Based on the conjunctions and grammatical rules between sentences, we get three kinds of relations: progressive, adversative and summary.

(2) Three kinds of relations between sentences are introduced into attention network as prior knowledge. The sentiment polarity of sentences with adversative relationship should be opposite as far as possible, and the sentiment polarity of sentences with progressive relationship should be consistent as far as possible. Sentences with summary relationship can better represent the sentiment tendency of the whole document. Considering the three kinds of relations between sentences, a sentence level attention mechanism based on the relationship constraints between sentences is proposed. The attention formula uses the sentence-level attention formula in Paper [23].

(3) The sentence vectors of each sentence are input into the BiLSTM network based on attention mechanism constraints, and the vector representation of the document is obtained.

After the document vector representation is obtained, the document vector is input into the multi-layer perception network and the sentiment category is output. The objective function of sentiment classification based on multi-dimension and multi-level modeling is shown in formula (1).

$$\min_{w} \sum_{i=1}^{N} \left(w^T x_i - y_i \right)^2 + \lambda_1 \|w\|_1 + \lambda_2 \sum_{i=1}^{N} \sum_{j \neq i} A_{ij} \left(\alpha_i - \alpha_j \right)^2 + \lambda_3 \sum_{i=1}^{N} \sum_{j \neq i} B_{ij} \left(\beta_i - \beta_j \right)^2 \tag{1}$$

Here, N is the number of text, w is the sentiment classification model, x_i is the vector representation of the ith text, y_i is the sentiment polarity of the ith text, α_i, α_j is the attention factor of the word layer, β_i, β_j is the attention factor of the sentence layer, A_{ij} is the similarity of sentiment word i and sentiment word j, B_{ij} is the similarity of sentence i and sentence j, and $\lambda_1, \lambda_2, \lambda_3$ is a hyper parameter.

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B. Multi-Dimensional Sentiment Modeling Method

We proposed a multi-dimension sentiment modeling method to model text content from three dimensions: linguistic symbols, emoticons symbols and punctuation symbols. Multi-dimension sentiment modeling methods mainly include word-level multi-dimension sentiment modeling and sentence-level multi-dimension sentiment modeling.

The main steps of multi-dimension sentiment modeling at the word level are as follows.

(1) Because emoticons symbols and punctuation symbols contain sentiment information, the web social media text containing emoticons and punctuation symbols are all input into the pre-training language model (such as BERT).

(2) When using pre-training language model to model the word level of web social media text, emoticons and punctuation symbols are treated as sentiment words to get the language symbol word vector, emoticons symbol word vector and punctuation symbol word vector.

(3) Language symbol word vector, emoticons symbol word vector and punctuation symbol word vector constitute a multi-dimension sentiment model of web social media text.

The main steps of multi-dimension sentiment modeling at the sentence level are as follows.

(1) The prior knowledge of sentiment words is introduced into attention network. Considering that the attention coefficient of similar sentiment words should be as close as possible, a word level attention mechanism based on sentiment dictionary constraint is proposed. The attention formula uses the word-level attention formula in Paper [23].

(2) The word vector of language symbol, emoticon symbol and punctuation symbol are input into BiLSTM network based on attention mechanism, and the sentence vector of language symbol is output.

(3) The word vector of emoticon symbol is output directly as the sentence vector of emoticon symbol, and the word vector of punctuation symbol is output directly as the sentence vector of punctuation symbol.

(4) The resulting sentence vectors of language symbols, emoticons symbols and punctuation symbols are joined together to obtain the sentence vectors.

IV. EXPERIMENTAL SETTINGS

A. Dataset and Evaluation Metric

To validate the performance of sentiment classification methods of web social media based on multi-dimension and multi-level modeling on different social media text datasets. We select about 100000 microblog data with two emotions as datasets1 (https://github.com/SophonPlus/ChineseNlpCorpus/blob/master/datasets/weibo_senti_100k/intro.ipynb), and about 300000 microblog data with four emotions as datasets2 (https://pan.baidu.com/s/16c93E5x373nsGozyWevITg?_at_=1617119005896#list/path=%2F). For the four emotions in dataset2, we regard anger, disgust and depression as negative emotions and happiness as positive emotions. We choose two English Twitter datasets based on the existing Twitter datasets on the Internet as datasets3 and datasets4. The distribution of these four web social media text datasets is shown in Table 2.

TABLE II
DISTRIBUTION OF FOUR DATASETS

Review datasets	Total number	Number of positive text	Number of negative text
Datasets1(Sina Weibo)	119988	59993	59995
Datasets2(Sina Weibo)	306477	199496	106981
Datasets3(U.S.airline)	11541	2363	9178
Datasets4(SemEval2016)	17981	11991	5990

Since our task is to sentiment classification of web social media, we use the *k*-fold cross-validation (*k*=5) and Accuracy (*AC*) to evaluate the models we proposed. The definition of the *AC* metrics is showed in formula (2).

$$AC = \frac{R_1 + R_2}{W_1 + W_2 + R_1 + R_2} \tag{2}$$

Here, R_1, R_2, W_1, W_2 are defined in Table 3.

TABLE III
DEFINITION OF FOUR PARAMETERS R_1, R_2, W_1, W_2

	Positive sentiment in datasets	Negative sentiment in datasets
Identifying positive sentiment	R_1 = true positive	W_1 = false positive
Identifying negative sentiment	W_2 = false negative	R_2 = true negative

B. Parameters Settings

Stochastic gradient descent (SGD) with a mini-batch size of 32 is used to train MDMLSM. The word embedding is pre-trained with Bert. The dimension of word embedding and output layer of MLP is set to be 200. All parameters in networks are initialized using normalized initialization. The hyper-parameters $\lambda_1, \lambda_2, \lambda_3$ and learning rate μ are empirically set to be 0.04, 0.02, 0.04 and 0.03. We apply dropout with 0.5 on the hidden layer to reduce overfitting. The activation function in each layer is *tanh*.

C. Experiments Settings

The goal of our experiment evaluation is to answer the following questions.

(1) Can our method solve the problem of text context semantics missing?

(2) Comparing with the existing sentiment classification methods, can our method improve the performance of sentiment classification in different datasets?

Since our method consists of two components: the multi-dimension sentiment modeling method and the multi-level sentiment modeling method. In order to thoroughly and carefully evaluate the performance of our method, we have carried out three groups of experiments.

(1) To study the effect of the multi-dimension sentiment modeling method on the performance of sentiment classifications, we designed an experiment to evaluate the performance of the multi-dimension sentiment modeling method.

(2) To study the multi-level sentiment modeling method on the performance of sentiment classifications, we designed an

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experiment to evaluate the performance of the multi-level sentiment modeling method.

(3) Based on above two experiences, to study the whole performance of our method, we compared our method with the existing sentiment classification methods. The experience result proved that our method performs better than the existing baseline method.

V. RESULTS AND DISCUSSION

A. Evaluation Of Multi-Dimension Sentiment Modeling Method

To study the performance of sentiment classification method using only the multi-dimension sentiment modeling method, we compared the multi-dimension sentiment modeling method (MDSM) with the sentiment classification methods based on Word2Vec+CNN [9], based on Word2Vec+BiLSTM [10], based on Bert+CNN [24] and based on Bert+BiLSTM [25]. The methods are described as follows.

Word2Vec+CNN: Sentiment classification method based on Word2Vector and CNN. First, Word2Vec are used to initialize the word vector, then CNN is used to extract the sentiment characteristics of web social media, and finally the sentiment classification of web social media is implemented through a fully connected network.

Word2Vec+BiLSTM: Sentiment classification method based on Word2Vector+BiLSTM. First, Word2Vec are used to initialize the word vector, then BiLSTM is used to extract the sentiment characteristics of web social media, and finally the sentiment classification of web social media is implemented through a fully connected network.

Bert+CNN: Sentiment classification method based on Bert+CNN. First, BERT are used to initialize the word vector, then CNN is used to extract the sentiment characteristics of web social media, and finally the sentiment classification of web social media is implemented through a fully connected network.

Bert+BiLSTM: Sentiment classification method based on Bert+BiLSTM. First, BERT are used to initialize the word vector, then BiLSTM is used to extract the sentiment characteristics of web social media, and finally the sentiment classification of web social media is implemented through a fully connected network.

MDSM+Word2Vec+CNN: Sentiment classification method based on Word2Vec, CNN and MDSM. Firstly, the information of language symbols, emoticon symbols and punctuation symbols in web social media are treated as language symbols. Then, the word vector is initialized with word2vec, and the sentiment features of web social media are extracted by CNN. Finally, the sentiment classification method of web social media is realized through fully connected network.

MDSM+Word2Vec+BILSTM: Sentiment classification method based on Word2Vec, BiLSTM and MDSM. Firstly, the information of language symbols, emoticon symbols and punctuation symbols in web social media are treated as language symbols. Then, the word vector is initialized with word2vec, and the sentiment features of web social media are extracted by BiLSTM. Finally, the sentiment classification method of web social media is realized through fully connected network.

MDSM+BERT+CNN: Sentiment classification method based on BERT, CNN and MDSM. Firstly, the information of language symbols, emoticon symbols and punctuation symbols in web social media are treated as language symbols. Then, the word vector is initialized with BERT, and the sentiment features of web social media are extracted by CNN. Finally, the sentiment classification method of web social media is realized through fully connected network.

MDSM+BERT+BiLSTM: Sentiment classification method based on BERT, BiLSTM and MDSM. Firstly, the information of language symbols, emoticon symbols and punctuation symbols in web social media are treated as language symbols. Then, the word vector is initialized with BERT, and the sentiment features of web social media are extracted by BiLSTM. Finally, the sentiment classification method of web social media is realized through fully connected network.

We compared the classification performance of eight different methods on four different datasets. The experimental results are shown in Tables 4 and Figure 2.

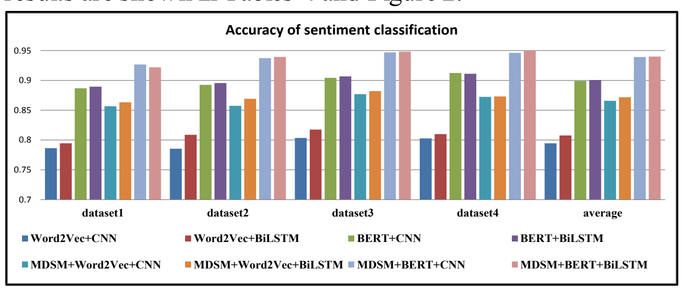

Fig. 2. The performance comparison of multi-dimensional sentiment modeling methods and benchmark methods

As can be seen from Table 4 and Figure 2, the average AC of MDSM+Word2Vec+CNN and MDSM+Word2Vec+Bi-LSTM are higher than that of Word2Vec+CNN and Word2Vec+ BiLSTM in four different datasets. The average AC of MDSM+Word2Vec+CNN is about 8.97% ((0.8658-0.7945)/ 0.7945) higher than that of Word2Vec+ CNN. The average AC of MDSM+Word2Vec+BiLSTM is about 7.95% ((0.8719-0.8077)/0.8077) higher than that of Word2Vec+BiLSTM. The experiment results show that MDSM+Word2Vec+CNN and MDSM+Word2Vec+Bi-LSTM are more effective than Word2Vec+CNN and Word2Vec+BiLSTM in sentiment classification of web social media.

At the same time, we can see that the average AC of MDSM+BERT+CNN and MDSM+BERT+Bi-LSTM are higher than that of BERT+CNN and BERT+BiLSTM. The average AC of MDSM+BERT+CNN is about 4.29% ((0.9393-0.899)/0.899) higher than that of BERT+CNN. The average AC of MDSM+BERT+BiLSTM is 4.35% ((0.9399-0.9007)/0.9007) higher than that of BERT+BiLSTM. The experiment results show that MDSM+BERT+CNN and MDSM+BERT+Bi-LSTM are more effective than BERT+ CNN and BERT+BiLSTM in the sentiment classification of web social media.

B. Evaluation Of Multi-Level Sentiment Modeling Method

To study the performance of sentiment classification method using only the multi-level sentiment modeling method, we compared the multi-level sentiment modeling method (MLSM) with the sentiment classification methods based on Word2Vec+CNN, based on Word2Vec+BiLSTM, based on Bert+CNN and based on Bert+BiLSTM. The methods are described as follows.

MLSM+Word2Vec+CNN: Sentiment classification method based on Word2Vec, CNN and MLSM. First, Word2Vec is used to initialize the word vector, and then CNN based on attention mechanism is used to extract the sentiment characteristics of web social media from the three levels of words, phrases and sentences. Finally, the sentiment classification of web social media is implemented through the fully connected network.

MLSM+Word2Vec+BiLSTM: Sentiment classification method based on Word2Vec, BiLSTM and MLSM. First, Word2Vec is used to initialize the word vector, and then BiLSTM based on attention mechanism is used to extract the sentiment characteristics of web social media from the three levels of words, phrases and sentences. Finally, the sentiment classification of web social media is implemented through the fully connected network.

MLSM+BERT+CNN: Sentiment classification method based on BERT, CNN and MLSM. First, BERT is used to initialize the word vector, and then CNN based on attention mechanism is used to extract the sentiment characteristics of web social media from the three levels of words, phrases and sentences. Finally, the sentiment classification of web social media is implemented through the fully connected network.

MLSM+BERT+BiLSTM: Sentiment classification method based on BERT, BiLSTM and MLSM. First, BERT is used to initialize the word vector, and then BiLSTM based on attention mechanism is used to extract the sentiment characteristics of web social media from the three levels of words, phrases and sentences. Finally, the sentiment classification of web social media is implemented through the fully connected network.

We compared the classification performance of eight different methods on four different datasets. The experimental results are shown in Tables 5 and Figure 3.

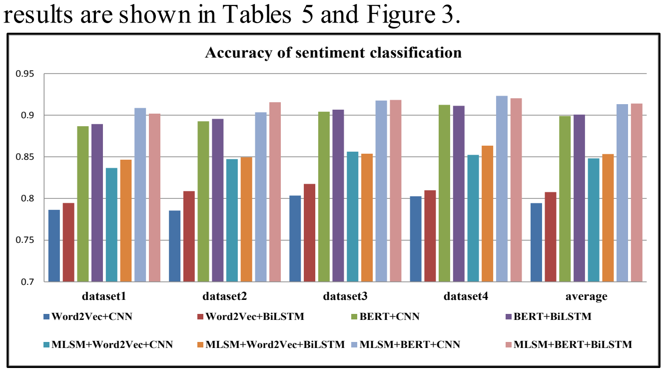

Fig. 3. The performance comparison of multi-level sentiment modeling methods and benchmark methods

As can be seen from Table 5 and Figure 3, the AC of MLSM+Word2Vec+CNN and MLSM+Word2Vec+Bi-LSTM are higher than that of Word2Vec+CNN and Word2Vec+ BiLSTM in four different datasets. The average AC of MLSM+Word2Vec+CNN is about 6.75% ((0.8481-0.7945)/0.7945) higher than that of Word2Vec+ CNN. The average AC of MLSM+Word2Vec+Bi-LSTM is about 5.65% ((0.8533-0.8077)/0.8077) higher than that of Word2Vec+ BiLSTM. The experiment results show that MLSM+ Word2Vec+CNN and MLSM+Word2Vec+Bi-LSTM are more effective than Word2Vec+CNN and Word2Vec+ BiLSTM in the sentiment classification of social media.

At the same time, we can see that the average AC of MLSM+BERT+CNN and MLSM+BERT+BiLSTM are higher than that of BERT+CNN and BERT+BiLSTM. The average AC of MLSM+BERT+CNN is about 1.58% ((0.9132-0.899)/0.899) higher than that of BERT+CNN. The accuracy of MLSM+BERT+BiLSTM is 1.39% ((0.914-0.9007)/0.9007) higher than that of BERT+BiLSTM. The experimental results show that MLSM+BERT+CNN and MLSM+BERT+BiLSTM are more effective than BERT+CNN and BERT+BiLSTM in the sentiment classification of web social media.

C. Evaluation Of Multi-Dimension And Multi-Level Sentiment Modeling Method

In order to evaluate the overall performance of our method, we compared our method with the sentiment classification methods based on CNN [9], based on LSTM [10], based on HAN [15], based on BERT [22] and based on XLNet [23]. The experimental results are shown in Tables 6 and Figure 4.

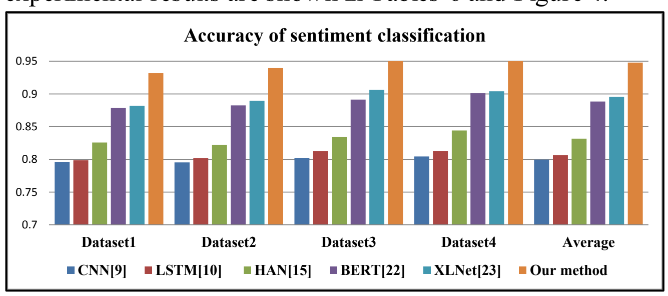

Fig. 4. The performance comparison of our method and benchmark methods

As can be seen from Table 6 and Figure 4, the average AC of our method are higher than that of the existing five sentiment classification methods in four different datasets. Compared with the best method in existing five sentiment classification methods, the average AC of our methods is about 5.86% ((0.9479-0.8954)/0.8954) higher than that of XLNet in sentiment classification. The experimental results show that our method is more effective than the existing sentiment classification methods in the sentiment classification of web social media.

In different datasets, the performance of sentiment classification methods based on multi-dimension and multi-level modeling is consistent and stable. The main reason is that based on multi-level and multi-dimension modeling, we can extract multi-level and multi-dimension sentiment information. The multi-level and multi-dimension sentiment information provides a rich information source to solve the lack of context semantics of web social media text.

In order to study the performance of our method under the condition of limited training data, we select 10%, 20%, 30%,

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40%and 50% data as training data respectively. Under the condition of different size of training data, we compared our method with the sentiment classification methods based on Bert and based on XLNet. The experimental results are shown in Figure 5.

As can be seen from Figure 5, under the condition of limited training data, the accuracy of sentiment classification of different methods has different degrees of decline. However, the performance of our method is always better than the existing methods under the same training data set. At the same time, we can find that when the number of training data sets is smaller, the performance of our method is improved more than the existing methods. This shows that the performance of our method is better under the condition of limited training data set.

TABLE IV
PERFORMANCE COMPARISON OF DIFFERENT METHODS ON FOUR DATASETS

Method	Metric	Dataset1	Dataset2	Dataset3	Dataset4	Average
Word2Vec+CNN	AC	0.7863	0.7855	0.8035	0.8027	0.7945
Word2Vec+BiLSTM	AC	0.7946	0.8088	0.8175	0.8099	0.8077
BERT+CNN	AC	0.8868	0.8926	0.9042	0.9124	0.899
BERT+BiLSTM	AC	0.8894	0.8955	0.9067	0.9112	0.9007
MDSM+Word2Vec+CNN	AC	0.8566	0.8573	0.877	0.8723	0.8658
MDSM+Word2Vec+BiLSTM	AC	0.8633	0.8692	0.882	0.8731	0.8719
MDSM+BERT+CNN	AC	0.9266	0.9374	0.947	0.9462	0.9393
MDSM+BERT+BiLSTM	AC	0.9219	0.9395	0.9481	0.9501	0.9399

TABLE V
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Word2Vec+CNN	AC	0.7863	0.7855	0.8035	0.8027	0.7945
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BERT+BiLSTM	AC	0.8894	0.8955	0.9067	0.9112	0.9007
MLSM+Word2Vec+CNN	AC	0.8366	0.8473	0.8562	0.8523	0.8481
MLSM+Word2Vec+BiLSTM	AC	0.8466	0.8494	0.8538	0.8634	0.8533
MLSM+BERT+CNN	AC	0.9086	0.9034	0.9176	0.9232	0.9132
MLSM+BERT+BiLSTM	AC	0.9019	0.9155	0.9183	0.9203	0.914

TABLE VI
PERFORMANCE COMPARISON OF DIFFERENT METHODS ON FOUR DATASETS

Method	Metric	Dataset1	Dataset2	Dataset3	Dataset4	Average
CNN[9]	AC	0.7863	0.7855	0.8035	0.8027	0.7945
LSTM[10]	AC	0.7946	0.8088	0.8175	0.8099	0.8077
HAN[23]	AC	0.8258	0.8225	0.8342	0.8443	0.8317
BERT[22]	AC	0.8784	0.8825	0.8915	0.9012	0.8884
XLNet[23]	AC	0.8819	0.8895	0.9061	0.9041	0.8954
Our method	AC	0.9319	0.9395	0.9561	0.9641	0.9479

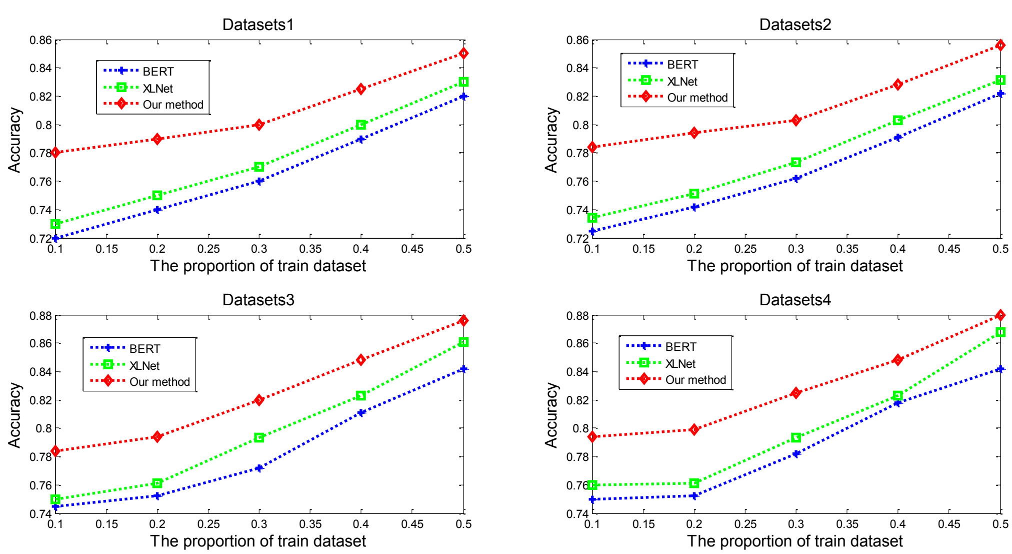

Fig. 5. The performance comparison of different methods

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VI. CONCLUSIONS

In order to solve the problems in the existing sentiment classification methods of web social media, we propose a sentiment classification method of web social media based on multi-dimension and multi-level modeling. Our methods have partly solved the lack of context semantics of web social media text by extracting multi-levels and multi-dimensions sentiment information. The experimental results show that our method greatly improves the accuracy of sentiment classification of web social media compared with the existing methods.

In the future, we will further explore a better network structure to achieve multi-dimensional and multi-level modeling of web social media. At the same time, we will explore sentiment classification method of web social media by fusing multi-modal information in web social media.

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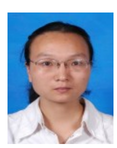

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