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Quantum-like implicit sentiment analysis with sememes knowledge

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ABSTRACT

Sentiment analysis, which can discriminate the sentiment tendency of subjective texts, is one of the important research works in the field of natural language processing. Sentiment analysis can be divided into explicit sentiment analysis and implicit sentiment analysis according to whether the text contains explicit sentiment words. Most of the current research work focuses on explicit sentiment analysis, while implicit sentiment analysis has become one of the most challenging research tasks because the sentiment characteristics are too implicit. In this paper, "Fused with Sememe Knowledge Quantum-like Chinese Implicit Sentiment Analysis (FSKQ)" is proposed, which introduces the density matrix in quantum theory and takes sememe, the smallest common sense semantic unit in natural language, as an external knowledge base to build a sememe-based density matrix. The matrix can be regarded as a complete knowledge system with strong generalization, which models the global information of the most fine-grained semantic knowledge. Its incorporation into the text vector results in a high quality of text representation, which effectively improves the performance of the model in Chinese implicit sentiment analysis. Ablation experiments and comparison experiments are conducted in the SMP ECISA2019 dataset, and the results show that the F1 score of the model is improved by 2.6% compared with the best model, which proves the effectiveness and superiority of the idea. In addition, in order to verify the performance of the proposed method in terms of text representation quality, it is also applied to existing models in the aspect-level sentiment analysis and event detection, and it is compared with the original model without using the idea and the baseline model on Twitter, Lap14, Rest14/15/16 and ACE2005 datasets. The results show that compared with the original model and the baseline model in this field, the model combined with the idea improves the accuracy and F1 score, which further proves the effectiveness, superiority and generalization of the FSKQ model.

1. Introduction

With the explosive growth of sentiment-laden text data in online social platforms, sentiment analysis has become one of the important research works in the field of natural language processing. Text sentiment analysis is the process of processing, generalizing and reasoning about the information related to the sentiment tendency of subjective texts. At the expression level, texts can be classified into explicit and implicit expressions according to whether they contain explicit sentiment words or not (Liu, 2012), and the two examples below can intuitively demonstrate the difference between them, as shown in Fig. 1.

The example sentence 1 in Fig. 1 belongs to explicit sentiment expression in which "good" is an explicit sentiment word that shows clear positive sentiment orientation. However, not all sentiment expressions have explicit sentiment words. The example sentence 2 in Fig. 1 is an implicit sentiment expression, which does not contain explicit sentiment words, but the express or wears a mask due to the hazy weather, showing a negative implicit sentiment. Since emotions are often expressed in an introverted and implicit way, a large number of implicit sentiments are generated in natural language. The corpus constructed by the research team of Shanxi University based on Chinese social media platform shows that there are 52,992 emotional sentences in 35,617 weibo/comments, including 25,885 explicit sentiment sentences and 27,107 implicit sentiment sentences, with implicit sentiment expression accounting for 51.2%. Accurately analyzing the sentiment tendencies of these expressions can effectively analyze public opinion, improve users' product experience and improve service quality. It can be seen that Chinese text implicit sentiment analysis has a wide range of application scenarios and important research significance, and is one of the important research contents in the field of natural language processing.

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Example1:

(Explicit Sentiment): 这形式真好! （This is a good form!)

Example2:

(Implicit Sentiment):今天的北京又开始雾霾了，不得已戴上我的碎花口罩。（It’s hazy in Beijing again today, so I have to wear my flower mask.）

Fig. 1. Example sentences showing explicit and implicit sentiment.

It can be seen from the above two example sentences that there are explicit sentiment words in explicit sentiment expressions, and their sentiment tendencies can be determined, so there have been a lot of research results in this field (Das & Kalita, 2017). However, it is difficult to conduct Chinese implicit sentiment analysis because of its “weak features” (Wang, Hou, Li, & Zhang, 2020), that is, since there are no strong features corresponding to explicit sentiment words in implicit sentiment expressions, it is difficult to perform sentiment analysis on them based on obvious semantic information. It is more difficult to conduct research and there are fewer research outcomes. Earlier scholars have attempted to analyze implicit sentiment from linguistic and cognitive perspectives based on traditional statistical methods (Wilks, 1975). In recent years, deep learning and pre-training models have provided new ideas for related methods, and have pushed the research work related to implicit sentiment analysis to a new level. Wei, Liao, Yang, Wang, and Zhao (2020) used a multi-polarity orthogonal attention mechanism to integrate external sentiment dictionary knowledge into the sentiment analysis model to enhance the ability to analyze implicit sentiment. Zhou, Wang, Zhang, and He (2021) only focused on the research on event-centered implicit sentiment expression, and judged its sentiment tendency on the basis of identifying the event in the sentence. The embedded representation of sentiment dictionary knowledge introduced by the former is the average of all sentiment word representations, the external knowledge calculation process is simpler and more crude, and the knowledge system is not complete enough. At the same time, it is difficult for sentiment dictionary knowledge to match implicit sentiment to express more and more diverse expressions and contents. A similar view is expressed in the paper by Wei et al. (2020), who argued that sentiment analysis methods should integrate common-sense external knowledge. The latter work only focuses on event-centered implicit sentiment analysis and other forms of expression in implicit sentiment (e.g., metaphor-based expression) is not considered. According to Ziff’s law, it is known that due to word frequency differences, there is inevitably a low-frequency word set in the corpus of natural language, and it is difficult for the model to guarantee the training quality of the low-frequency words in it, which affects the subsequent model analysis result, and this problem is especially prominent in short texts. In summary, the main limitations of the current Chinese implicit sentiment analysis methods are: (1) Incomplete external knowledge system. Its process of constructing the knowledge system is too simple and crude; (2) poor method generalization. It is difficult to effectively analyze all expression forms and contents of implicit sentiment analysis; (3) low quality of text representation. Due to the low-frequency word sets in the corpus, training a short text corpus based on Chinese implicit sentiment expressions is difficult to obtain high quality of text representations.

To address the limitations of the above implicit sentiment analysis methods, this paper proposes a fused with sememe knowledge quantum-like Chinese implicit sentiment analysis method. The method introduces the density matrix in quantum language model, constructs a sememe knowledge-based density matrix, and integrates it into the text representation to achieve better Chinese implicit sentiment analysis effect. As the smallest and indivisible common-sense semantic unit in linguistics, sememe has more fine-grained general semantic information than words, and can effectively capture the relationship between words to obtain high quality of word vector representation, effectively alleviating the problem of “low quality of text representation” of existing methods (Niu, Xie, Liu, & Sun, 2017). The idea of density matrix in quantum language model (Mackey, 1963; Zhang, Ma, & Song, 2018) takes each sememe knowledge as a superposition state and model its global semantic information by density matrix. This matrix can be regarded as a complete external knowledge system, which can effectively alleviate the problem of “incomplete external knowledge system” of existing methods. Based on the density matrix of sememe knowledge, the method combines common sense sememe knowledge with the density matrix method with strong generalization, which makes up for the limitation of “poor generalization” of the existing methods. In order to verify this method, the author conducts ablation experiments, comparison experiments and generalization experiments, and the experimental results prove the effectiveness, superiority and generalization of the proposed method.

The innovations and main contributions of the text work are as follows:

- In the task of Chinese implicit sentiment analysis, sememe knowledge is introduced for the first time to enhance the text representation, which effectively supplements the fine-grained semantic information in the text representation, and obtain high quality of text representation results, effectively alleviating the problem of “low quality of text representation”.
- In the Chinese implicit sentiment analysis task, the density matrix of the quantum language model is introduced for the first time and used to build a sememe-based knowledge system, which effectively alleviates the problem of “incomplete external knowledge system”.
- The idea of sememe-based density matrix knowledge proposed in this paper is applied to other research fields of natural language processing (such as aspect-level sentiment analysis, event detection, etc.), and has excellent performance. It is proved that the idea of this paper has certain portability and generalization, and provides a new idea for the process of integrating external knowledge into natural language processing models.
- The code that works has been published and is available at this link: https://github.com/Minghui-Hou/FSKQ.

The rest of this paper is organized as follows. In the second part, the related research work is briefly introduced. In the third part, the theoretical basis and proposed method of this paper are introduced. In the fourth part, the experimental data set, evaluation indicators and experimental details are introduced, and the experimental results are analyzed. The fifth part is summary and prospect of this paper.

2. Related work

Text sentiment analysis is a process of sentiment orientation analysis of subjective texts. It can be divided into explicit sentiment analysis and implicit sentiment analysis according to whether the text contains explicit sentiment words or not (Liu, 2012).

For explicit sentiment analysis, it is easy to analyze its sentiment tendency due to the strong features corresponding to the explicit sentiment words, and there have been many research findings. Earlier research works focused on approaches based on sentiment dictionaries and design matching rules. In 2007, Popescu and Etzioni (2007) found a relationship between adjacent words and sentiment tendency in local regions of text. Then the words that are dependent on the feature words were acquired through syntactic analysis, and the sentiment analysis was carried out through artificial rules. In 2008, Ding, Liu, and Yu (2008) used sentiment dictionaries for sentiment word matching, and furthermore considered words representing transitive and negative meanings in sentences, improving the accuracy of sentiment analysis. Due to the cost and generalizability of sentiment dictionary and design matching rule approaches, researchers started to explore traditional feature-based machine learning methods. Based on the n-gram approach, Pak et al. (2010) performed sentiment analysis on text in twitter. For the multi-classification task, Liu, Bi, and Fan (2017) compared and analyzed the experimental results of multiple machine learning models under different feature engineering. Such methods require experienced researchers to construct high-quality feature engineering, which greatly restricts the development of related research work. The development of deep learning method provides a new way to solve this problem. In 2018, Saroufim, Almatarky, and Hady (2018) used sentiment emoticons to automatically label a large amount of texts and used a migration learning approach to refine the network weights with a small scale hand-labeled training data, and its performance on sentiment analysis data set was improved. In 2019, Zhang and Zhang (2019) analyzed tree-structured sentences through graph convolution model, which significantly improved the effectiveness of text sentiment analysis tasks. In 2020, Ke, Ji, Liu, Zhu, and Huang (2020) introduced sentiment knowledge into a pre-trained model to construct a unified sentiment representation for sentiment analysis and achieved SOTA level in their experiments. In 2021, for the structured sentiment analysis, Barnes, Kurtz, Oepen, Øvrelid, and Velldal (2021) proposed a method for constructing dependency graphs using syntactic dependency information and conducted experiments on five datasets in four languages, which performed better than the baseline method.

Compared with the booming of explicit sentiment analysis, implicit sentiment analysis lacks the strong characteristics corresponding to explicit sentiment words due to its implicit expression, and the related research work is relatively difficult and there are few research results. From the perspective of linguistics and cognition, Wilks (1978) defined metaphorical expression as a set of combined paradigms to express the relationship between metaphor and context. After that, Zhang and Liu (2011) believed that the sentiment tendencies could be implicitly expressed in sentences containing specific words. Shutova, Teufel, and Korhonen (2013) identified corresponding metaphorical expressions by clustering words. On this basis, a weakly supervised, and unsupervised approach are used to learn the distribution information of metaphors and thus identify metaphorical expressions in sentences. According to contextual content without an obvious sentiment tendency, Balahur, Hermida, and Montoyo (2012) analyzed the sentiment tendency of sentences based on a common sense knowledge base. Zhao, Qin, and Liu (2012) integrated pseudo-context into implicit sentiment analysis. Tong, Tan, and Tan (2013) studied the influence of implicit expression on the expression of implicit sentiment through theoretical evaluation. Mehndiratta, Sachdeva, and Soni (2017) analyzed the detection method of sarcastic remarks based on a deep learning model. Liao, Wang, Li, and Li (2017) proposed a representation learning framework based on tree convolution. Based on the syntactic analysis results of the text, the implicit sentiment was analyzed, and the experimental results were carefully analyzed, providing new ideas for the research of Chinese implicit sentiment analysis. Liao (2018) attempted to analyze Chinese implicit sentiment by defining and extracting sentiment tuples. Wei et al. (2020) proposed an orthogonal attention model that introduces external sentiment dictionary knowledge for Chinese implicit sentiment analysis and it performs better on F1 scores than LSTM and GRU-based models. Wang et al. (2020) defined two major problems in Chinese implicit sentiment analysis: “weak features” and “multiple confusing weak features”, and designed a hierarchical knowledge enhancement and multi-pooling approach to try to solve the two major problems. Pan, Jingling, and Lin (2020) fused semantic features of the context into the attention mechanism to effectively improve the effect of Chinese implicit sentiment analysis. Zhao, Xiong, Ju, Li, and Xie (2020) proposed a hybrid neural network model, and the experimental results on Chinese implicit sentiment dataset showed that the method can effectively analyze Chinese sentiment expressions. Zuo, Zhao, Chen, and Chen (2020) applied the heterography idea to implicit sentiment analysis and the effect was improved compared with TreeLSTM, TreeGCN and other models.

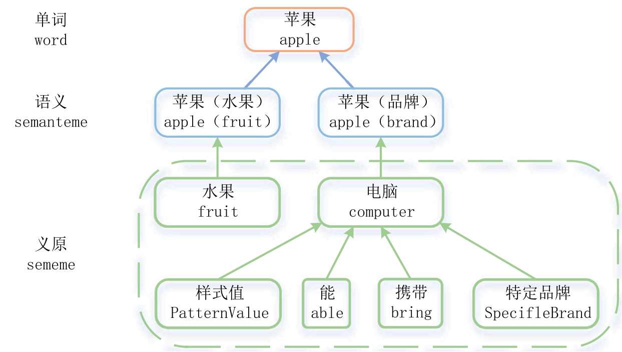

Fig. 2. Sememe knowledge structure.

By constructing event triples to represent events, Zhou et al. (2021) specifically analyzed the event-centric implicit sentiment expression.

In conclusion, due to the “weak features” in Chinese implicit sentiment expression, it is difficult to obtain good results by simply mining the information of the text. Therefore, researchers began to pay attention to the method of integrating high-quality external knowledge, but related work still has problems such as incomplete external knowledge, poor generalization, and low text representation quality. Based on the limitations of these methods, the author proposes a new fused with sememe knowledge quantum-like Chinese implicit sentiment analysis to try to solve the above problems, and the details of the method are described in the following section.

3. Proposed methods

In response to the problems such as incomplete external knowledge system, poor generalization and low quality of text representation in the current Chinese implicit sentiment analysis, a new sentiment analysis method-fused with sememe knowledge quantum-like Chinese implicit sentiment analysis model is proposed. In this section, the structure and principles of the model are explained.

3.1. Sememe knowledge

As far as we know, the concept of sememe was introduced by Dong Zhen-dong and Dong Qiang in the field of natural language processing. Sememe are generally defined as the most basic, indivisible semantic conceptual units that do not have further definitions or decompositions. They constructed a systematic sememe knowledge base — HowNet (Dong & Dong, 2003). The HowNet is the most comprehensive and widely used sememe knowledge base of generics. The knowledge base is a very detailed and well-developed knowledge system containing more than two thousand sememes, and they are used to annotate more than 100,000 Chinese characters. Its structure is shown in Fig. 2.

As shown in Fig. 2, the first layer is the words, the second layer is the semantic information corresponding to each word, and the third layer is the sememe information corresponding to each semantic information. For example, the word “apple” has two completely different semantic meanings, “fruit” and “brand”. The two semantics are further explained by sememe. (The semantics of “brand” can be described in more detail by the five sememes, “patternvalue”, “bring”, “able”, “computer”, and “specificbrand”.) Sememe knowledge has a strong ability to describe the fine-grained information of text, and can describe the text closer to its essence, so it has attracted the attention of many researchers, and related research includes word sense disambiguation (Zhang, Gong, & Wang, 2005), multi-label sentiment analysis (Liu & Chen, 2015), text representation learning (Niu et al., 2017), language model (Gu et al., 2018), and inferring the semantic orientation of subjective words for more accurate sentiment analysis (Du & Tan, 2010). With the rise of large models such as BERT, some researchers have explored the construction of semantic knowledge graphs for Chinese classical poetry based on HowNet in large models, achieving good results (Zhao, Bai, Wei, & Wu, 2023). The data in this paper are all short texts from social media platforms with little background information, which makes it difficult to obtain high-quality representation results of target texts even for models with strong learning ability. The sememe knowledge base can be used to capture the spatial similarity of the text and supplement the fine-grained knowledge of the text that is closer to the semantic nature of the text, thus obtaining a higher quality text representation and effectively alleviating the problem of "low text representation quality" in the current Chinese implicit sentiment analysis methods.

3.2. Density matrix in quantum language model

First, it should be noted that the quantum language model is not a calculation process running on a quantum computer, nor it is necessary to physically model quantum-level microscopic particles. Instead, it solves related problems by using the mathematical methods of quantum theory (QT) (Zhang, Ma, & Song, 2018). One of the important concepts of the quantum language model is the density matrix, which models the global semantic information of a sentence and is used to represent a sentence. Assuming that there are words in a sentence, where each word is represented by a d-dimensional word vector and each word in the sentence is represented by $|v_i\rangle$, the density matrix is constructed as shown in Eq. (1).

$$\rho = |v_i\rangle \langle v_i| \tag{1}$$

where $|v_i\rangle \in \mathbb{R}^{d\times 1}$, $\langle v_i| \in \mathbb{R}^{1\times d}$, $|v_i\rangle$ and $\langle v_i|$ are the same vector.

Due to the theoretical similarities between quantum theory and language processing, it has been studied with related theories in the field of natural language, such as quantum linguistic information retrieval (Sordoni, Nie, & Bengio, 2013), quantum-like language models (Zhang, Niu, et al., 2018), and so on. In this paper, the idea of density matrix in quantum physics is introduced to construct a sememe-based density matrix and it is integrated into the text representation, which effectively alleviates the problems of "poor generalization" and "incomplete external knowledge system" in the current Chinese implicit sentiment analysis methods, and provides new ideas for integrating external knowledge into natural language processing models.

3.3. A fused with sememe knowledge quantum-like implicit sentiment analysis model

To address the problems of "low quality of text representation", "incomplete external knowledge system" and "poor generalization" of current Chinese implicit sentiment analysis methods, the author proposes a fused with sememe knowledge quantum-like Chinese implicit sentiment analysis method. In this method, the idea of density matrix in the quantum language model is introduced to construct a sememe-based density matrix, and it is integrated into the text representation to obtain better results of Chinese implicit sentiment analysis. The structure of the model is shown in Fig. 3.

As shown in Fig. 3, the model mainly consists of five layers: the Sememe-Based Knowledge Layer (SBKL), the Corpus Embedding Layer (CEL), the Density Matrix Layer (DM), the Fusion Layer, and the Output Layer. The principle of the model is described as follows.

3.3.1. CEL (Corpus Embedding Layer)

At the corpus embedding layer of the model, the pre-trained BERT model is used to embed Chinese implicit sentiment expression (Kenton & Toutanova, 2019). This model can be used for representation learning based on word level information in Chinese text, which can alleviate the errors caused by word segmentation errors and the problem that a single character has meaning, as shown in Eq. (2).

$$C = [c_1, c_2, c_3, \dots, c_n] \tag{2}$$

where $c_i (i = 1, 2 \dots n)$ represents Chinese characters, i.e., the result of slicing Chinese characters in unit of characters. adding spaces between Chinese characters, and the input text is sliced in Chinese characters and input into the model, as shown in Eq. (3).

$$M_C = BERT(C) \tag{3}$$

Sentiment analysis is a classification task, and the head label vector M_C corresponding to the sentence is used in this paper. In order to verify the effectiveness and generalization of the method, generalization experiments are also conducted, in which word vectors pre-trained by the Glove model are used.

3.3.2. SBKL (Sememe-Based Knowledge Layer)

At the sememe-based knowledge layer of the model, the model obtains the sememe-based representation results. Sememe Attention over Target (SAT) method (Niu et al., 2017) in SE-Wel model is used to obtain the sememe-based vector representation, as shown in Eq. (4).

$$V_{SBK} = \sum_{i=1}^{n} att\left(s_i\right) \cdot s_i \tag{4}$$

where V_{SBK} denotes the sememe-based representation vector, and s_i denotes the semantic information embedding representation of the i th word. The data in the experiments of this paper are short texts from social media platforms. It is difficult to obtain high-quality representation results of the target text even for a model with strong learning ability. With the help of sememe knowledge base, fine-grained sememe knowledge closer to the semantic essence of text can be supplemented on the basis of capturing the spatial similarity of text. The resulting high-quality text representation is closer to the linguistic essence and has certain generalization, and at the same time can alleviate the problem of insufficient training of low-frequency word sets in corpus by the model.

3.3.3. DM (Density Matrix)

The density matrix (Zhang, Ma, & Song, 2018) is an important concept in quantum language models and an important representation in end-to-end quantum-like language models. This method can model the global semantic information of a sentence into a density matrix based on obtaining a word vector and it can be used as the result of the representation corresponding to that sentence. In this model, the idea of density matrix is introduced. On the basis of obtaining multiple sememe vectors, the global semantic information of multiple sememe vectors is modeled to construct sememe-based density matrix, which can be regarded as a sememe-based complete knowledge system. Fig. 4 shows the construction process.

As shown in Fig. 4, the sememe-based vector is learned in SBKL, and then the density matrix is obtained by outer product and summation, as shown in Eq. (5).

$$M_D = \sum_{j=1}^{n} \left|v_S^j\right\rangle \left\langle v_S^j\right| \tag{5}$$

where $\left|v_S^j\right\rangle \in \mathbb{R}^{d\times 1}$ is the left vector, which $\left\langle v_S^j\right|$ is a sememe-based vector representation. is the right vector, which is the transpose vector corresponding to the left vector. Through the outer product operation of multiple vectors and sum, the density matrix M_D is obtained, where $M_D \in \mathbb{R}^{d\times d}$ is the square matrix. The density matrix is the result of modeling the global information based on the sememe knowledge representation, which can be regarded as a more complete sememe-based knowledge system.

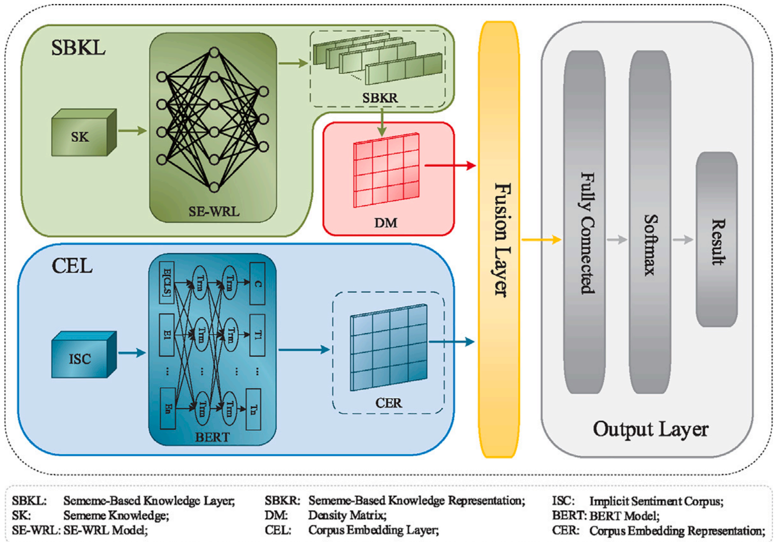

Fig. 3. The overall framework of the fused with sememe knowledge quantum-like Chinese implicit sentiment analysis model.

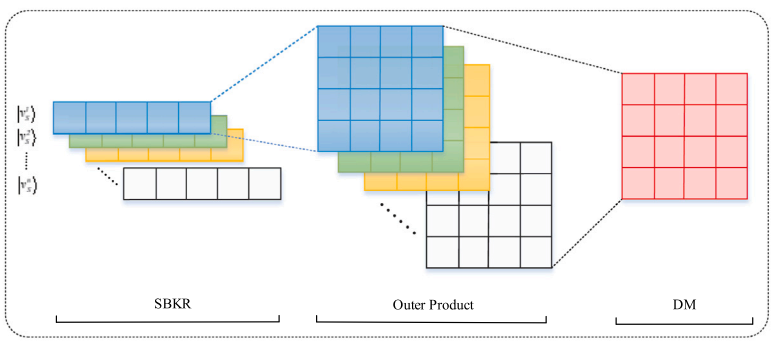

Fig. 4. Schematic diagram of the density matrix construction.

3.3.4. Fusion layer

The fusion layer is a fusion of the text representation vector M_C obtained in the corpus embedding layer (CEL) and the sememe-based density matrix constructed from the sememe-based knowledge layer (SBKL) into the final representation, as shown in Eqs. (6) and (7).

$$M_E = M_C \oplus M_D \tag{6}$$

$$M_E = concat\left(M_C, M_D\right) \tag{7}$$

where M_E is the fused representation result. In this paper, two ways of fusion, stitching and element summation operation are applied. $\oplus$ operation indicates the way of element summation and $concat(\cdot)$ indicates the way of stitching.

3.3.5. Output layer

As shown in Fig. 3, the output layer mainly consists of a fully connected layer and a softmax layer. The fully connected layer maps the fused representation M_E of the model to the feature vector v in the label space. The softmax function is also used for normalization, and the output at the fully connected layer is transformed into the result of sentiment classification, as shown in Eq. (8).

$$y = softmax\left(W^{*}v + b\right) \tag{8}$$

W is the parameter matrix of the fully connected layer, b is the bias, $softmax(\cdot)$ is the normalization function. $y \in \mathbb{R}^m$ is the sentiment analysis result of the model, where m is the number of sentiment categories contained in the text.

The fused with the sememe knowledge quantum-like Chinese implicit sentiment analysis model is shown in Algorithm 1.

Algorithm 1 Fused Sememe Knowledge Representation Learning

Input: $\boldsymbol{C}$: Chinese Implicit Sentiment Corpus
$\boldsymbol{S}$: Sememe Knowledge
Output: $\boldsymbol{y}$: Classifier Output Result

$V_{SBK} = SE-WEL(S)$
$\boldsymbol{M}_C = BERT(C)$
Def Fusion Sememe-Based Knowledge Embedding:
  initialize $\boldsymbol{M}_D$
  for $\boldsymbol{j}$ in V_{SBK} :
    $\boldsymbol{M}_S^j = \left|v_S^j\right\rangle\left\langle v_S^j\right|$
    $\boldsymbol{M}_D = \boldsymbol{M}_D + \boldsymbol{M}_S^j$
  end
end
$\boldsymbol{M}_E = Fusion(\boldsymbol{M}_C, \boldsymbol{M}_D)$
$y = output(\boldsymbol{M}_E)$
return y

4. Experiments and discussions

In this section, first, the experimental data set, evaluation index and experimental setup are introduced. Then, the ablation experiment, the comparison experiment and the generalization experiment are conducted to verify the validity, superiority and generalization of the method. The experimental results are also illustrated and analyzed.

Table 1
Distribution of experimental data sets.

	Neutral	Positive	Negative
Training	6989	3828	3957
Testing	2553	1232	1358

```
<Doc ID="5">
<Sentence ID="1"> 因为你是老太太 (Because you're an old lady.) </Sentence>
<Sentence ID="2" label="1"> 看完了，满满的回忆，很多那个时代的元素 (After reading, full of memories, many elements of that era.) </Sentence>
</Doc>
```

Fig. 5. Schematic diagram of the experimental data format.

4.1. Experimental data

The dataset is the Chinese implicit sentiment analysis dataset released in SMP2019, which comes from online social media platforms (e.g. Weibo, forums, etc.), and is filtered by sentiment dictionaries. After it is filtered by sentiment dictionaries, the textual data contents are all implicit sentiment expressions without explicit sentiment words. The distribution of the experimental data set is shown in Table 1.

The sentiment polarities in the dataset are classified as Positive, Negative and Neutral, corresponding to the labels 1-Positive, 2-Negative and 0-Neutral, respectively. The dataset is published in XML format, as shown in Fig. 5.

The <Doc></Doc> tag pair in Fig. 5 is a complete piece of text. The text is divided into sentences using the <Sentence></Sentence> tag pair, where the statements with "tag" are the target statements with sentiment polarity, and the "tag" indicates the sentiment tendency corresponding to the current sentence.

4.2. Evaluation indicators

As shown in Table 1, there is a certain data imbalance due to the high number of implicit sentiment expressions in the data set. In order to evaluate the model performance more comprehensively and objectively, Accuracy, Precision, Recall and F1 Score are used to evaluate the model. The expressions of each evaluation indicator are shown in Eqs. (9)–(12), respectively.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$P = \frac{TP}{TP + FP} \tag{10}$$

$$R = \frac{TP}{TP + FN} \tag{11}$$

$$F1 = 2\frac{PR}{P + R} \tag{12}$$

(True Positive) means the positive class is determined as positive, (False Positive) means the negative class is determined as positive, (False Negative) means the positive class is determined as negative, and (True Negative) means the negative class is determined as negative.

4.3. Implementation detail

The experimental environment of the text is as follows, OS: Windows 10 Professional (64-bit), processor: Intel Core i7-9700K CPU 2.6GH, graphics card: RTX2070super, RTX2080, RTX2080Ti, RAM: 16G, programming language: Python 3.6, development platform. JetBrains PyCharm Community 2019.1 x64.

The key hyperparameters of the optimal model are set as follows: epoch is set to 50, the maximum length of sentence is set to 110, batch_size is set to 24, and the learning rate is set to 5e−5.

Table 2
Ablation experiments of FSKQ model.

Model	Acc (%)	F1 (%)
BERT	80.2	79.3
FSK	80.8	84.2
FSKQ (concat)	81.7	85
FSKQ (add)	**82.6**	**85.8**

4.4. Experimental design and result analysis

In this section, first, the ablation experiments of the model are designed to verify the effectiveness of the ideas. Second, a comparison experiment with the current Chinese implicit sentiment analysis model with better performance is conducted to verify the superiority of the method. Finally, the method is performed in explicit sentiment analysis and event detection tasks to verify its generalization.

4.4.1. Results and analysis of ablation experiments

In order to verify the effectiveness of the fused with sememe knowledge quantum-like Chinese implicit sentiment analysis method (FSKQ), in this section, different levels of ablation experiments are conducted for the model. Due to the extremely strong representation capability of the pre-trained model, it has now become a standard in the field of natural language processing. The BERT pre-training model is also used for text representation, and sememe knowledge is (FSK) is directly fused. The idea of quantum language model is introduced to construct a sememe-based density matrix, and it is integrated into FSKQ, where FSKQ (concat) denotes the fusion of splicing and FSKQ (add) denotes the fusion of summation. The ablation experiments are shown in Table 2.

Table 2 shows that the model without sememe knowledge and density matrix ideas (i.e., BERT) performs poorly with an accuracy of 80.2% and an F1 score of 79.3%. Compared with the fused sememe knowledge model (FSK), the accuracy and F1 score decrease by 0.6% and 4.9%, respectively, which proves the effectiveness of FSK. As a non-separable semantic unit, sememe can be used as an important supplementary information for text representation, which can effectively enhance the quality of text representation and thus improve the model performance. The fused with sememe knowledge quantum-like Chinese implicit sentiment analysis model (FSKQ (add)) is the best model in the ablation experiment, with an accuracy of 82.6% and an F1 score of 85.8%. Compared with the model without fusing sememe knowledge and the idea of density matrix (BERT), its accuracy is improved by 2.4% and the F1 score is improved by about 6.5%. Compared with the directly fused sememe knowledge model (FSK), its accuracy is improved by 0.9% and the F1 score is improved by 1.4%. Compared with BERT, FSKQ (concat) achieves a 1.5% improvement in accuracy and a 5.7% improvement in F1 score. Compared with the FSK model, the FSKQ (concat) has a 0.9% improvement in accuracy and a 0.8% improvement in F1 score. Both the FSKQ (concat) and FSKQ (add) models introduce the idea of density matrix to construct a sememe-based density matrix, which can be regarded as a complete sememe knowledge system and it models the sememe knowledge representation-based global information. The model fused with the knowledge system performs better than the directly fused sememe knowledge model (FSK), and this experimental result verifies the effectiveness of the idea of density matrix.

The effectiveness of the sememe knowledge and the idea of density matrix is verified through ablation experiments. In the next comparison experiments, the best-performing model in the ablation experiments is compared with a variety of Chinese implicit sentiment analysis methods to verify the superiority of the method.

Table 3
Comparative experiments between FSKQ and baseline model.

Model	Acc (%)	F1 (%)
TF-IDF	72	–
CNN_text	71.6	–
RNN_text	72.1	–
WC_region	50.8	–
GRU	–	69.1
LSTM	–	70.7
BiLSTM+multi-att	–	73
Transformer	–	72.6
BiLSTM+Attention	78	–
DRNN	76	–
BiLSTM+MO (Wei et al., 2020)	–	73.7
BERT	80.2	79.3
Hybrid neural network	–	80
ERNIE	82	81
OpenClap	82	82
STACKINGENSEMBLE (No. 1)	**85.2**	–
LGBM (No. 2)	84.9	83.2
FSKQ	82.6	**85.8**

4.4.2. Comparative experimental results and analysis

In order to verify the superiority of the fused with sememe knowledge quantum-like Chinese implicit sentiment analysis method (FSKQ), the model is compared with models, which better performance, are widely used in related fields for experiments. Here, the FSKQ (add) model that works best in the ablation experiments is selected, and the model is denoted as FSKQ. The comparison experiments include the classical statistical machine learning based TF-IDF, the basic deep learning based models CNN_text, RNN_text, etc., the attention mechanism based BiLSTM+Attention, Transformer, etc., as well as a variety of pre-training models BERT, ERNIE, etc. with excellent performance, and it is also compared with the top two models in the evaluation competition (the results of the models were publicly presented at the evaluation conference). Some experimental results are obtained from the public presentations by the winners. The comparison experiments are shown in Table 3.

The comparative experimental results in Table 3 show that the accuracy of the traditional TF-IDF is 72%. The accuracy of the classical basic deep learning based models such as CNN_text and RNN_text is similar to that of the TF-IDF. The accuracy of WC_region model is lower, with only 50.8%. RNN-based methods such as LSTM, GRU, and BiLSTM are also used for the Chinese implicit sentiment analysis task, and the effect is improved in score compared with the above methods, but they have an average performance, and their accuracy and F1 scores do not exceed 80%. Even the F1 score of the popular Transformer model is only 72.6%. The performance of these classical models also illustrates the difficulty of working on Chinese implicit sentiment analysis from the side. The pre-trained model BERT model released by Google further improves the work of implicit sentiment analysis to a new level, with its accuracy and F1 reaching 80.2% and 79.3%, respectively. The ERNIE model goes further than the BERT model, with an accuracy and F1 improvement of 1.8% and 1.7%, respectively. OpenClap model released by Tsinghua University and ERNIE perform very close to each other, and its F1 score is only 1% higher than that of ERNIE. The accuracy of SE and LGBM models, the top two models in the SMP2019 evaluation competition, is 85.2% and 84.9%, respectively, and the F1 score of the second-ranked LGBM model is 83.2%. The accuracy of the proposed FSKQ model is 2.6% lower than that of SE model, and the F1score is 2.6% higher than that of the optimal model. Due to the large number of neutral sentiment expressions in the experimental dataset, there is a certain imbalance in the data distribution, and the F1 score can evaluate the model more comprehensively and objectively compared to the accuracy.

The results of the comparison experiments prove the effectiveness and superiority of the method. Next, generalization experiments are conducted to apply the sememe-based idea of density matrix to other natural language processing tasks to further demonstrate the strong portability and generalization of the idea in this paper.

4.4.3. Generalization experiment results and analysis

In order to verify the generalization of the proposed method of FSKQ, the method of this paper is applied to the existing models in the fields of explicit sentiment analysis and event detection, and the comparison experiments are conducted on Twitter, Lap14, Rest14/15/16 and ACE2005 datasets with the models in the corresponding fields, and the generalization experiments are shown in Tables 4 and 5.

As shown in Table 4, the method of this paper is applied in the field of explicit sentiment analysis to construct a sememe-based density matrix and it is integrated into the model Aspect specific Graph Convolutional Network (ASGCN) (Zhang, Li, & Song, 2019). Summation and splicing are tried here, corresponding to the ASGCN ($FSKQ\_add$) and ASGCN ($FSKQ\_concat$) models in the table, respectively. The above two models are compared with SVM (Kiritchenko, Zhu, Cherry, & Mohammad, 2014), LSTM (Tang, Qin, Feng, & Liu, 2016), MemNet (Tang, Qin, & Liu, 2016), AOA (Huang, Ou, & Carley, 2018), IAN (Ma, Li, Zhang, & Wang, 2017), TNet-LF (Li, Bing, Lam, & Shi, 2018), and the original ASGCN model in experiment. The experimental data include Twitter (Dong et al., 2014), Lap14, Rest14, Rest15, and Rest16. The latter four datasets are from SemEval 2014 task 4 (Pontiki Maria & John, 2014), SemEval 2015 task 12 (Pontiki Maria & Papageorgiou, 2015), and SemEval 2016 task 5 (Pontiki et al., 2016), respectively. In the Twitter dataset, the ASGCN ($FSKQ\_concat$) and TNet-LF models are equal in terms of accuracy, but the F1 score of ASGCN ($FSKQ\_concat$) decreased by 0.28%. In the Lap14 dataset, the ASGCN ($FSKQ\_add$) model performs best, with the accuracy of 75.71% and the F1 score of 71.34%. In the Rest14 dataset, the model also achieves the optimal performance with the accuracy of 81.43% and the F1 score of 73.19%. In the Rest15 dataset, its accuracy is the same as the original ASGCN model with 79.89%, and the F1 score is the best, with 65.03%. In the Rest16 dataset, the original ASGCN model has the highest accuracy of 88.99%, but the ASGCN ($FSKQ\_concat$) model tops the list with an F1 score of 71.05%. Relative to the original ASGCN model, the ASGCN model with the ideas in this paper achieves the best performance in both evaluation indicators of Twitter, Lap14, Rest14, Rest15, and the F1 score of Rest16. Compared with other methods in this field, the ASGCN model using the ideas of this paper improves its performance on all five major datasets. In addition, since there are more event-centered sentiment expressions in Chinese implicit sentiment analysis, the application of the ideas in the event detection is also explored, as shown in Table 5.

Table 5 shows the fused sememe knowledge representation based density matrix is integrated into the Nugget Proposal Network (NPN) (Lin, Lu, Han, & Sun, 2018) model by using summation and splicing, corresponding to NPN ($FSKQ\_add$) and NPN ($FSKQ\_concat$) in the table, respectively. The above two models are compared with the FBRNN (Ghaeini, Fern, Huang, & Tadepalli, 2016), DMCNN (Chen, Xu, Liu, Zeng, & Zhao, 2015), C-BiLSTM (Zeng, Yang, Feng, Wang, & Zhao, 2016), HNN (Han et al., 2017), and Rich-C (Chen & Ng, 2012) models in the ACE2005 dataset in experiments. The experimental results show that the F1 scores of NPN($FSKQ\_add$) on the trigger identification and the trigger classification are 68.2% and 64.2%, respectively. The F1 scores of NPN($FSKQ\_concat$) on these two tasks are 67.6% and 63.8%, respectively, and the former performs better. Compared with the original NPN model, NPN ($FSKQ\_add$) improves the F1 score by 1.1% in the trigger identification and by 1% in the trigger classification. Compared with other models in this field, the performance of NPN ($FSKQ\_add$) is equal to that of HNN in the trigger identification. In the trigger classification task, compared with the Rich-C model with the best performance, NPN ($FSKQ\_add$) improves by 1% in the event detection task, and it achieves the best performance.

Table 4
Performance of FSKQ in explicit sentiment analysis tasks.

	Twitter		Lap14		Rest14		Rest15		Rest16	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
SVM	63.4	63.3	70.49	N/A	80.16	N/A	N/A	N/A	N/A	N/A
LSTM	69.56	67.7	69.28	63.09	78.13	67.47	77.37	55.17	86.8	63.88
MemNet	71.48	69.9	70.64	65.17	79.61	69.64	77.31	58.28	85.44	65.99
AOA	72.3	70.2	72.62	67.52	79.97	70.42	78.18	57.02	87.5	66.21
IAN	72.5	70.81	72.05	67.38	79.26	70.09	78.54	52.65	84.74	55.21
TNet-LF	**72.98**	**71.43**	74.61	70.14	80.42	71.03	78.47	59.47	89.07	70.43
ASGCN	72.15	70.4	75.55	71.05	80.77	72.02	**79.89**	61.89	**88.99**	67.48
ASGCN (FSKQ_add)	72.35	70.72	**75.71**	**71.34**	**81.43**	**73.19**	**79.89**	**65.03**	88.58	67.05
ASGCN (FSKQ_concat)	**72.98**	71.15	74.82	70.67	81.25	72.86	79.83	63.04	88.69	**71.05**

Table 5
Performance of FSKQ in event detection tasks.

	Trigger identification			Trigger classification		
	P	R	F1	P	R	F1
FBRNN (char)	61.3	45.6	52.3	57.5	42.8	49.1
FBRNN (word)	64.1	63.7	63.9	59.9	59.6	59.7
DMCNN (char)	60.1	61.6	60.9	57.1	58.5	57.1
DMCNN (word)	66.6	63.6	65.1	61.6	58.8	60.2
C-BiLSTM	65.6	66.7	66.1	60	60.9	60.4
HNN	74.2	63.1	**68.2**	77.1	53.1	63
Rich-C	62.2	71.9	66.7	58.9	68.1	63.2
NPN	71.5	63.2	67.1	67.3	59.6	63.2
NPN (FSKQ_add)	75.5	62.2	**68.2**	71	58.5	**64.2**
NPN (general_concat)	73.5	62.6	**67.6**	69.3	59.1	**63.8**

The generalization experimental results in this section show that FSKQ performs better in the task of explicit sentiment analysis and event detection compared to the original model without using the method in this paper and other models in this field, and the experimental effect is improved, further proving the effectiveness, portability and generalization of the method.

5. Conclusion

To address the problems of incomplete external knowledge system, poor generalization and low quality of text representation in Chinese implicit sentiment analysis methods, a new method is proposed: fused with sememe knowledge quantum-like Chinese implicit sentiment analysis method. However, there are still many challenges in the field of sentiment analysis: (1) The evolution of sentiment: emotional expressions may change with the context and time. Therefore, researchers can accurately identify subjects and roles in sentences and analyze the evolution process of sentiment based on context and temporal information. (2) Multi-modal sentiment analysis: in real-world scenarios, emotions are often expressed together with images, sounds and other modalities. Therefore, for implicit sentiment analysis tasks in Chinese, effective methods for fusing multi-modal data can be explored to improve the accuracy and robustness of implicit sentiment analysis. (3) Data scarcity: currently, Chinese sentiment analysis datasets are scarce and small in scale, with low-quality annotations. in addition to increasing the scale of dataset construction, transfer learning can also be used to leverage sentiment analysis data in other languages to improve the effectiveness of Chinese implicit sentiment analysis.

CRediT authorship contribution statement

Hongbin Wang: Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Minghui Hou:** Conceptualization, Software, Data curation, Formal analysis, Validation, Writing – original draft.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work; there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Data availability

Data will be made available on request.

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