\(\rho\)-hot Lexicon Embedding-based Two-level LSTM for Sentiment Analysis

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Abstract—Sentiment analysis is a key component in various text mining applications. Numerous sentiment classification techniques, including conventional and deep learning-based methods, have been proposed in the literature. In most existing methods, a high-quality training set is assumed to be given. Nevertheless, constructing a high-quality training set that consists of highly accurate labels is challenging in real applications. This difficulty stems from the fact that text samples usually contain complex sentiment representations, and their annotation is subjective. We address this challenge in this study by leveraging a new labeling strategy and utilizing a two-level long short-term memory network to construct a sentiment classifier. Lexical cues are useful for sentiment analysis, and they have been utilized in conventional studies. For example, polar and privative words play important roles in sentiment analysis. A new encoding strategy, that is, \(\rho\)-hot encoding, is proposed to alleviate the drawbacks of one-hot encoding and thus effectively incorporate useful lexical cues. We compile three Chinese data sets on the basis of our label strategy and proposed methodology. Experiments on the three data sets demonstrate that the proposed method outperforms state-of-the-art algorithms.

Index Terms—Sentiment analysis, LSTM, lexicon embedding, labeling, encoding.

1 INTRODUCTION

Text is important in many artificial intelligence applications. Among various text mining techniques, sentiment analysis is a key component in applications such as public opinion monitoring and comparative analysis. Sentiment analysis can be divided into three problems according to input texts, namely, sentence, paragraph, and document levels. This study focuses on sentence and paragraph levels.

Text sentiment analysis is usually considered a text classification problem. Almost all existing text classification techniques are applied to text sentiment analysis [1]. Typical techniques include bag-of-words (BOW)-based [2], deep learning-based [3], and lexicon-based (or rule-based) methods [4].

Although many achievements have been made and sentiment analysis has been successfully used in various commercial applications, its accuracy can be further improved. The construction of a high-accuracy sentiment classification model usually entails the challenging compilation of training sets with numerous samples and sufficiently accurate labels. The reason behind this difficulty is two-fold. First, sentiment is somewhat subjective, and a sample may receive different labels from different users. Second, some texts contain complex sentiment representations, and a single label is difficult to provide. We conduct a statistical analysis of public Chinese sentiment text sets in GitHub. The results show that the average label error is larger than 10%. This error value reflects the degree of difficulty of sentiment labeling.

Privative and interrogative sentences are difficult to classify when deep learning-based methods are applied. Although lexicon-based methods can deal with particular types of privative sentences, their generalization capability is poor.

We address the above issues with a new methodology. First, we introduce a two-stage labeling strategy for sentiment texts. In the first stage, annotators are invited to label a large number of short texts with relatively pure sentiment orientations. Each sample is labeled by only one annotator. In the second stage, a relatively small number of text samples with mixed sentiment orientations are annotated, and each sample is labeled by multiple annotators. Second, we propose a two-level long short-term memory (LSTM) network to achieve two-level feature representation and classify the sentiment orientations of a text sample to utilize two labeled data sets. Lastly, in the proposed two-level LSTM network, lexicon embedding is leveraged to incorporate linguistic features used in lexicon-based methods.

Three Chinese sentiment data sets are compiled to investigate the performance of the proposed methodology. The experimental results demonstrate the effectiveness of the proposed methods. Our work is new in the following aspects.

- A highly effective labeling strategy is adopted. Labeling a high-quality training set is difficult in sentiment analysis. In our labeling strategy, samples are divided into ones with relatively pure sentiment orientations and ones with relatively complex sentiment orientations. This procedure is easily performed in practice.
- A two-level LSTM network is proposed. Our labeling procedure yields two training sets with different
sentiment levels; therefore, we propose a two-level LSTM network that can effectively utilize the two data sets.

- Lexicon embeddings are introduced. We introduce a new embedding method to incorporate useful cues usually used in lexicon-based methods and to ultimately utilize lexical cues.
- A new encoding strategy is introduced. One-hot encoding is the most widely used encoding strategy for categorical data. An effective encoding strategy, \( \rho \)-hot encoding, is proposed in this work to address the limitations of one-hot encoding.

The rest of this paper is organized as follows. Section 2 briefly reviews related work. Section 3 describes our methodology. Section 4 reports the experimental results, and Section 5 concludes the study.

2 RELATED WORK

2.1 Text Sentiment Analysis

Sentiment analysis aims to predict the sentiment polarity of an input text sample. Sentiment polarity can be divided into negative, neutral, and positive in many applications.

Existing sentiment classification methods can be roughly divided into two categories, namely, lexicon-based and machine learning-based methods \[6\]. Lexicon-based methods \[7\] construct polar and privative word dictionaries. A set of rules for polar and privative words is compiled to construct polar and privative word dictionaries. A set of rules for polar and privative words is compiled to construct polar and privative word dictionaries. A set of rules for polar and privative words is compiled to construct polar and privative word dictionaries.

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Fig. 1 characterizes a typical lexicon-based sentiment classification approach. The approach iteratively checks each word in an input sentence from left to right. The weight score of each word is calculated according to the procedure shown in Fig. 1. The final sentiment score is the average score of the words with weight scores. The scores of positive, neutral, and negative sentiments are denoted as “+1″, “0″, and “-1″, respectively. According to the lexicon-based algorithm shown in Fig. 1, the sentiment score of “it is not bad” is 0.25, and the sentiment score of “it is good” is 1. However, the score of “it is not so bad” is -0.75, and this score is definitely wrong. Therefore, machine learning (including feature learning) methodologies have become mainstream in sentiment analysis.

2.3 Deep Learning-based Sentiment Classification

Deep learning (including word embedding \[13\]) has been applied to almost all text-related applications, such as translation \[14\], quality assurance \[15\], recommendation \[16\], and categorization \[17\]. Popular deep neural networks are divided into convolutional neural networks (CNNs) \[18\] and recurrent neural network (RNNs) \[19\] \[20\]. Both are utilized in sentiment classification \[21\]. Kim investigated the use of CNN in sentence sentiment classification and achieved promising results \[3\]. LSTM \[22\], a classical type of RNN, is the most popular network used for sentiment classification. A binary-directional LSTM \[23\] with an attention mechanism is demonstrated to be effective in sentiment analysis.

Deep learning-based methods rarely utilize the useful resources adopted in lexicon-based methods. Qiao et al. \[24\] incorporated lexicon-based cues into the training of an LSTM-based model. Their proposed method relies on a new loss function that considers the relationships between polar or certain types of words (e.g., privative) and those words next to them in input texts. Our study also combines lexical cues into LSTM. Nevertheless, unlike Qiao et al.’s study that implicitly used lexical cues, the present work explicitly uses lexical cues in the LSTM network. Shin et al. \[25\] combined the lexicon embeddings of polar words with word embeddings for sentiment classification. The difference between our approach and the method proposed by Shin et al. is discussed in Section 3.3.5.

Numerous studies on aspect-level sentiment analysis exist \[26\]. This problem is different from the sentiment classification investigated in this study.

3 METHODOLOGY

This section first introduces our two-stage labeling procedure. A two-level LSTM is then proposed. Lexicon embedding is finally leveraged to incorporate lexical cues.

3.1 Two-stage Labeling

As stated earlier, sentiment is subjective, and texts usually contain mixed sentiment orientations. Therefore, texts sentiment orientations are difficult to label. In our study, three
sentiment labels, namely, positive, neutral, and negative, are used. The following sentences are taken as examples.

S1: The service is poor. The taste is good, but the rest is not so bad.
S2: The quality of the phone is good, but the appearance is just so-so.

In user annotation, the labels of these two sentences depend on users. If a user is concerned about service, then the label of S1 may be “negative”. By contrast, for another user who does not care about service, the label may be “positive”. Similarly, a user may label S2 as “positive” if he cares about quality. Another user may label it as “negative” if the conjunction “but” attracts the users attention more. Another user may label it as “neutral” if they are concerned about quality and appearance.

The underlying reason is that sentiment is more subjective than semantics. In related research on subjective categorization, such as visual aesthetics, each sample is usually repeatedly annotated by multiple annotators, and the average label is taken as the final label of the sample. This labeling strategy can also be applied to text sentiment annotation. However, we argue that this strategy is unsuitable for a (relatively) large number of samples. The reason lies in the following two aspects.

- Multiple annotators for a large number of data sets require a large budget.
- In our practice, annotators claim that their judgment criteria on sentiment become fused on texts with mixed sentiment orientations (e.g., S1 and S2) over time during labeling, and they become bored accordingly.

A two-stage labeling strategy is adopted in this study. In the first stage, each sentence/paragraph is divided into several clauses according to punctuation. The sentiment of each partitioned clause is relatively easy to annotate; therefore, each clause is labeled by only one user. In the second stage, a relatively small-sized sentence/paragraph set is labeled, and each sentence is labeled by all involved annotators. We still take the two sentences, S1 and S2, as examples. S1 and S2 are split into clauses, as shown below.

- S1:
  - S1.1: The service is poor
  - S1.2: The taste is good
  - S1.3: but the rest is not so bad.

- S2:
  - S2.1: The quality of the phone is good
  - S2.2: but the appearance is just so-so.

Each of the above clauses is labeled by only one annotator. The annotation in the first stage is easy to perform; thus, the number of clauses can be larger than the number of sentences used in the second labeling stage.

### 3.2 Two-level LSTM

Given two training data sets (denoted by T1 and T2), a new learning model should be utilized. LSTM is a widely used deep neural network in deep learning-based text classification.

LSTM is a typical RNN model for short-term memory, which can last for a long period of time. An LSTM is applicable to classify, process, and predict time series information with given time lags of unknown size. A common LSTM block is composed of a cell, an input gate, an output gate, and a forget gate. The forward computation of an LSTM block at time $t$ or position $t$ is as follows [22]:

$$
\begin{align*}
  i_t &= \sigma(W_i[c_{t-1}, h_{t-1}, x_t] + b_i) \\
  f_t &= \sigma(W_f[c_{t-1}, h_{t-1}, x_t] + b_f) \\
  o_t &= \sigma(W_o[c_{t-1}, h_{t-1}, x_t] + b_o) \\
  d_t &= \sigma(W_d[c_{t-1}, h_{t-1}, x_t] + b_d) \\
  c_t &= i_t \odot d_t + f_t \odot c_{t-1} \\
  h_t &= o_t \odot \tanh(c_t)
\end{align*}
$$

where $x_t$ is the input vector at time $t$ (or position $t$); $i_t$ and $d_t$ are the input vectors of the input unit and input gate, respectively; $o_t$ and $h_t$ are the output and hidden vectors at time $t$, respectively; $f_t$ is the output of the forget gate at time $t$; $c_t$ is the internal state of the memory cell in an LSTM block at time $t$; and $\sigma$ is the sigmoid active function.

1. CNN is another widely used text classification model. Our idea can also be applied to CNN.
When LSTM is used to classify an input sentence, the hidden vectors of each input vector are summed to form a dense vector that can be considered the feature representation of the input sentence, i.e.,

\[ v_t = \sum h_t \tag{2} \]

In many applications, a bi-directional LSTM (bi-LSTM) structure is usually used, as shown in Fig. 2(a). In bi-LSTM, forward and backward information are considered for information at time \( t \); hence, the context is modeled. Bi-LSTM is thus significantly reasonable for text processing tasks. In our two-level LSTM, bi-LSTM is used in each level.

The output hidden state at time \( t \) of a bi-LSTM block can be described as follows:

\[
\begin{align*}
\vec{h}_t &= \vec{\sigma}_t \odot \tanh(\vec{c}_t) \\
\hat{h}_t &= \hat{\sigma}_t \odot \tanh(\hat{c}_t) \\
h_t &= [\hat{h}_t, \vec{h}_t] 
\end{align*}
\tag{3}
\]

where \( \hat{h}_t, \vec{h}_t, \vec{\sigma}_t, \) and \( \hat{\sigma}_t, \vec{c}_t, \hat{c}_t \) are the corresponding vectors at time \( t \) in the forward LSTM block; and \( \hat{h}_t, \vec{h}_t, \hat{\sigma}_t, \) and \( \vec{\sigma}_t, \hat{c}_t, \vec{c}_t \) are the corresponding vectors at time \( t \) in the backward LSTM block. \( H = \{ h_t, \cdots, h_T \} \). When attention is used, the dense feature vector \( \gamma \) of an input sentence is calculated as follows:

\[
\alpha = \text{softmax}(w^T H) \\
\gamma = H \alpha^T \tag{4}
\]

where \( \alpha \) is the vector that consists of attention weights. The bi-LSTM with attention is shown in Fig. 2(b).

Our proposed network consists of two levels of LSTM network. In the first level, a bi-LSTM is used and learned on the basis of the first training set \( T_1 \). This level is a conventional sentiment classification process. The input of this level is a clause, and the input \( x_t \) is the embedding of the basic unit of the input text. The network is shown in Fig. 3(a).

In the second level, a bi-LSTM is also used and learned on the basis of the second training set \( T_2 \). The input of this level is a sentence or a paragraph. The input \( x_t \) is the embedding of the corresponding vectors at time \( t \) in the backward LSTM block. \( H = \{ h_t, \cdots, h_T \} \). When attention is used, the dense feature vector \( \gamma \) of an input sentence is calculated as follows:

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The above two limitations affect the final sentiment analysis performance. To this end, we propose a new encoding strategy.

\[
\rho - \text{hot encoding} : \nu_\rho = \rho \cdot \nu_1 \otimes 1_{n \times 1} \tag{6}
\]

where \( \nu_\rho \) is the \( \rho \)-hot encoded vector, \( \rho \) is the proportion parameter, \( \nu_1 \) is the one-hot encoded vector, and \( 1_{n \times 1} \) is an \( n \)-dimensional vector. If \( \rho \) and \( n \) are equal to 1, then \( \rho \)-hot encoding is reduced to one-hot encoding. The parameter \( n \) is applied to increase the length of the final encoded vector.

### 3.3 Lexical Embedding

The proposed lexicon embedding is based on \( \rho \)-hot encoding. Therefore, \( \rho \)-hot encoding is first described.

#### 3.3.1 \( \rho \)-hot encoding

For categorical data, one-hot encoding is the most widely used encoding strategy when different categories are independent. For example, if one-hot encoding is used to represent three categories, namely, positive, neutral, and negative, the encoding vectors for the three categories are \([1, 0, 0]^T\), \([0, 1, 0]^T\), and \([0, 0, 1]^T\), respectively.

In this work, many lexical cues are categorical data, and different categories are independent. These lexical cues can directly be represented by one-hot encoding. The encoded vectors for lexical cues are then concatenated with other vectors, such as character/word embedding. However, one-hot encoding presents two main limitations when the encoded vector is concatenated with other vectors.

- The value difference between the elements of one-hot encoded vectors and those of other encoded vectors (e.g., word embedding vectors) may be large. Fig. 4 shows the histogram of the values of the elements of the word embedding vectors. The magnitude of most elements is smaller than 1.
- The lengths of one-hot encoded vectors are usually shorter than those of other encoded vectors. Consequently, the proportion of one-hot encoded part is small in the concatenated vectors.

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#### 3.3.2 Embedding for key lexical words

Most lexicon-based sentiment methods rely on four types of words, namely, positive, negative, neutral, and privative. These words are useful cues for predicting the sentiment labels of input texts. The incorporation of these words should also be useful. A previous study has shown that a typical document comprises approximately 8% of such sentences.

Sentiments expressed in a conditional sentence can be difficult to determine due to the semantic condition. The sentiment polarities of interrogative sentences are also difficult to classify according to our empirical study.

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2. In English texts, the basic unit is usually a word; in Chinese texts, the basic unit is a Chinese word or character.

3. The third part is lexicon embedding which will be introduced in Section 3.3.4.
Five types of words, namely, positive (Pos), negative (Neg), privative (Pri), suppositive (Sup), and interrogative (Int), are represented by the proposed encoding method. The rest words, which do not belong to any of the above five types, are named "others (Oth)" instead of "neutral" because some words, such as "the", are unrelated to "sentiment". The value of $n$ in Eq. (6) is set as 10. The encoded vectors are as follows.

\[
\text{Pos} : \begin{bmatrix} \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T \\
\text{Neg} : \begin{bmatrix} 0_{1\times10}, \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T \\
\text{Pri} : \begin{bmatrix} 0_{1\times10}, 0_{1\times10}, \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T \\
\text{Sup} : \begin{bmatrix} 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T \\
\text{Int} : \begin{bmatrix} 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T \\
\text{Oth} : \begin{bmatrix} 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, \rho_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10}, 0_{1\times10} \end{bmatrix}^T 
\]

In the proposed $\rho$-hot embedding, the parameter $\rho$ can be learned during training. The representation of the third clause (“but the rest is not so bad”) of S1 in Subsection 3.1 is taken as an illustrative example. The new embedding of each word in this clause is as follows.

\[
\begin{bmatrix}
\phi(\text{but}) \\
\phi(\text{the}) \\
\phi(\text{rest}) \\
\phi(\text{is}) \\
\phi(\text{not}) \\
\phi(\text{so}) \\
\phi(\text{bad}) \\
\end{bmatrix} = 
\begin{bmatrix}
0^{10x1} \\
0^{10x1} \\
0^{10x1} \\
0^{10x1} \\
0^{10x1} \\
0^{10x1} \\
0^{10x1} \\
\end{bmatrix}
\]

Certain types (e.g., positive, negative, and privative) of words should play more important roles than other words do in texts; therefore, their embeddings are also used in the attention layer. A new LSTM based on our lexicon embedding is proposed, as shown in Fig. 5. The attention layer and final dense vector of the network in Fig. 3(a) are calculated as follows.

\[
\alpha_t = \text{softmax}(W_\alpha \begin{bmatrix} h_t \\ l_t \end{bmatrix} + b_l)
\]

\[
\gamma = \sum_t \alpha_t h_t
\]

where $\alpha_t$ is the attention weight for the $t$-th input, $W_\alpha$ is the lexicon embedding for key lexical words for the $t$-th input, and $\gamma$ is the final dense vector. Eq. (2) is used in the first-level LSTM.

3.3.3 Embedding for POS

POS is usually used as a key cue in sentiment analysis [28]. To this end, we use additional lexicon embedding. The new lexicon embedding includes several major types of POS, namely, interrogative, exclamatory, and others. This new lexicon embedding is also applied to the attention layer. The motivation lies in that certain types of POS should play important roles in sentiment.

The proposed $\rho$-hot embedding is still applied to POS types in this study. According to our initial case studies, eight POS types are considered. They are noun, adjective, verb, pronoun, adverb, preposition, accessory, and others. The eight POS types are represented by the proposed $\rho$-hot
encoding. We let $n$ in Eq. (6) be 10. The first three POS types are as follows.

- Noun: $[\rho_{1 \times 10}, 0_{1 \times 10}, 0_{1 \times 10}, 0_{1 \times 10}, \cdots, 0_{1 \times 10}]^T$
- Adj: $[0_{1 \times 10}, \rho_{1 \times 10}, 0_{1 \times 10}, 0_{1 \times 10}, \cdots, 0_{1 \times 10}]^T$
- Verb: $[0_{1 \times 10}, 0_{1 \times 10}, \rho_{1 \times 10}, 0_{1 \times 10}, \cdots, 0_{1 \times 10}]^T$

When POS embedding is used, the attention layer and final outputs of the network in Eq. (3) become

$$
\alpha_t = \text{softmax}(W_\alpha \begin{bmatrix} h_t \\ l_t \\ \eta_t \end{bmatrix} + b_t)
$$

$$
\gamma = \sum_t \alpha_t h_t
$$

where $\eta_t$ is the lexicon embedding for key lexical words for the $t$-th input.

### 3.3.4 Embedding for conjunction

Conjunction words play important roles in sentiment analysis [29]. For example, conjunctions such as “but” and “moreover” usually indicate the focus of texts and attract readers attention. Therefore, conjunctions are considered in the input of the second-level LSTM.

Once a set of conjunction words is compiled, $\rho$-hot embedding is used. In our experiments, the number of conjunction words is 169. Therefore, the parameter $n$ in Eq. (2) is set as 1.

When conjunction embedding is used for the second-level layer, the attention layer and final outputs of the network in Fig. 3(b) are calculated as follows.

$$
\beta_t = \text{softmax}(W_\beta \begin{bmatrix} y_t^{(1)} \\ h_t^{(2)} \\ \omega_t^a \\ \omega_t^e \end{bmatrix} + b_t')
$$

$$
\gamma^{(2)} = \sum_t \beta_t \begin{bmatrix} h_t^{(2)} \\ y_t^{(1)} \end{bmatrix}
$$

where $\beta_t$ is the attention weight for the $t$-th input clause; $h_t^{(2)}$ is the hidden vector of the second-level LSTM; $\omega_t^a$ and $\omega_t^e$ are the conjunction embeddings for the first and last words in the $t$-th input clause, respectively; and $\gamma^{(2)}$ is the final dense vector used for the final classification.

### 3.4 The Learning Procedure

The algorithmic steps of the entire learning procedure for the proposed $\rho$-hot lexicon embedding-based two-level LSTM (called $\rho$TI-LSTM) are shown in Algorithm 1. In Algorithm 1, T1 refers to the training data that consist of clauses and the labels obtained in the first-stage labeling procedure. T2 refers to the training data that consist of sentences and the labels obtained in the second-stage labeling procedure. The structure of $\rho$TI-LSTM is presented in Fig. 6.

The proposed two-level LSTM can be applied to texts with arbitrary languages. Word information is required in lexical construction regardless of whether character or word embedding is used. The reason is that the three types of lexicon embeddings are performed at the word level. Therefore, when character embedding is used, the lexicon embedding of each character is the lexicon embedding of the word containing it.
4 EXPERIMENTS

This section shows the evaluation of the proposed methodology in terms of the two-level LSTM network and each part of the lexicon embedding.

4.1 Experimental Data and Labeling

We compile three Chinese text corpora from online data for three domains, namely, “hotel”, “mobile phone (mobile)”, and “travel”. All texts are about user reviews. Each text sample collected is first partitioned into clauses according to Chinese tokens. Three clause sets are subsequently obtained from the three text corpora.

The labels “+1”, “0.5”, and “0” correspond to the three sentiment classes “positive”, “neutral”, and “negative”, respectively. The text data are labeled according to our two-stage labeling strategy.

- In the first stage, only one user is invited to label each clause sample as the sentiment orientations for clauses (or sub-sentences) are easy to label.
- In the second stage, five users are invited to label each text sample in the three raw data sets. The average score of the five users on each sample is calculated. Samples with average scores located in [0, 0.4] are labeled as “positive”. Samples with average scores located in [0.6, 1] are labeled as “negative”. Others are labeled as “neutral”. The details of the labeling results are shown in Table 1.

In each experimental run, the training set is compiled on the basis of the training data listed in Table 1. The compiling rule is specified before each experimental run. The test data are fixed to facilitate experimental duplication and comparison by other researchers.

4.2 Competing Methods and Parameter Setting

In our experiments, three competing algorithms, namely, BOW, CNN, and (conventional) LSTM, are used.

For BOW, term frequency-inverse document frequency is utilized to construct features. Ridge regression is used as a classifier. For CNN, a three-channel CNN is used. For LSTM, one-layer and two-layer bi-LSTM with attention are adopted, and the results of the network with superior performance are presented. CNN and LSTM are performed on TensorFlow, and default parameter settings are followed.

The key parameters are searched as follows. The embedding dimensions of characters and words are searched in the range of 300. The number of neuron units of each layer is searched in the range of 128, 256, and 512. The number of convolution kernels of each convolution layer is searched in the range of 64, 128, and 256. The learning rate is searched in the range of 1e-2, 1e-3, and 1e-4.

All the training and test data and the labels are available online.

In our experiments, the five types of key lexical words introduced in Subsection 3.3.2 are manually constructed. The details of the five types of words are listed in Table 2. The conjunction words are also manually constructed. The number of conjunction words used in the experiments is 169.

| TABLE 1 | Details of the three data corpora. Each corpus consists of raw samples (sentences or paragraphs) and partitioned clauses (sub-sentences). |
|---------|-------------------------------------------------------------|
| Data corpus | raw | clauses |
| Travel   | Pos.  | 1567 | 3490 |
|          | Neu.  | 576  | 5168 |
|          | Neg.  | 1957 | 2633 |
|          | Total | 4100 | 11291 |
| Hotel    | Pos.  | 1586 | 3987 |
|          | Neu.  | 401  | 2123 |
|          | Neg.  | 1838 | 5154 |
|          | Total | 3825 | 11264 |
| Mobile   | Pos.  | 1400 | 2788 |
|          | Neu.  | 589  | 2375 |
|          | Neg.  | 1494 | 2955 |
|          | Total | 3483 | 8118 |

In our Github project page, the five types of key lexical words are also available and introduced.

| TABLE 2 | Numbers of five types of key lexical words. |
|---------|---------------------------------------------|
| Data corpus | Travel | Hotel | Mobile |
| Positive   | 366    | 254   | 358  |
| Negative   | 327    | 194   | 382  |
| Privative  | 61     | 61    | 61   |
| Interrogative | 48   | 48    | 48   |
| Suppositive | 18    | 18    | 18   |

5. Token-based token is inaccurate for English text partition. Nevertheless, the segment results for Chinese texts are acceptable. A more reasonable way will be investigated in our future work.

6. Five graduate students, including three males and two females, were invited to label the data.

7. https://github.com/Tju-AI/two-stage-labeling-for-the-sentiment-orientations/tree/master/data

8. The five types of key lexical words are also available and introduced in our Github project page.
The parameter \( n \) in \( \rho \)-hot encoding is searched in \([1, 3, \ldots, 15]\).

4.3 Results

4.3.1 Results of existing baseline methods

In this subsubsection, each of the three raw data sets (associated with their labels) shown in Table 1 is used. The clause data are not used. In other words, the training data used in this subsubsection are the same as those used in previous studies. For each data corpus, 1000 raw data samples are used as the test data, and the rest are used as the training data. The involved algorithms are detailed as follows.

- **CNN-C** denotes the CNN with (Chinese) character embedding.
- **CNN-W** denotes the CNN with (Chinese) word embedding.
- **CNN-Lex-C** denotes the algorithm which also integrates polar words in CNN which is proposed by Shin et al. [25]. The (Chinese) character embedding is used.
- **CNN-Lex-W** denotes the algorithm which also integrates polar words in CNN which is proposed by Shin et al. [25]. The (Chinese) word embedding is used.
- **Bi-LSTM-C** denotes the Bi-LSTM with (Chinese) character embedding.
- **Bi-LSTM-W** denotes the Bi-LSTM with (Chinese) word embedding.
- **Lex-rule** denotes the rule-based approach shown in Fig. 1. This approach is unsupervised.
- **BOW** denotes the conventional algorithm which is based on bag-of-words features.

The accuracies of the above algorithms are listed in Table 3. Overall, Bi-LSTM outperforms CNN and BOW. This conclusion is in accordance with the conclusion that RNN performs efficiently against CNN in a broad range of natural language processing (NLP) tasks on the basis of extensive comparative studies [31]. In addition, CNN-lex outperforms CNN under both character and word embeddings, which suggests that lexicon cues are useful in sentiment analysis. Lex-rule achieves the lowest accuracies on all the three data sets. Considering that the performances of (traditional) CNN, Lex-rule, and BOW are relatively poor, they are not applied in the remaining parts.

### Table 3

| Data corpus      | Travel | Hotel | Mobile |
|------------------|--------|-------|--------|
| CNN-C            | 0.723  | 0.698 | 0.727  |
| CNN-W            | 0.731  | 0.729 | 0.748  |
| CNN-Lex-C        | 0.744  | 0.734 | 0.731  |
| CNN-Lex-W        | 0.798  | 0.764 | 0.755  |
| Bi-LSTM-C        | 0.754  | 0.753 | 0.805  |
| Bi-LSTM-W        | 0.746  | 0.785 | 0.809  |
| Lex-rule         | 0.556  | 0.539 | 0.684  |
| BOW              | 0.713  | 0.678 | 0.702  |

On all the three data corpora, the proposed two-level network (without lexicon embedding) with character embedding, TI-LSTM-C, outperforms all the other involved algorithms. On the travel and the mobile corpora, TI-LSTM-W outperforms Bi-LSTM-W. The results in Table 4 indicate that the performances of TI-LSTM on the mixed training and test data (R+C) are better than those of Bi-LSTM. This comparison indicates that the proposed two-level LSTM is effective.

In addition, for the involved algorithms, most results achieved on “R+C” are better than the best results only achieved on ‘R’ listed in Table 3. This comparison suggests that the introduced two-stage labeling is useful.

The results also show that in the two-level LSTM, character embedding is more effective than word embedding.

4.3.3 Results of lexicon embedding-based two-level LSTM

In this experimental run, lexicon embedding is used in the proposed two-level LSTM or \( \rho \)-TI-LSTM. Table 5 shows the results. The optimal parameter \( n \) is about 11.

The performances of TI-LSTM with lexicon embedding (i.e., \( \rho \)-TI-LSTM) are consistently better than those of TI-LSTM without lexicon embedding (i.e., TI-LSTM) listed in Table 5. The improved accuracies of \( \rho \)-TI-LSTM over TI-LSTM on the three data corpora are explicitly listed in Table 6.

4.4 Discussion

The experimental evaluation discussed in Subsection 4.3 verifies the effectiveness of the proposed method, \( \rho \)-TI-LSTM. Unlike the conventional RNN, \( \rho \)-TI-LSTM contains [100, 150, 200, 250, 300].
lexicon embedding that consists of new technique and components, including $\rho$-hot encoding, embedding for polar words, embedding for POS, and embedding for conjunctions. Therefore, this subsection evaluates the performances of the involved technique and embeddings separately.

4.4.1 The effect of different parameters on $\rho$-hot encoding

Our $\rho$-hot encoding differs from one-hot encoding in two aspects. The first aspect is that the nonzero values in one-hot encoding are only equal to 1, whereas the nonzero values in $\rho$-hot encoding are $\rho$. The second aspect is that only one element in one-hot encoding is nonzero, whereas $n$ elements in $\rho$-hot encoding are nonzero.

In this experiment, we test whether $\rho$-hot encoding is useful in two experimental runs. In the first run, the value of $\rho$ is manually set to 0.5 and 1 in the experimental run without optimization. The parameter $n$ in Eq. (6) is set as 15. The classification accuracies vary according to different $\rho$ values on all the three data corpora. When $\rho$ equals 1, the accuracies are the lowest in most cases shown in Fig. 7.

The results shown in Fig. 7 indicate that the value of $\rho$ does affect the performance of the entire network. Consequently, the classical one-hot encoding, which fixes the value of nonzero elements as 1, is ineffective. In our experiments, the learned value of $\rho$ is approximate 0.4.

In the second run, the performances under different $n$ (i.e., 1, 5, 10, 15) are tested. Table 7 shows the comparison results. The value of $n$ does affect the performance of the entire network, thereby indicating that the introduction of the $n$-duplicated strategy in encoding is effective. In the experiments, when $n$ is increasing, the accuracies first increase and then decrease. The main reason may lie in the fact that when $n$ becomes large, the proportion of lexicon embedding becomes large accordingly. An over-length input feature vector may incur “curse of dimensionality” and thus weaken the performance of the proposed two-level network.

4.4.2 The effect of polar words

In this experimental run, we test whether the labeled polar (negative and positive) words do affect the performance of the entire method when they are used in lexicon embedding. To this end, we order the polar words according to their frequencies in the training data. Top 0%, 50%, 100% polar words are used. The corresponding classification accuracies are depicted in Fig. 8.

In most cases, the accuracies are the lowest when no polar words are used in the lexicon embedding. When all polar words are used, the proposed network achieves the highest accuracies.

In the experiment, only one user is invited to manually compile the dictionary for a data corpus. One and a half hour is needed for each data corpus. In our viewpoint, it is worth manually compiling the polar words for sentiment analysis by considering the performance improvement and time-consumption.

4.4.3 The effect of POS cues

In this experimental run, we test whether POS cues do play positive roles in the entire model. To this end, we remove POS in the lexicon embedding of the proposed method. The results are shown in Fig. 9.

In most cases, the accuracies with POS embedding are greater than those without POS embedding, thereby indicating that the application of POS to lexicon embedding is useful.

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### Table 5

| Data corpus | Travel | Hotel | Mobile |
|-------------|--------|-------|--------|
| $\rho$TI-LSTM-C (R+C) | 0.816  | 0.837 | 0.826  |
| $\rho$TI-LSTM-W (R+C) | 0.800  | 0.810 | 0.841  |

### Table 6

The accuracy improvement of two-level LSTM when lexicon embedding was used over those of two-level LSTM without lexicon embedding. The values of the last row are the accuracy improvement over the highest accuracies on each data corpus with existing algorithms.

| Data corpus | Travel | Hotel | Mobile |
|-------------|--------|-------|--------|
| +0.6% | +2.4% | +0.6% |
| +3% | +2.8% | +2.1% |
| +6.02% | +5.2% | +5.01% |

(Compared with the highest in Tbl. 3)

### Table 7

The accuracies of $\rho$TI-LSTM with different $n$ values in $\rho$-hot encoding.

| $n$ | Travel | Hotel | Mobile |
|-----|--------|-------|--------|
| 1   | 0.790  | 0.814 | 0.807  |
| 5   | 0.799  | 0.824 | 0.825  |
| 10  | 0.803  | 0.831 | 0.814  |
| searched | 0.816 | 0.837 | 0.826 |

| $\rho$TI-LSTM-W | 1 | 0.792 | 0.798 | 0.820 |
| #1-C | #1-W | #2-C | #2-W | #3-C | #3-W |
| 1 | 0.804 | 0.810 | 0.827 |
| 5 | 0.800 | 0.802 | 0.836 |
| 10 | 0.800 | 0.810 | 0.841 |

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Figure 7. Classification accuracies under different $\rho$ values. #1-C and #1-W represent $\rho$TI-LSTM-C and $\rho$TI-LSTM-W on the first (travel) corpus; #2-C and #2-W represent $\rho$TI-LSTM-C and $\rho$TI-LSTM-W on the second (hotel) corpus; #3-C and #3-W represent $\rho$TI-LSTM-C and $\rho$TI-LSTM-W on the third (hotel) corpus, respectively.
and #3-W represent ρ on the first (travel) corpus, respectively; #2-C and #2-W represent LSTM-C and ρC and ρW on the second (hotel) corpus, respectively; #3-C and #3-W represent ρTl-LSTM-C and ρTl-LSTM-W on the third (hotel) corpus, respectively.

4.4.4 The effect of conjunction cues

In this experimental run, we test whether conjunction cues do play positive roles in the entire model. To this end, the lexicon embedding for conjunction words is also removed from the proposed method. The results are shown in Fig. 10.

The algorithm with conjunction embedding outperforms that without conjunction embedding consistently, thereby indicating that the application of conjunction to lexicon embedding is useful.

5 Conclusion

High-quality labels are crucial for learning systems. Nevertheless, texts with mixed sentiments are difficult for humans to label in text sentiment classification. In this study, a new labeling strategy is introduced to partition texts into those with pure and mixed sentiment orientations. These two categories of texts are labeled using different processes. A two-level network is accordingly proposed to utilize the two categories of texts are labeled using different processes. A two-level network is accordingly proposed to utilize the two categories of texts are labeled using different processes. A two-level network is accordingly proposed to utilize the two categories of texts are labeled using different processes. A two-level network is accordingly proposed to utilize the two categories of texts are labeled using different processes.

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