Neural Computing and Applications
https://doi.org/10.1007/s00521-022-07028-4

ORIGINAL ARTICLE

SKG-Learning: a deep learning model for sentiment knowledge graph construction in social networks

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Received: 18 March 2021 / Accepted: 30 January 2022

Abstract

Traditional sentiment analysis methods pay little attention to the inseparable relations between evaluation words and evaluation aspects, and the relations between evaluation words and topics. There have been many studies of knowledge graph (KG), which can effectively store and manage massive amounts of information and is suitable to associate emotion words with evaluation aspects and topics. This study proposes SKG-Learning based on a deep learning model to construct a sentiment knowledge graph (SKG) for sentiment analysis. Entity and relation are the cornerstones of SKG; thus, the task of SKG-Learning is divided into named entity recognition and relation extraction. We propose a bidirectional long short-term memory model (Bi-LSTM) with background knowledge embedding and co-extraction of features (BBC-LSTM) to extract entities. BBC-LSTM completes the embedding of background knowledge such as topic and emotion information and uses three-dimensional tensors to co-extract the deep features of aspect entities and sentiment entities. It solves the problems that it is difficult to recognize entities from insufficient context, and traditional models usually neglect the relevance between sentiment entities and aspect entities. A relation extraction model based on an encoder–decoder model (ED-Learning) is proposed to extract and classify the relation between sentiment and aspect entity, that is, the emotional tendency of sentiment entity toward aspect entity. Experiments show that the proposed methods can more efficiently extract entities and relations from social network texts. We confirm the validity of an SKG constructed by the SKG-Learning model in an emotional analysis task.

Keywords Sentiment analysis · Sentiment knowledge graph · Named entity recognition · Relation extraction

1 Introduction

With the global sweep of social networks, people are accustomed to leaving their opinions on different topics such as politics, economics, and culture on the Internet. In the era of big data, mining the emotional tendency of comments through artificial intelligence technology is helpful for grasping public sentiment trends, opinions, and requirements [1]. Government agencies often use sentiment analysis to understand social trends to establish good images while commercial companies conduct precision marketing. Sentiment analysis, also known as opinion

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Published online: 25 February 2022

mining, involves natural language processing, machine learning, data mining, information retrieval, and other research fields. It mainly aims to automatically uncover the underlying attitudes that people hold toward entities.

In recent research, there are three kinds of text sentiment analysis methods: (1) Methods based on sentiment lexicons achieve sentiment analysis by constructing emotion dictionaries and other degree adverb dictionaries [2, 3]. Although the lexicon-based methods do not need the labeled text, they raise the problems of poor generalization and are inapplicable to real-time scenarios. (2) Methods based on machine learning construct a text classifier by extracting and learning sentence features [4, 5]. However, classification results are highly dependent on the feature structures. (3) Methods based on deep learning can learn low-dimensional features of texts without feature engineering [6, 7]. Compared with traditional methods, the accuracy of methods based on deep learning has been greatly improved. Nevertheless, the existing models still have some disadvantages. Firstly, ignoring lots of external knowledge and failing to consider that evaluation words may express different emotional information in different contexts. In this paper, the evaluation words are emotional words such as users' views and preferences on certain aspects of goods while emotional information refers to the personal views and preferences disclosed by users in the evaluation processes. Besides, these methods focus on extracting the emotion polarities rather than mining more fine-grained emotions which is particularly important for detailed emotional analysis.

Actually, in specific sentiment analysis scenarios, it is more practical to consider the target aspects described by the emotional words. For example, suppose there're comments about the phone: "The size of the phone is so big and it is hard to carry, but it has plenty of memory." and "There is a big discount on mobile phones, it was a really good buy." The word "big" is used to describe "size" and "discount," respectively. However, it conveys two opposite attitudes. Specifically, it can be inferred that customers may be surprised by the big discount, and anger with the phone size. In different topics, evaluation words also present different emotions. As another example, the sentiment entity "warm" in the restaurant topic belongs to the "happiness" category, while in the laptop topic, it conveys "anger." This idea is recognized by experts. For example, Guo proposed that using the combination of evaluation aspect and emotion polarity can better perform sentiment analysis [8].

The rapidly developing knowledge graph (KG) model is effective at organizing and storing massive information (big data) [9]. It is also used to associate evaluation words with evaluation objects and topics, which can help text semantic analysis [10]. More importantly, the structure of KG facilitates the analysis and reasoning of knowledge. Therefore, this paper proposes the SKG-Learning model to construct a sentiment knowledge graph (SKG) to perform sentiment analysis. The key to constructing an SKG lies in named entity recognition (NER) and relation extraction (RE). The results of NER are entities, in which aspect entities are often objects while sentiment entities are used for evaluating the objects. Sentiment entities tend to be adjectives in this paper. RE based on the results of NER is aimed at extracting the relations between entities, and we mainly consider the relations between the aspect and sentiment entities.

NER methods are based on either rules and dictionaries, machine learning, or deep learning, where the last has been the mainstream method in recent years [11]. However, the extracted entities are those such as people, locations, and organizations, which are not consistent with the part of speech and word meaning of sentiment entities. More importantly, they do not consider the close relations between sentiment entities and aspect entities. Also, current methods rarely focus on the more detailed classification of emotions, by which can obtain more fine-grained attitudes of users.

As another vital step of SKG-Learning, RE is also a kind of classification task [12]. RE-based deep learning can be categorized as either supervised, remote supervised, or unsupervised. Supervised learning has the highest accuracy and is more suitable for extracting relations between entities in a specific field. Therefore, we reference supervised learning methods. Joint extraction of entities and relations currently receives much attention [13]. However, they pay little attention to the classification of emotions for the aspect entities and do not notice the emotional tendencies of sentiment entities toward different aspects are distinct.

Based on the discussion above, NER methods based on deep learning perform better than other methods. However, these methods are not effective in special entity recognition and need to be adjusted and improved. In addition, RE methods based on joint extraction neglect the emotion classification of aspect entities, thus they cannot provide an accurate classification of emotional tendencies of different sentiment entities toward different aspect entities. To address the above problems, we propose a bidirectional long short-term memory model (Bi-LSTM) with background knowledge embedding and co-extraction of features (BBC-LSTM) and a relation extraction model based on an encoder–decoder model (ED-Learning) to extract entities and relations. Our main contributions are the following:

(1) In order to provide better help for emotion analysis, we propose a new SKG framework that connects the evaluation words and objects, and the SKG-Learning model for constructing SKG.

(2) We use the BERT language model, which contains a multilayer transformer that extracts a more global word representation from context, to embed entity with the topic information. The external knowledge base SenticNet4 is also introduced to embed emotional information in the model, enhancing its classification performance.
(3) We consider the relevance between entities and use three-dimensional tensors to jointly extract the deep features of aspect entities and sentiment entities, thereby improving the classification quality and reducing identification error.
(4) Encoder–decoder with Bi-LSTM and an attention mechanism simultaneously extract and classify relations of multiple entity pairs in a sentence.

The rest of the paper is organized as follows: Section 2 introduces the KG and the key technologies used to construct it. Section 3 presents the framework of SKG and SKG-Learning, which is proposed to construct it, and then formalizes the problem. Section 4 describes the BBC-LSTM and ED-Learning model of SKG-Learning. Section 5 describes our experiments and results. Section 6 verifies the effectiveness of SKG in sentiment analysis. We discuss the performance of parameter adjustment methods in Sect. 7. Conclusions and plans for future work are presented in Sect. 8.

2 Related work

We introduce two kinds of knowledge graphs and analyze research on sentiment analysis based on the KG. We then describe the key technologies for constructing a KG and their current research status.

2.1 Knowledge graph(KG)

The KG originated from various structured knowledge bases, such as the language knowledge base Wordnet [14] and world knowledge base Freebase [15]. Google proposed the concept of the KG in 2012 to enhance search engines. The KG follows the resource description framework (RDF) technical standard [16], which uses the form of triples (head entity, relation, and tail entity) to represent knowledge. The KG connects various information (i.e., big data) to form a relational network, which is a practical method to organize knowledge. The KG can be classified as general KG and domain KG. General KG includes Freebase, YAGO, DBpedia, and Google KG. Research on constructing domain KG has produced variations such as cybersecurity KG [17], IOT KG [18], and Uyghur KG [19].

The network structure of KG facilitates analysis and reasoning of knowledge, so it can better perform sentiment analysis on social network texts. Research on sentiment analysis based on KG includes unsupervised word-level sentiment analysis, as proposed by Mireille Fares et al. [10]. Jie Zhou studied graph convolutional network grammar and knowledge modeling for sentiment classification based on KG [20]. However, these studies have not given structured definitions of SKG. More importantly, the deep connections between sentiment entities and aspect entities are not fully considered, leading to incorrect results in entity recognition.

2.2 Named entity recognition

NER is one of the core tasks of SKG-Learning. Its main work is to identify the positions of target entities and classify entities based on their attribute categories. NER plays an important role in the construction of a knowledge base [21], question and answer system [22], information retrieval [23], and machine translation [24]. NER research has the categories of methods based on rules and dictionaries, machine learning, and deep learning.

2.2.1 NER methods based on machine learning

Methods based on machine learning generally require manual feature operations combined with statistical algorithms such as maximum entropy (ME) models, Markov models, and the conditional random field (CRF). In recent years, traditional machine learning methods have been used and improved. Kanimozhi used CRF for NER in the biomedical field [25]. Syachrul used an improved hidden Markov model to recognize the characters in the Indonesian Qur'an [26]. Traditional machine learning and deep learning algorithms are often used together.

2.2.2 NER methods based on deep learning

Since Guillaume et al. first applied the combined model of bidirectional long short-term memory (Bi-LSTM) with CRF to carry out NER tasks, this method has been verified by many studies [27], and NER based on deep learning has become the mainstream method. Chiu et al. used hybrid neural networks to automatically detect word- and character-level features [28]. With the further development of deep learning, multi-task learning, transfer learning, and reinforcement learning have also been used. For example, Wang et al. proposed a multi-task learning framework to jointly train bilingual word embeddings and the downstream NER task [29].

While the above three methods play an important role in NER, they have some problems.

(1) Methods based on rules and dictionaries rely too much on rules and dictionaries. On the one hand, building rules is time-consuming and labor-intensive. On the other hand, the portability of those methods is poor. In fact, social network texts do not completely follow a strict syntactic structure.
(2) Methods based on machine learning alleviate the problems of rule-based and dictionary-based methods to a certain extent. However, linear mapping cannot learn emotional semantic features well and requires lots of feature engineering work.
(3) Methods based on deep learning are more automated than traditional methods and can mine the deep semantics of text. However, they are incompletely suitable for extracting emotional entities different from general entities, nor can they give the more detailed entity classification needed in this study. More importantly, sentiment and aspect entities are identified separately, ignoring the close connection between them.

2.3 Relation extraction

Another core task of SKG-Learning, RE aims to extract relations between entities and classify them as positive or negative, based on the semantic information of a sentence. RE methods based on deep learning can be categorized as either unsupervised, remote supervised, or supervised. (1) Unsupervised methods. Unsupervised relation extraction was first proposed by Hasegawa et al. at the ACL conference in 2004 [30]. A pulse-coupled neural network (PCNN) combined with multiple examples was proposed by Zeng as one of the main operations in an RE task [31]. (2) Remote supervised method. Sun et al. used reinforcement learning to solve an RE problem [32]. Qu et al. enhanced the performance of the model by using a word-level attention mechanism [33]. (3) Supervised method. Sun et al. proposed a supervised hierarchical recurrent convolutional neural network to extract relations [34]. Li Pengfei et al. proposed a Knowledge-oriented Convolutional Neural Network (K-CNN) for causal relation extraction and got a good outcome [35].

Unsupervised RE methods are less dependent on the manual annotation of the corpus and adaptable in the multi-domain. However, the obtained relations do not have semantic information and are hard to be regularized. Remote supervised learning methods generally can save much manpower and material resources and have little dependence on manually labeled data. However, such methods have difficulty avoiding the excessive noise caused by false labels. Supervised learning methods have the highest accuracy and are capable of extracting relations between entities in a specific field. Therefore, we adopt supervised learning for the RE method in this paper.

The joint extraction of relations and entities is another popular research direction. These methods are based on either multi-task learning or sequence tagging, which consider the connection between NER and RE. Katiyar extracted entities and relations using Bi-LSTM combined with an attention mechanism and was first to apply sequence tagging in RE [36]. However, few studies focus on the emotional classifications of aspect entities, which are needed to classify the polarities of relations for constructing the proposed SKG.

3 Model overview

We introduce SKG and its related definitions, propose the SKG-Learning model to construct SKG, and formalize the problem.

3.1 Related definitions

KG describes knowledge using interconnected nodes and edges, where nodes represent entities, and edges represent the relations between entities. Different from general knowledge graphs, entities are divided into sentiment and aspect entities in SKG. Sentiment entities are usually adjectives used to evaluate aspect entities while relations reflect the emotional tendencies (positive or negative) that sentiment entities toward aspect entities or ownerships between entities and their attribute category. We provide some relevant definitions.

Definition 1 (Sentiment Knowledge Graph (SKG)) Formalize the SKG as a graph $G = (V, R, L)$, where $V = \{v_1, v_2 \ldots v_n\}$ represents the set of nodes that may belong to the set of entity nodes E or the set of attribute nodes C, $V = (E \cup C)$, and $E \cap C = \emptyset$. $R = \{r_{11}, r_{12}, \ldots, r_{1p}, \ldots, r_{pq}\}$ is the set of edges, and $L = \{l_{11}, l_{12}, \ldots, l_{1p}, \ldots, l_{pq}\}$ is a set of triples.

Definition 2 (Entity) In the SKG, entities can be divided into two types, aspect entities set E^a and sentiment entities set E^s, and $E = (E^a \cup E^s)$. For example, entities are expressed as $E^a = \{$ "chicken," "salads," "milk" $\}$ and $E^s = \{$ "delicious," "mess," "reasonable" $\}$ in the restaurant topic.

Definition 3 (Entity attribute) There are two types of entity attributes, attributes set C^s of sentiment entities E^s and attributes set C^a of aspect entities E^a, and $C = (C^a \cup C^s)$. According to the emotion theory of psychologists Ekman and Friesen, sentiment attributes are divided into six categories. $C^s = \{$ "anger," "fear," "disgust," "happiness," "sadness," "surprise," } [37]. Aspect attributes of aspect entities may differ by topic. For example, in the restaurant topic, attributes $C^a = \{$ "food," "price," "ambience," " service" " anecdotes/miscellaneous" $\}$.

Definition 4 (Relation) There are two kinds of relations in SKG. Relations between sentiment entities and aspect entities: $R^{sa} = \left(R_p^{sa} \cup R_n^{sa}\right)$, in which r_p^{sa} represents positive and r_n^{sa} represents negative, respectively. Ownership between an entity and its attribute category: $R^{ec} = (R^{ac} \cup R^{sc})$. For example, when "chicken" is described by "delicious," the emotional polarity, that is, the relation between sentiment entity and aspect entity, is positive, which is expressed as "delicious" $\stackrel{r_p^{sa}}{\rightarrow}$ "chicken." The attribute category of "chicken" is "food," and the attribute category of "delicious" is "happiness," expressed as "chicken" $\stackrel{r^{ac}}{\rightarrow}$ "food" and "delicious" $\stackrel{r_p^{sc}}{\rightarrow}$ "piness."

Definition 5 (Sentiment Knowledge Triples) In the SKG, triplets L are divided into the triplets of sentiment entities and aspect entities, and the triplets of entities and their attribute category. Triplet can be formally represented as $l^{sa} = < e^a, r^{sa}, e^s >$, $l^{sc|ac} = < e^s, r^{sc|ac}, c^s >$. For example, there is a positive relation between "chicken" and "delicious," and the triplet between sentiment entity and aspect entity is expressed as $l = <$ "chicken," " r_p^{sa}," "delicious" $>$. The attribute category of "delicious" is "happiness," and the attribute category of "chicken" is "food." Which are, respectively, expressed as $<$ "delicious," "r^{sc}, " "happiness" $>$ and $<$ "chicken," "r^{ac}," "food" $>$.

In this paper, the entity extraction and the entity attribute's classification will be modeled as a sequence labeling task. Based on the results of the extraction of entity and entity attribute, relation between aspect entity and sentiment entity, and sentiment knowledge triple will be extracted by the RE method proposed in Sect. 4.2, and the SKG will be constructed by the SKG-Learning.

The definition of SKG is shown in Fig. 1. There are two types of entities in an SKG; sentiment entities are represented by yellow nodes while aspect entities are by green nodes. The directed edge sent out from a sentiment entity points to the aspect entity it describes. In the SKG, an aspect entity, sentiment entity, and the relation between them constitute a sentiment knowledge triple, which is the unit of an SKG. In order to accurately analyze the sentiment information, we classify sentiment entities and aspect entities based on their attribute categories. In Fig. 1, orange nodes represent the attribute categories that aspect entities belong to while blue nodes represent the attribute categories that sentiment entities belong to. Entities are connected with their attribute categories by dotted edges. A sentiment entity may express a different mood, depending on the aspect it describes. Therefore, sentiment entities have different attributes in an SKG, as shown in Fig. 1. For example, when e^s "tough" is used to describe e^a "character," the emotion polarity of the commenter is positive, and the attribute category of "tough" is "happiness." But when "tough" is used for "situation," the emotion polarity is negative, and "tough" belongs to the attribute category "sadness."

3.2 Framework of SKG-Learning

The SKG proposed in this paper is a special knowledge graph. The NER and RE are the footstones in the construction of traditional knowledge graphs. Based on the construction of traditional knowledge graphs, we propose SKG-Learning in this paper. The framework of SKG-Learning, as shown in Fig. 2, has four main parts.

(1) Jointly recognizing sentiment and aspect entities from given texts. Initially, external knowledge and topic information are spliced to get word vectors embedded with background knowledge. Then Bi-LSTM is used to extract the shallow semantic features. Considering the close association between sentiment and aspect entities, a three-dimensional tensor is used to co-extract their deep features. Then Bi-LSTM is used again to extract deep context features. Word vectors are labeled by CRF to obtain the entity attribute category and entity type corresponding to each word.

(2) Labeling the sentiment polarities of entities. Based on the results of NER, the boundaries of entities are labeled. CNN and Bi-LSTM are used to extract the sentiment features of entities in the encoder. An attention mechanism is introduced to the encoder–decoder model to extract sentiment features at the entity level. Then the decoder converts the vectors to a sequence of labels, and the label corresponding to each word is obtained.

(3) Extracting the relations between sentiment entities and aspect entities, and sentiment knowledge triples. Based on the proximity principle, entities labeled A and S and whose emotional polarities are consistent with each other are divided into an entity pair, and the emotional polarity of entity pair is the relation between entities. Then an entity pair and relation between entities compose a sentiment knowledge triple.

(4) Constructing an SKG based on entities and their attribute categories, as well as sentiment knowledge triples. An SKG should be constructed based on its

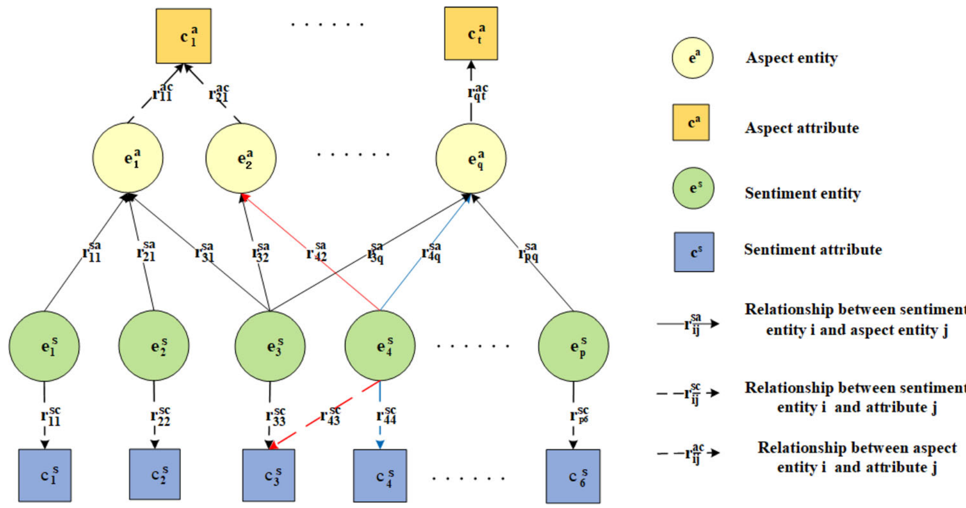


Fig. 1 SKG

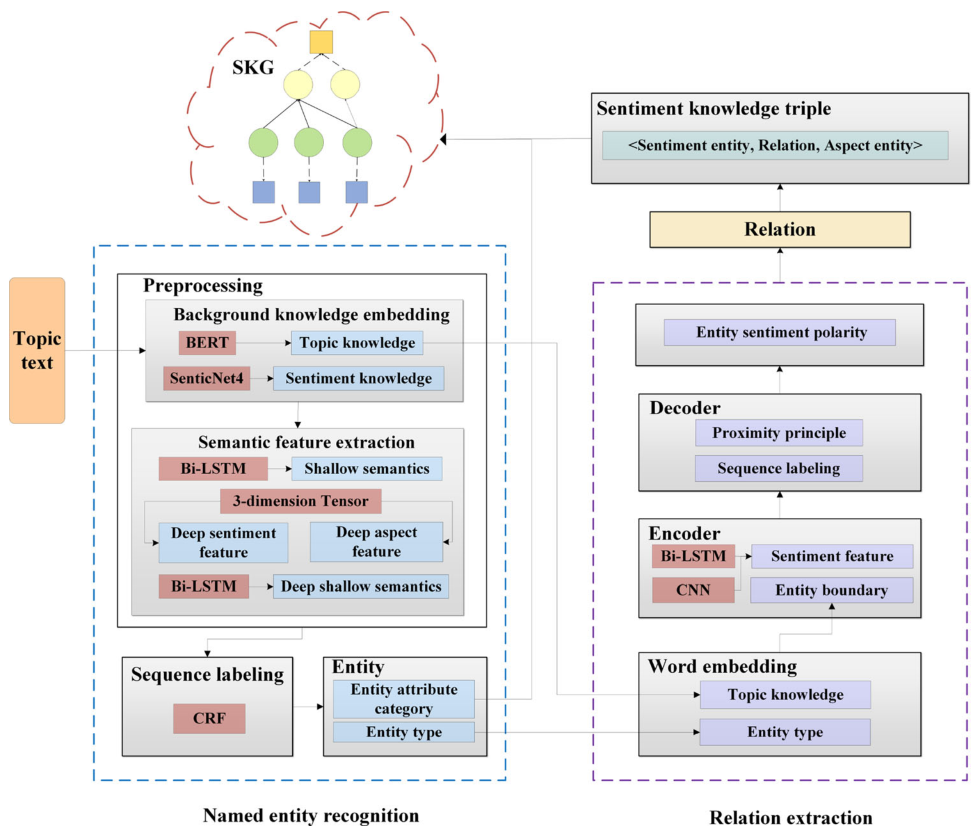


Fig. 2 Framework of SKG-Learning

specific topic, since the feature distribution of entities in different topics may have a large deviation.

At present, there is no reference research on the construction of the sentiment knowledge graph. As a special knowledge graph, the composition of SKG includes entities and relations. The construction of SKG proposed in this paper mainly focuses on extracting entities and relations, and does not consider other parts in the construction of traditional knowledge graphs.

4 Proposed methods

We present SKG-Learning model to construct SKG, where the core work of SKG-Learning includes NER and RE. We next describe the proposed methods, BBC-LSTM for NER and ED-Learning for RE.

4.1 Bi-LSTM with background knowledge embedding and co-extraction of features (BBC-LSTM)

Given a piece of natural language text, predicting the category of each word is the key issue of the BBC-LSTM model. BBC-LSTM is modeled as a sequence labeling task with a single input and double output. It separates the extraction of sentiment features from aspect features, since sentiment features are quite different from general semantic features. However, considering the correlation between entities, we jointly extract deep features of these two kinds of entities.

(1) Suppose $S = \{w_1, w_2, \ldots, w_n\}$ is the word vector of input sentence from social network texts.
(2) $Y^l = \{y_1^l, y_2^l, \ldots, y_t^l\}$ represents the output of BBC-LSTM, where $Y^l = Y^s \cup Y^a$, and Y^s, and Y^a are the prediction results of sentiment entities and aspect entities, respectively.
(3) The true classifications of sentiment and aspect entities are $X^s = \{x_1^s, x_2^s, \ldots, x_t^s\}$ and $X^a = \{x_1^a, x_2^a, \ldots, x_t^a\}$, respectively.
(4) The model's goal is to minimize the gap between Y^s and X^s, and between Y^a and X^a, by deep learning training.

Figure 3 shows the overall framework of BBC-LSTM. The target sentence, "I think the meatball parm is good," is converted to $S = \{w_1, w_2, \ldots, w_n\}$. The sentence is marked with sentiment entity labels and aspect entity labels after using BBC-LSTM to extract entities. The aspect entity labels in this example are "O," "O," "O," "B-fd," "I-fd," "O," and "O," and the sentiment entity labels are "O," "O," "O," "O," "O," "O," and "B-hp." According to the labels, we can judge that "meatball parm" belongs to the "food" category of the aspect entity, and "good" belongs to the "happiness" category of the sentiment entity. We next discuss the various layers of the model.

4.1.1 Embedding layer

In order to obtain word embedding with bountiful semantics, BERT and SenticNet4 are introduced to embed word vectors with related topic knowledge and sentiment semantics. As shown in Figs. 1 and 4, the yellow vector e^t represents the topic embedding learned by the BERT model, while the green, one-dimensional e^s represents the sentiment embedding from external knowledge base SenticNet4. These two vectors are spliced by the $\oplus$ operation to obtain an embedding vector e containing rich background knowledge. The formal expression is

$$e = e^t \oplus e^s \tag{1}$$

Next, we elaborate on how to obtain the word vectors e^t containing topic information and e^s containing emotional information.

(1) Training of word vector e^t

There is a close relation between entity and topic, and the meaning of entity may be different in different topics. BERT is a recently developed language representation model. It trains a deep bidirectional representation of a large unlabeled corpus using stacked Transformer encoders. Then, the representation is fine-tuned with an additional output layer for downstream NLP tasks. Therefore, we use BERT to get a more global word representation for embedding entity with topic information. Compared to language models such as word2vec, BERT can give a word representation with richer language features and greater generalization capabilities.

To capture the features and learn the parameters of each transformer layer of BERT in a specific topic environment, we use the same data as the target topic as the training data on the BERT model. Through much repeated training, multiple bidirectional transformer layers for a specific topic are obtained. After the dataset is input to the BERT model, the corresponding topic embedding e^t can be obtained.

(2) Extraction of word vector e^s

Indeed, it is difficult to classify entities in an insufficient context relying solely on the semantics extracted from the context. Therefore, the sentiment knowledge base SenticNet4 is introduced to provide emotion information to simulate the situation in which the human brain stores knowledge.

SenticNet4 containing about 50,000 entries providing the semantics, emotion classification, and polarity of words [38]. It provides words with sentiment information including the four dimensions of "pleasantness," "attention," "sensitivity," and "aptitude." For example, the sentiment information of the word "rude" is pleasantness = − 0.74, attention = 0, sensitivity = 0.85, aptitude = − 0.91. The value range of each dimension is (− 1,1) and is not directly used to construct a sentiment embedding e^s, since it does not meet the range of e^t. Therefore, before splicing, the value obtained from SenticNet4 is processed as follows to make it correspond to the standard interval [a,b]:

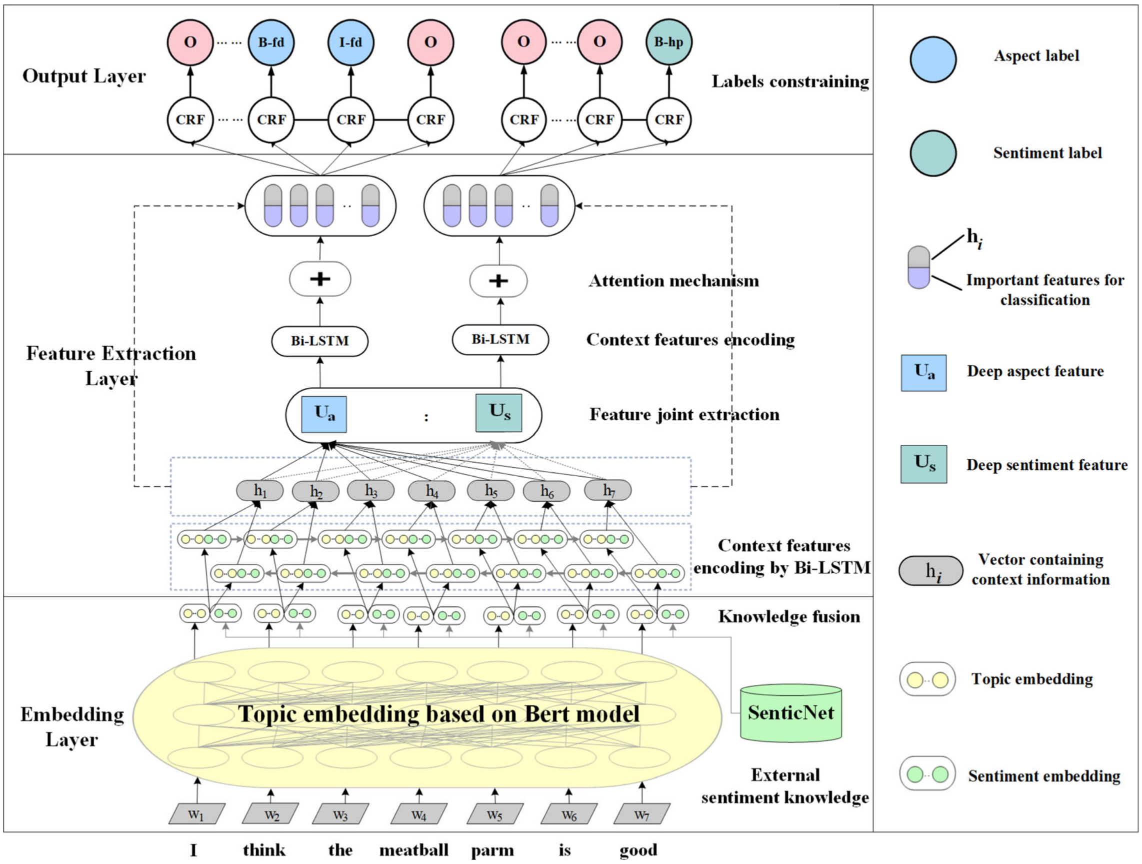


Fig. 3 BBC-LSTM model for entity recognition

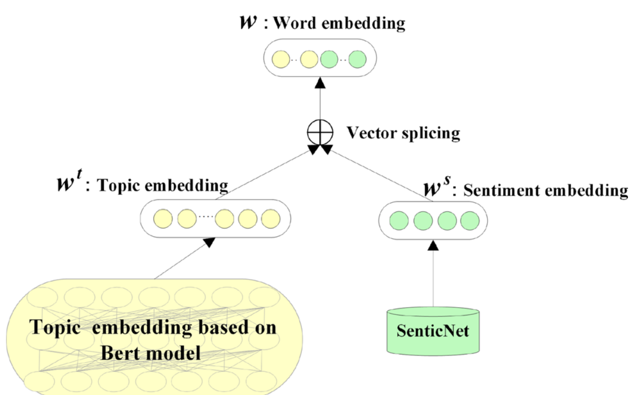


Fig. 4 Composition of word embedding with background knowledge

$$k = a + \frac{(b - a)(x - \min)}{(\max - \min)} \tag{2}$$

where x is the value extracted from the structured data of SenticNet4, and [min,max] is the range of structured data. According to Eq. (2), the sentiment embedding of the word "rude" is $e^s = [0.13, 0.925, 0.5, 0.045]^{\mathrm{T}}$. The sentiment embeddings of most words can be obtained from SenticNet4. However, its coverage is not comprehensive. A large number of internet vocabularies, common prepositions, and nouns without emotion do not appear in SenticNet4, and for these words, we set $e^s = [0.5, 0.5, 0.5, 0.5]^{\mathrm{T}}$.

4.1.2 Semantic feature extraction layer

As mentioned in Sect. 2, traditional methods ignore the close connection between sentiment features and aspect features. To solve this problem, we adopt a pair of three-dimensional tensors to jointly extract deep features of words after Bi-LSTM is used to extract shallow semantic information [39]. Next, we discuss the feature extraction process. In the sentiment analysis, sentiment needs to be analyzed based on context. Since the long-range feature capture capability of LSTM is stronger than that of Transformer, in order to capture more comprehensive feature information, Bi-LSTM is used twice to extract shallow and deep context information, respectively. Bi-LSTM is used twice in the feature extraction layer to encode the context information. Take the first Bi-LSTM as an example. It encodes the sentence forward and backward to obtain a context vector h_i. h_i is calculated as

$$h_i = \left(h_i^f \oplus h_i^b\right) 1 \le i \le n \tag{3}$$

where h_i^f and h_i^b, respectively, represent the vector encoded by forward and backward LSTM. The three-dimensional tensor is used to extract the deep semantic features of a word:

The BBC-LSTM model extracts deep features of entities by jointly extracting features of sentiment entities and aspect entities. The extraction process of deep features for sentiment entities is shown in Fig. 5, and v_i^s is calculated as

$$v_i^m = U^m(h_i, \alpha) = \tanh\left(h_i^T Q^m \alpha^m\right) \tag{4}$$

where v_i^m is the semantic feature of the entity, and $alpha^m$ is a d-dimensional prototype vector. Q^m is a three-dimensional tensor that can be regarded as k matrices of dimension d × d, mapping k kinds of possible semantic or syntactic relations between $alpha^m$ and h_i^T.

$$v_i^s = U^s(h_i, \alpha) = \tanh\left(\left[h_i^T Q^s \alpha^s : h_i^T D^s \alpha^a\right]\right). \tag{5}$$

Among them, $[a : b]$ represents concatenation of the vectors a and b, and the tensor D^s can be used to interactively learn the mapping relation between h_i and prototype vector $alpha^a$, thereby jointly extracting features of the sentiment and aspect entities. Finally, v_i^s is obtained. Similarly, for the aspect entity,

$$v_i^a = U^a(h_i, \alpha) = \tanh\left(\left[h_i^T Q^a \alpha^a : h_i^T D^a \alpha^s\right]\right). \tag{6}$$

Bi-LSTM is used again to performing context encoding. In particular, to reduce the burden of the network, we focus on the features of sentiment and aspect entities, ignoring non-entity words. An attention mechanism is used to filter the deep features for classification. Taking the sentiment entity as an example, the important feature is calculated as follows:

$$\beta_i^s = u^{sT} v_i^s \tag{7}$$

$$e_i^s = \exp\left(\beta_i^s\right) / \sum_j^n \exp\left(\beta_j^s\right) \tag{8}$$

$$r_i^s = \sum_{i=1}^n e_i^s v_i^s \tag{9}$$

where u^s represents the deep semantic features encoded by Bi-LSTM. $beta_i^s$ is the attention coefficient of the sentiment entity, which is used to obtain the weight vector e_i. Finally, the deep feature r_i^s of word w_i is obtained by the weighted summation method. Considering that the deep features may be slightly lost after passing multiple networks, BBC-LSTM splices r_i^s and h_i as

$$q_i = \left(h_i \oplus r_i^s\right). \tag{10}$$

At this point, the final feature representation q_i of the sentiment entity is obtained. The feature representation of the aspect entity is also extracted through the above process.

4.1.3 Output layer

Because the entity may be composed of multiple words, CRF is applied to constrain labels in the output layer [40]. Two sets of vectors obtained from the feature extraction layer are sent to the fully connection layer and SoftMax layer, and then the probability distribution of the emotion

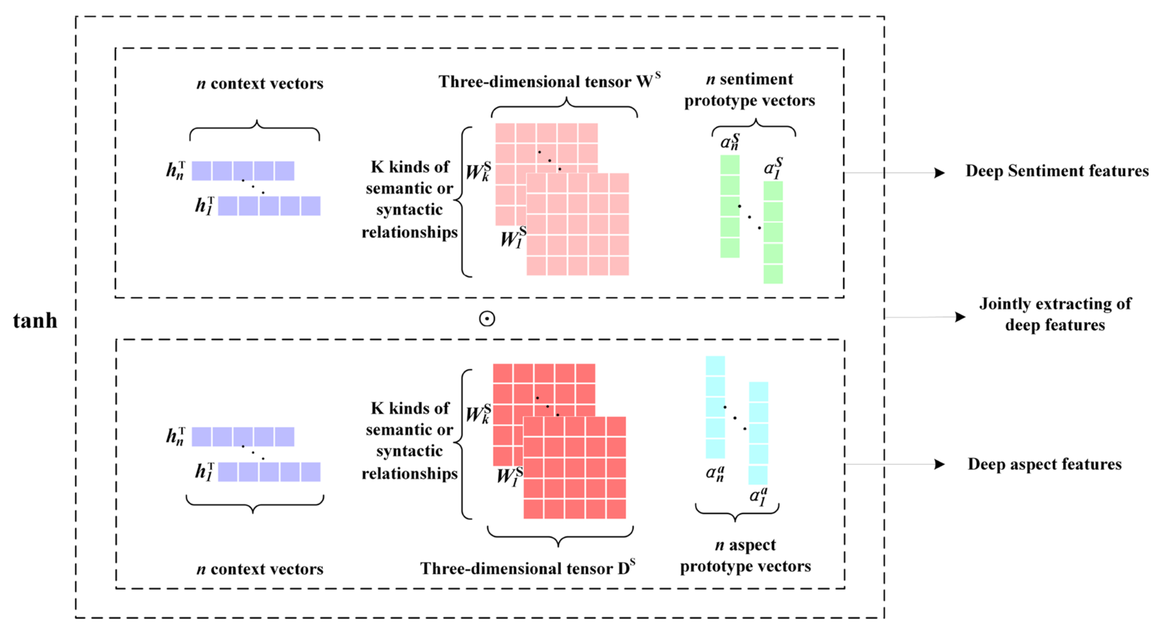


Fig. 5 Co-extraction of deep features of sentiment entity

category and location information of each word are obtained. The calculation is

$$y_i = \text{softmax}(\xi T q_i) \tag{11}$$

where (T is the weight of the fully connection layer, and y_i is the vector to be processed by CRF. Eventually, $Label^s$ of sentiment entities and $Label^a$ of aspect entities are obtained. If a word is labeled as two types of entities, only one will be selected as the label, according to the probability score. The labeling method references the traditional labeling strategy and classification tasks and is finally expressed in the form of "location-category." The traditional marking strategy BIO is introduced as a prefix to distinguish the entity boundary. Specifically, "B" is used to mark the first word of the entity. However, an entity may consist of multiple words, and "I" is applied to solve this problem. "O" means that the word is not the target entity. Taking a comment about a restaurant topic as an example, its entity annotation set and results of NER are shown in Table 1 and Fig. 6. Its sentiment entities are divided into 6 kinds of specific categories, while the aspect entities are divided into 5 categories.

BBC-LSTM enables SKG-Learning to recognize and classify an entity. Next, we will discuss how ED-Learning enables the SKG-Learning model to extract relations between entities.

4.2 Encoder–decoder based on deep learning

In Subsect. 4.1, we got the classification and location of entities. We now propose the ED-Learning model to simultaneously extract relations of multiple entity pairs in a sentence based on the results of NER. Entity types and sentiment polarities are extracted by ED-Learning. Entities are integrated to get sentiment knowledge triple ⟨ aspect entity, emotion tendency, sentiment entity ⟩ based on the proximity principle, and the relation between entities is obtained from the sentiment knowledge triple. The structure of ED-Learning is shown in Fig. 7. The modeling process is as follows.

(1) Suppose $WE = \{we_1, we_2, \ldots, we_n\}$ represents word vectors composed of topic embedding and entity type.

(2) $H = \{h_1, h_2, \ldots, h_n\}$ is the output of an encoder composed of a hybrid deep neural network, i.e., $H = Bi - LSTM[CNN(we_1, we_2, \ldots, we_n)]$.

(3) $Y = \{y_1, y_2, \ldots, y_n\}$ is the output of the decoder. Suppose the attention scores of words are $E = Attention(\{h_1, h_2, \ldots, h_n\}, S)$ where S is the hidden state of the decoder. Then the vector E is input to $LSTM$ to get $D = LSTM(\{h_1, h_2, \ldots, h_n\} * E^T)$, i.e., $Y = LSTM($ Pooling, S, $D)$.

(4) The output of the decoder, $Y = \{y_1, y_2, \ldots, y_n\}$, is sent to the output layer, and the label corresponding to each word is obtained.

(5) Suppose for observed value P, the loss is calculated by $Loss = SGD(\text{Y}, \text{P})$, and it is adjusted to the range of the loss threshold.

4.2.1 Input layer

The input $WE = \{we_1, we_2, \ldots, we_n\}$ not only contains topic embedding e^t learned by the BERT model, but is combined with the classification of NER u^p, as shown in Fig. 8, and the formal expression is shown as Eq. (12). u^p is a one-dimensional vector with possible values of 0, 1, and 2. If a word is a sentiment entity, then $u^p = 1$. If a word is an aspect entity, then $u^p = 2$. Otherwise, $u^p = 0$.

Table 1 Named entity annotation set of restaurant topic

Entity type	Label		Entity category
	First word	Non-first word	
Sentiment entity	B-ag	I-ag	Anger
	B-hp	I-hp	Happiness
	B-sd	I-sd	Sadness
	B-sp	I-sp	Surprise
	B-dg	I-dg	Disgust
	B-fa	I-fa	Fear
Aspect entity	B-fd	I-fd	Food
	B-sr	I-sr	Service
	B-pr	I-pr	Price
	B-ab	I-ab	Ambience
	B-ot	I-ot	Anecdotes/miscellaneous
Non-entity	O	O	Others

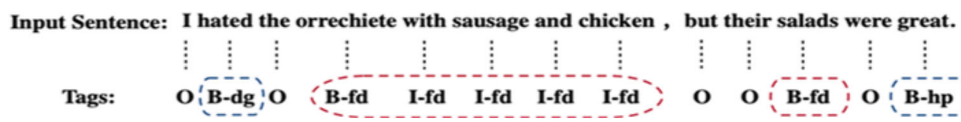


Fig. 6 Sequence labeling of a comment about a restaurant

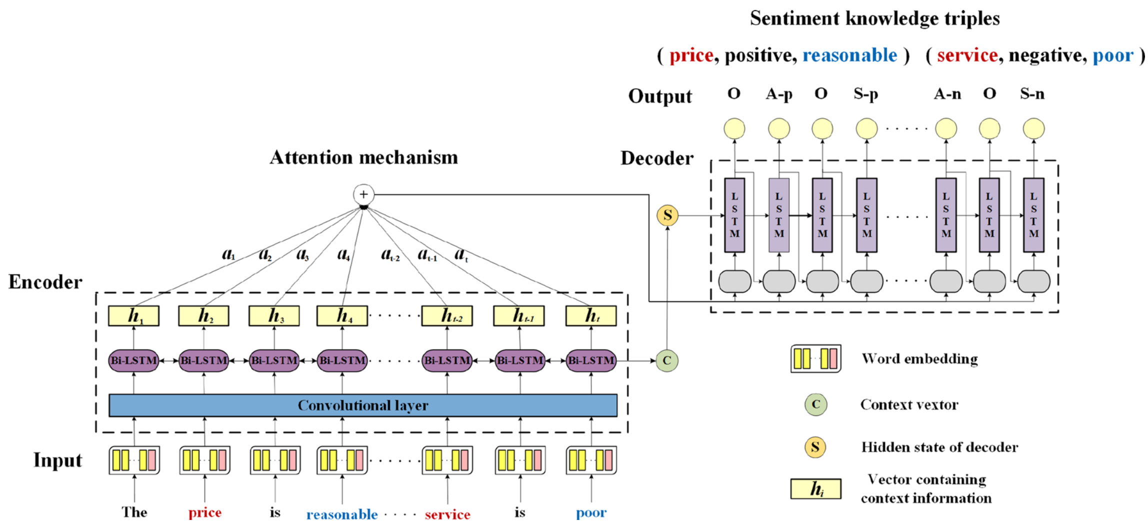


Fig. 7 ED-Learning model for relation extraction

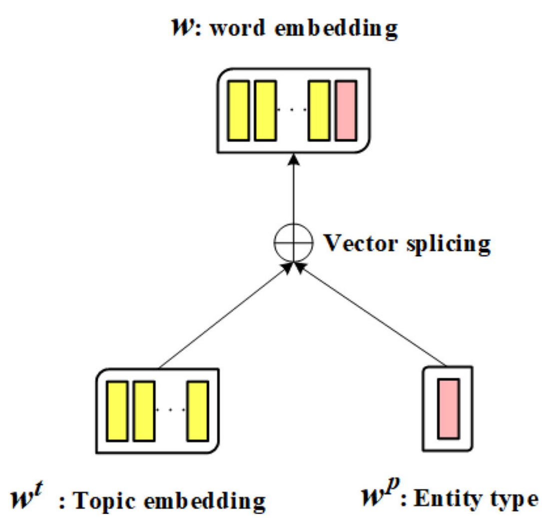


Fig. 8 ED-Learning model for relation extraction

$$we = e^t \oplus u^p \tag{12}$$

4.2.2 Encoder

The encoder consists of CNN and Bi-LSTM. The word vectors obtained from the embedding layer are input to the convolution layer to capture features before and after words of each word, so as to extract the sentiment features in terms of an entity rather than a single word. To get the vector corresponding to each word, it is necessary to fill "0" at the beginning and end of each sentence to ensure the number of word vectors input to the convolution layer equals the output vectors, as shown in Fig. 9.

In addition, considering that the number of words comprising an entity may differ, we adopt CNN with multiple convolution kernels. The $(\eta - h + 1)$-dimensional vector obtained by the $h \times k$ convolution kernel is calculated as

$$\gamma = (\gamma_1, \gamma_2, \ldots \gamma_{\eta-h+1}) \tag{13}$$

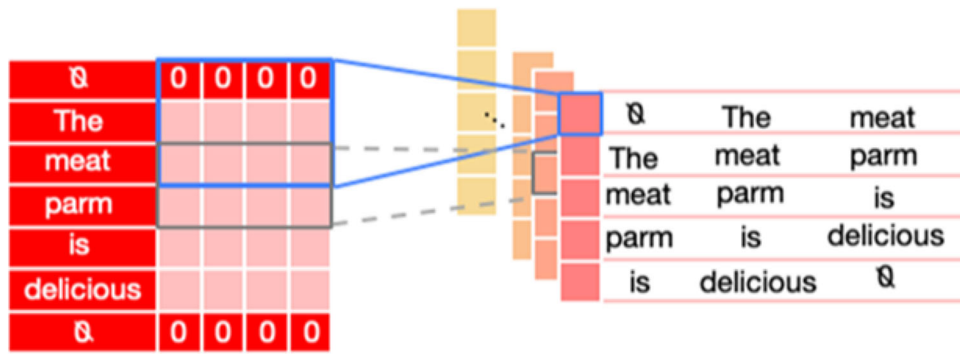
$$\gamma_i = f(\varpi we_{i:i+h-1} + b) \tag{14}$$

where $we_{i:i+j}$ represents a concatenation of $we_i \mid \ldots we_{i+j}$ feature vectors, f is a ReLU activation function, and ϖ and b are learning parameters. Then γ is input to Bi-LSTM to get the vector h_i of every time slice and further semantic feature C.

4.2.3 Decoder

In the decoder, LSTM is used to detect the boundary of the entity based on the known entity category. A global attention mechanism is introduced between the encoder and decoder to enhance the model's prediction performance. As shown in Fig. 10, a_{ij} is the attention weight of the i_{th} node in the encoder to the j_{th} node in the decoder. The higher the value of a_{ij}, the greater the influence of the i_{th} node in the encoder on the j_{th} node in the decoder.

Fig. 9 ED-Learning model for relation extraction



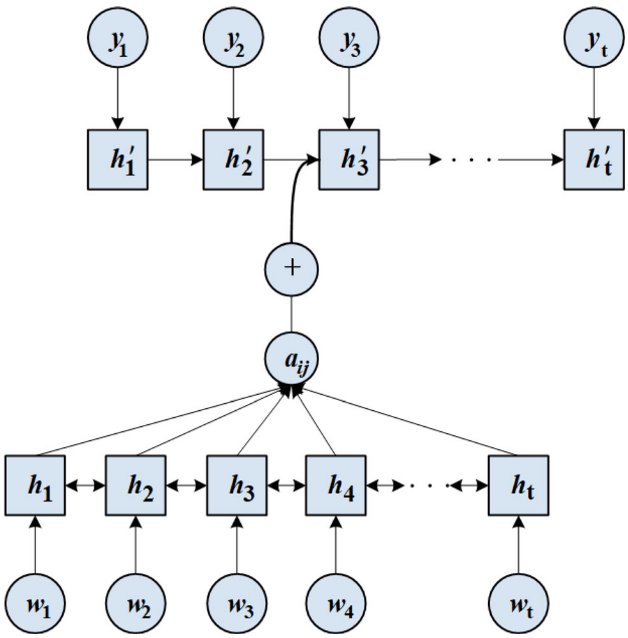


Fig. 10 Attention mechanism of ED-Learning model

$$a_{ij} = \frac{\exp(\theta_{ij})}{\sum_{k=1}^{n} \exp(\theta_{ik})} \tag{15}$$

$$\theta_{ij} = \text{score}(s_{i-1}, h_i) \tag{16}$$

where θ_{ij} is the initial weight score based on h_i and the hidden state s_{i-1} of the decoder.

4.2.4 Output layer

Considering that the category and boundary of an entity are obtained based on NER, there is no additional restriction on labels in RE. Therefore, after vectors obtained from LSTM are sent to the full connection layer and SoftMax layer, the label corresponding to each word is obtained. If the labels of words composing an entity are inconsistent, then the selection of the entity label is based on the probability scores of the labels. The label set of ED-Learning is shown in Table 2.

Table 2 Dataset size

Label	Positive	Negative	No emotion
Sentiment entity	S-p	S-n	–
Aspect entity	A-p	A-n	A-t
Others	O	O	O

As Table 2 shows, the label contains the type and emotion of an entity. A and S represent the aspect entity and sentiment entity, respectively; p and n represent positive and negative emotions, respectively. An aspect entity that does not express any emotion tendency is labeled by "A-t." Entities are integrated to get the sentiment knowledge triple, according to the following steps:

(1) Entities are divided according to their emotional tendency.
(2) Based on the proximity principle, entities labeled A and S are divided into an entity pair.
(3) Based on the emotional tendency of an entity pair, the relation between entities is obtained.

Entities in a sentence may not be distributed in pairs. In this study, an extra entity and an entity whose type differs from it and whose distance from it is less than 3 and whose emotional tendency is the same are also constructed as a pair of entities.

After BBC-LSTM and ED-Learning extract entities and relations, respectively, SKG is built based on entities and their attribute categories, as well as relations between entities.

5 Experiment and analysis of results

We conducted experiments on BBC-LSTM and ED-Learning, and compared their performance with several classic models and other improved models. We showed that it is necessary to consider the concrete topic in SKG-

Learning by comparing the attribute categories of entities in different topics.

5.1 Dataset description

The experimental dataset was taken from task 4 of SemEval2014 [41], which includes subtasks of fine-grained sentiment analysis (Aspect-Based Sentiment Analysis, ABSA). Task 4 contains two datasets, a restaurant dataset and laptop dataset. Table 3 shows the sizes of the training and test sets.

The goal of the original task is sentiment analysis, so the category and polarity of entities are given in the dataset. However, several entities are not located, which does not meet the goal of entity recognition in this paper. For example, for the sentence, "It is expensive," its aspect entity is not labeled. Therefore, all training sets and test sets were labeled manually before experiments.

By analyzing the distribution of attribute categories in the restaurant dataset, we found a data imbalance, as shown in Fig. 11. For sentiment entities, entities belonging to the "happiness" category accounted for the highest proportion. There is no balanced operation for sentiment entities of a dataset, since the imbalanced distribution of sentiment entities in the product comments is normal, and the sentiment entities in training and test sets follow the same distribution.

Similarly, a large proportion of aspect entities fell into the "others" category, which could lead to insufficient learning of entity features. Hence, the "others" entities were first pruned. Additionally, the data enhancement method of image recognition was employed to avoid overfitting. The steps of data enhancement are as follows:

(1) A batch of high-quality sentences, which contains both sentiment entities and aspect entities, and have complete semantics, are manually selected from the training set, so as to facilitate the co-extraction of entity features and relation extraction.
(2) We randomly scrambled the front and back of the sentences of the dataset according to commas.
(3) We input the scrambled data to the model as an additional training set for auxiliary training.

Table 3 Dataset size

Topic	Training set	Test set	Total
Restaurant	3041	800	3841
Laptop	3045	800	3845
Total	6086	1600	7686

5.2 Evaluation metrics

We used three common evaluation metrics in natural language processing: precision, recall, and F-measure. In our experiments, the calculation of evaluation metrics involved three parameters:

(1) $\text{correct}_{\text{num}}$: The number of entities that are correctly recognized. An entity is predicted correctly only when its boundary and attribute category are consistent with the entity labeled in advance.
(2) $\text{predict}_{\text{num}}$: The total number of identified entities.
(3) gold_{num}: The number of entities labeled in advance in the dataset.

Based on the above parameters, the evaluation metrics are calculated as follows:

$$\text{Precision} = \text{correct}_{\text{num}}/\text{predict}_{\text{num}} \tag{17}$$

$$\text{Recall} = \text{correct}_{\text{num}}/gold_{\text{num}} \tag{18}$$

$$F - \text{Measure} = (2 * \text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall}) \tag{19}$$

where precision is used to measure the accuracy of the model. Recall represents the ratio of recognized entities to the total entities in the dataset. The F-measure is also called the F1 value, and it combines precision with recall, comprehensively reflect the performance of the model.

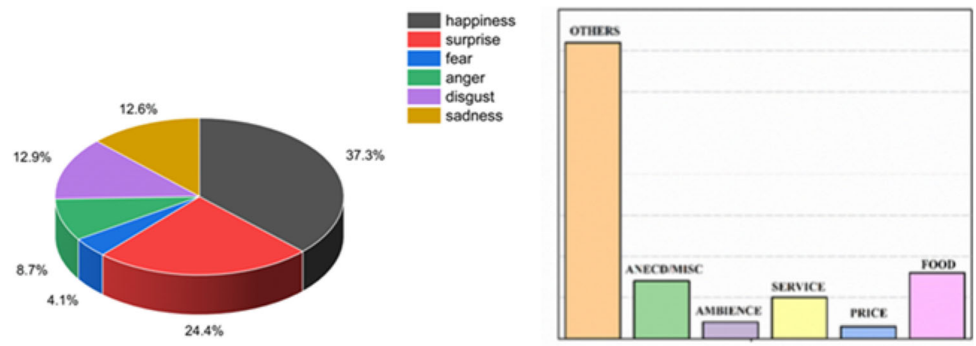
It should be emphasized that the experiment of entity recognition is based on exact matching, since only entities with clear boundaries that are classified correctly can be used to perform accurate emotion analysis. However, the experiment of relation extraction no longer needs to meet the requirements of exact matching, because the sequence labeling of relation extraction is based on the results of NER.

5.3 Experimental analysis and comparisons

To demonstrate the reliability of BBC-LSTM and ED-Learning, experiments were carried out from three aspects: parameter adjustment, comparisons with other models, and comparisons with different datasets.

5.3.1 Comparisons on k value of bilinear tensor

The BBC-LSTM model uses a three-dimensional tensor to jointly extract deep features of sentiment entities and aspect entities. The BBC-LSTM model uses a three-dimensional tensor to jointly extract deep features of sentiment entities and aspect entities. The k value of a three-dimensional tensor can be adjusted manually. Therefore, we used the restaurant dataset to explore the impact of



(a) Sentiment entities **(b)** Aspect entities

Fig. 11 Attribute category distribution of entities in restaurant dataset

different values of k on F1 from $epoch = 1$ to $epoch = 50$. The experimental results are shown in Fig. 12.

By analyzing F1, we believe the model can obtain relatively stable and good results when $k = 15$ and $epoch = 50$. Therefore, in our experiments, k was set to 15. The hyperparameters of NER and RE are described, respectively, in Tables 4 and 5.

5.3.2 Comparisons on NER

Initially, we introduced comparative models in the experiment:

(1) Bi-LSTM+CRF: One of the classic sequence tagging models and an exemplary NER model, in which sentiment entities and aspect entities are identified separately.

(2) BERT+Bi-LSTM+CRF: This model combines Bi-LSTM+CRF with the BERT model to verify the function of BERT, and identifies sentiment entities and aspect entities separately.

(3) CMLA [39]: This model simultaneously extracts the aspect entity and sentiment entity, but does not classify sentiment entities.

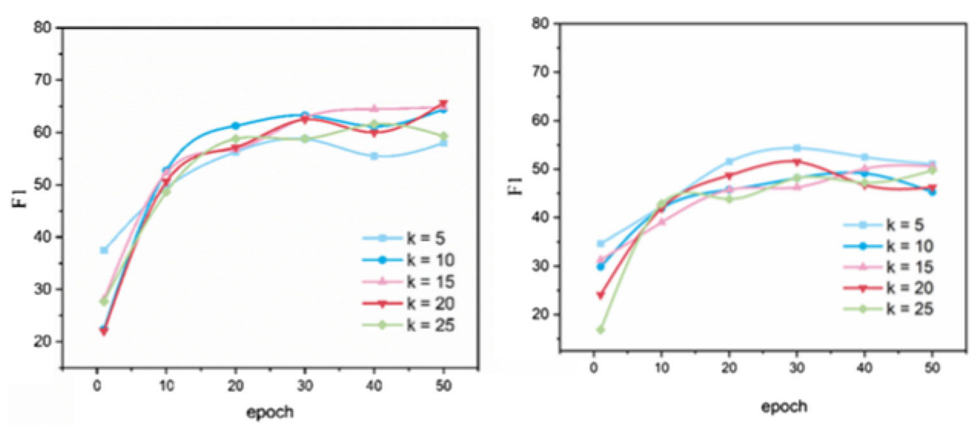
Table 4 Partial parameter settings of BBC-LSTM

Parameter type	Parameter value
Embedding_dim	200
k	15
Learning_rate	0.007
Drop_rate	0.5
Batch_size	1
Num_layer	2
Max_grad_norm	5
Gru_hidden_size	30
Label_dim	13

(4) IOG [42]: This model extracts the sentiment entity based on the known aspect entity and considers the association between entities.

(5) BBC-LSTM*: The BBC-LSTM model without the embedding layer.

Due to the particular nature of our work, few references have exactly the same task. Although IOG and CMLA can extract sentiment entity and aspect entity, they do not consider entity classification. Therefore, we adjusted the



(a) Recognition of aspect entity **(b)** Recognition of sentiment entity

Fig. 12 Attribute category distribution of entities in restaurant dataset

Table 5 Partial parameter settings of ED-Learning

Parameter type	Parameter value
Embedding_dim	200
Learning_rate	0.007
Drop_rate	0.5
Batch_size	1
Num_layer	2
Max_grad_norm	5
Gru_hidden_size	30

output of CMLA and IOG to make them perform simple classification.

The results of experiments considering both entity recognition and classification are shown in Table 6. We only extracted entities for fairness, and the results are shown in Table 7. It should be noted that the classifications of aspect entities in the laptop dataset were not involved in the comparison, since these were not given in advance.

Based on Tables 6 and 7, we make the following observations:

(1) The embedding layer makes a great contribution to the classification by comparing BBC-LSTM with the BBC-LSTM* model.

(2) It is necessary to introduce the BERT model by comparing BERT+Bi-LSTM+CRF with BERT+Bi-LSTM+CRF.

(3) Jointly extracting features of sentiment entities and aspect entities is meaningful for improving the accuracy of entities recognition by comparing Bi-LSTM+CRF and BERT+Bi-LSTM+CRF with other models.

(4) Although current models have a certain performance on NER tasks, they are not effective with entity classification owing to their design purpose.

(5) Comparing the results of Tables 6 and 7, we find that the classification performance of entities is relatively low, since the classification goal in this

Table 6 Comparisons on entity recognition and entity classification

Topic	Entity type	Metrics	Bi-LSTM +CRF	Bert+Bi-LSTM+CRF	CMLA	IOG	BBC-LSTM*	BBC-LSTM
Restaurant	Aspect entity	P	60.81	63.26	61.81	–	63.88	**67.19**
		R	57.42	58.90	59.86	–	58.39	**61.88**
		F1	59.06	61.00	60.82	–	61.01	**64.43**
	Sentiment entity	P	50.08	51.91	52.08	55.60	54.95	**56.88**
		R	44.73	45.90	**49.78**	46.38	46.12	46.18
		F1	47.25	48.72	50.90	50.56	49.54	**51.12**
Laptop	Sentiment entity	P	39.92	41.21	43.17	46.85	48.54	**50.47**
		R	34.20	36.12	**45.10**	43.95	44.13	45.08
		F1	37.08	38.50	44.11	45.35	46.23	**47.62**

Table 7 Comparisons on entity recognition only

Topic	Entity type	Metrics	Bi-LSTM+CRF	CMLA	IOG	BBC-LSTM
Restaurant	Aspect entity	P	81.15	83.20	–	**85.14**
		R	78.77	**85.69**	–	83.56
		F1	79.94	**84.43**	–	84.34
	Sentiment entity	P	78.22	81.18	81.70	**82.01**
		R	71.73	**82.53**	76.18	82.47
		F1	74.83	81.85	78.84	**82.24**
Laptop	Aspect entity	P	72.73	75.50	–	**78.44**
		R	66.86	**77.22**	–	75.21
		F1	69.67	76.35	–	**76.79**
	Sentiment entity	P	69.58	71.10	74.07	**74.86**
		R	64.45	**74.30**	69.32	73.60
		F1	66.88	72.66	71.62	**74.22**

Table 8 Controlled experiment of RE

RE methods	Restaurant			Laptop		
	P	R	F1	P	R	F1
Bi-LSTM+CRF	61.50	39.19	47.87	52.23	31.00	38.91
LSTM+LSTM+Bias	59.27	47.48	52.72	51.08	44.46	47.58
CMLA	65.14	71.59	68.21	53.58	59.34	56.31
EDAS	75.88	65.10	70.08	66.59	60.40	63.34
ED-learning	76.02	70.91	73.38	66.71	61.32	63.90

paper is different from general classification methods.

Therefore, it can be concluded that the comprehensive performance of BBC-LSTM is better than that of comparative models.

5.3.3 Comparisons on RE

We introduce the comparative models in the experiment:

(1) Bi-LSTM+CRF: As the baseline model of sequence tagging, it is a common RE model.
(2) LSTM+LSTM+Bias [13]: This model jointly extracts entities and relations based on a sequential tagging model.
(3) EDAS [43]: This model predicts the emotion polarity of an aspect entity. However, it does not predict the polarity of a sentiment entity, so we simply adjusted the model to make it consistent with our model.
(4) CMLA [39]: This model is used to extract entities. We adjusted the model to make the output consistent with our task.

It can be observed from Table 8 that the performance of EDAS and CMLA in this paper is slightly diminished when compared to other studies, which may come down to their design targets, whose context is different from ours. It can be seen that the ED-Learning model performs RE better than the other models.

We also analyzed the entity types obtained and counted the aspect entities extracted from the two datasets. The number of aspect entities in the laptop dataset is 398, while the number of aspect entities in the restaurant dataset is 1756, and there are only 6 duplicate entities in these datasets. Therefore, entities should be recognized based on specific topics, since the feature distributions of entities in different topics may have a large deviation, which can result in inaccurate sentiment analysis. Two examples are shown in Tables 9 and 10. In the restaurant topic, “warm” is recognized as the “happiness” attribute category, while in laptop, “warm” is recognized as “disgust.” A similar situation is also reflected with regard to the word “hot.”

Table 9 Sentiment knowledge triples of restaurant dataset

Sentiment entity	Relation	Aspect entity	Sentiment attribute	Aspect attribute
High-fat	Negative	Chicken	Anger	Food
Unaffordable	Negative	Price	Sadness	Price
Salty	Negative	Spaghetti	Disgust	Food
Special	Positive	Sauce	Surprise	Food
Warm	Positive	Place	Happiness	Anecdotes/miscellaneous
Worst	Negative	Waiter	Anger	Service
Great	Positive	Texture	Happiness	Food
Large	Positive	Window	Happiness	Ambiance
Hot	Positive	Cake	Happiness	Food

Table 10 Sentiment knowledge triples of laptop dataset

Sentiment entity	Relation	Aspect entity	Sentiment attribute	Aspect attribute
Love	Positive	Screen	Happiness	Component
Big	Positive	Storage	Happiness	Component
Warm	Negative	Temperature	Anger	Performance
Fast	Positive	Speed	Happiness	Performance
Crappy	Negative	Speaker	Disgust	Component
Hot	Negative	Playing game	Anger	Performance
Perfect	Positive	Design	Surprise	Appearance

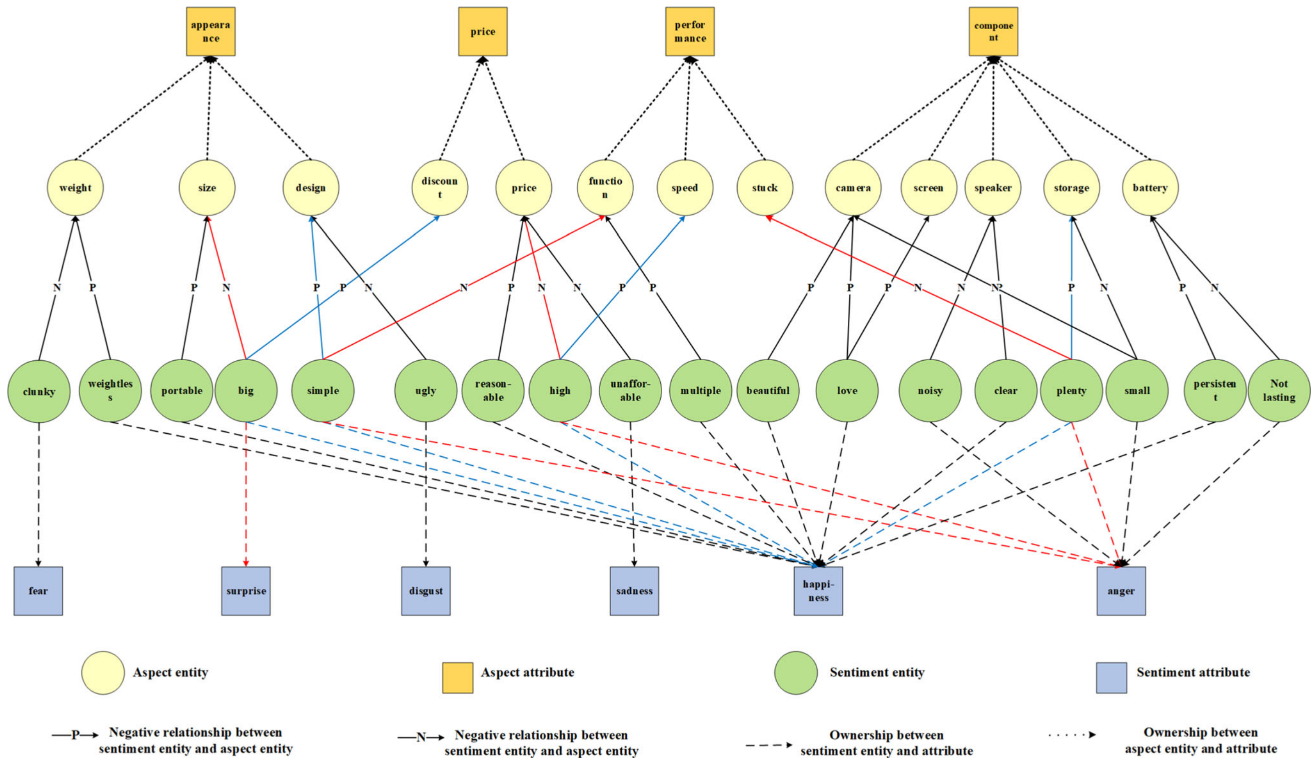
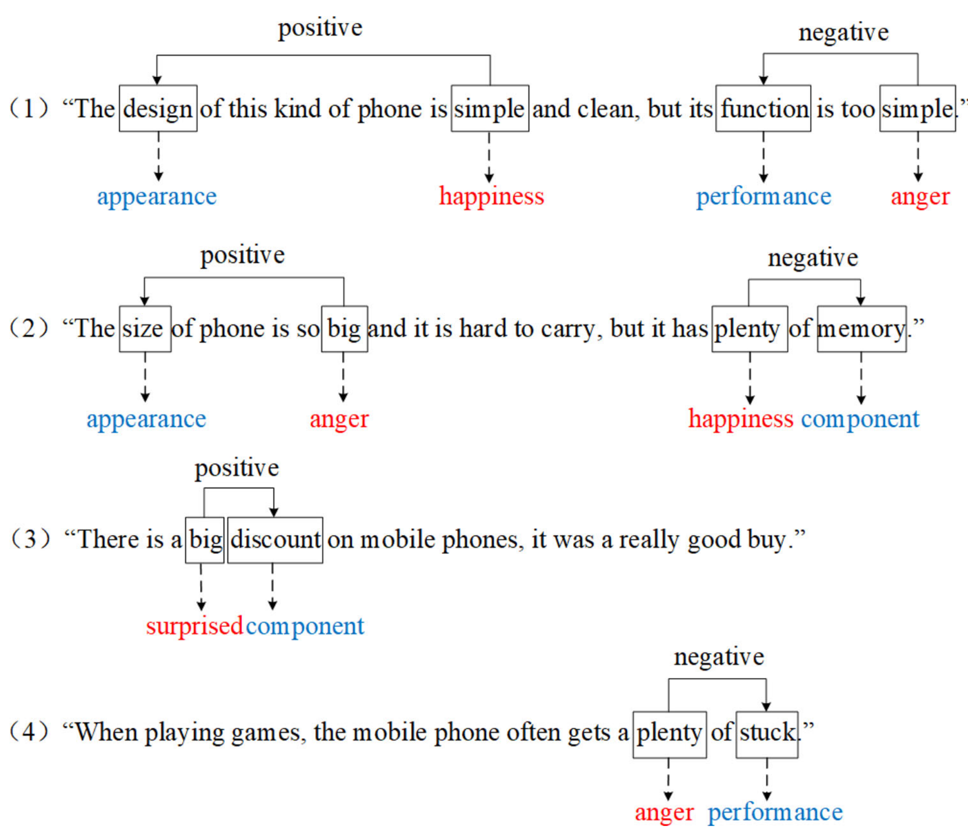


Fig. 13 Part of SKG of phone dataset

Fig. 14 Sentiment analysis of comments



6 Case study

In Sect. 4, we proposed the framework of SKG-Learning for constructing an SKG. In this section, a case study is used to confirm the validity of the SKG in sentiment analysis in a real-life problem. The problem is formulated as follows. SKG is built based on the proposed SKG-Learning model on a phone topic. Given a piece of comment, SKG is used to analyze the sentiment tendencies that customers toward objects. Part of the SKG of the phone is shown in Fig. 13. Suppose four pieces of comments are given as follows:

(1) “The appearance of this kind of phone is simple and clean, but its function is too simple.”

(2) “The size of phone is so big and it is hard to carry, but it has plenty of memory.”

(3) “There is a big discount on mobile phones, it was a really good buy.”

(4) “When playing games, the mobile phone often gets a plenty of stuck.”

The sentiment analysis based on SKG references the searching process of KG that is mainly divided into problem analysis, information retrieval, and answer processing. To be specific, entities are initially extracted by the NER method, then entity pairs are obtained by the RE method. The sentiment knowledge triples are searched and matched from SKG based on the extracted entity pairs. Finally, the correct answers are selected from the candidate set, and we get the sentiment knowledge triples:

(1) “The appearance of this kind of phone is simple and clean, but its function is too simple.”

Triples of sentiment and aspect entities:
< “simple,” “positive,” “design” >, < “simple,” “negative,” “function” >
Triples of sentiment entities and their attribute category:
< simple, positive, happiness >, < “simple,” “negative,” “anger” >
Triples of aspect entities and their attribute category:
< “design,” “positive,” “appearance” >, < “function,” “positive,” “performance” >

(2) “The size of phone is so big and it is hard to carry, but it has plenty of memory.”

Triples of sentiment and aspect entities:
< “big,” “positive,” “size” >, < “plenty,” “positive,” “memory” >
Triples of sentiment entities and their attribute category:
< “big,” “positive,” “anger” >, < “plenty,” “positive,” “happiness” >
Triples of aspect entities and their attribute category:
< “size,” “positive,” “appearance” >, < “memory,” “positive,” “component” >

(3) “There is a big discount on mobile phones, it was a really good buy.”

Triple of sentiment and aspect entity:
< “big,” “positive,” “anger” >
Triples of entities and their attribute category:
< “big,” “positive,” “anger” >
Triples of aspect entities and their attribute category:
< “discount,” “positive,” “price” >

(4) “When playing games, the mobile phone often gets a plenty of stuck.”

Triple of sentiment and aspect entity:
< “plenty,” “negative,” “stuck” >
Triples of entities and their attribute category:
< “plenty,” “negative,” “anger” >
Triples of aspect entities and their attribute category:
< “stuck,” “negative,” “performance” >

Based on the triples, the sentiment analysis results of comments are shown in Fig. 14. In the first piece of comment, “simple” is used to describe two different aspects. Based on the sentiment knowledge triples obtained by SKG, we can infer that customer likes the design of phone but is anger with the phone functions. In addition to extracting customers’ positive and negative attitudes, SKG can reflect more fine-grained emotions. In the sentence (2) and (3), customers use “big” to describe “size” and “discount.” According to the triples, we can infer that the customer is anger with the phone size but surprised with the big discount. Similarly, for the sentence (2) and (4), we can also get detailed moods of customers.

Above all, the specific emotion can be dug out accurately and correctly by SKG, which considers the close association between entities and extracts more fine-grained emotions of commenters. Therefore, SKG based on the SKG-Learning model is capable of performing fine-grained emotion analysis. What’s more, after minor modifications, the model in this paper can be extended to other fields. The model proposed in this paper considers the correlations between entities features, which are also very important for other fields. In the process of entity recognition in other fields, it is necessary to consider the context of entities.

7 Discussion

In this paper, we adopt two kinds of parameter adjustment methods, automatic parameter adjustment method-Hyperopt (a Python Library of Sklearn), and manual adjustment. However, the performance of Hyperopt is inferior to the manual adjustment since insufficient samples. Meanwhile, there are a few papers [8, 39] that used the method of manual adjustment and got good results. Therefore, we manually adjust the k value of a three-dimensional tensor.

8 Conclusion and future work

With the development of social networks and artificial intelligence, sentiment analysis has become a popular topic. In specific scenarios, it is more practical to get target entities described by evaluation words. Therefore, a new type of knowledge organization structure, SKG, was proposed, which associates emotion words with evaluation aspects and topics, and provides efficient storage and management of massive amounts of information. We proposed SKG-Learning to construct SKG, and the SKG-Learning model was divided into the NER and RE subtasks. Specifically, the BBC-LSTM model based on the common model Bi-LSTM+CRF was proposed to recognize entities. In BBC-LSTM, the BERT model and SenticNet4 were introduced to embed background knowledge in word vectors to extract sentiment entities, and to mitigate the classification problem caused by insufficient context information. What is more, considering the relevance between sentiment entities and aspect entities, a three-dimensional tensor was proposed to jointly extract the deep features of sentiment entities and aspect entities. ED-Learning was proposed based on an encoder–decoder model, which classified aspect entities according to their sentiment polarities, and obtained the emotional polarities of sentiment entities toward aspect entities, that is, the relations between sentiment and aspect entities. Experiments confirmed that the proposed NER and RE models perform better than classic models and other improved models. Moreover, comparing the attributes of entities in different topics illustrated the necessity of considering concrete topics in the SKG-Learning model. Finally, a real-life problem was adopted to confirm the validity of the SKG in sentiment analysis.

We showed that the BBC-LSTM and ED-Learning models that comprise SKG-Learning are effective at extracting entities and relations, and SKG is capable of performing emotional analysis. However, there are there major limitations that could be addressed in the future. First, the relations in this paper mainly refer to those between sentiment entities and aspect entities. Relations between aspect entities and between sentiment entities are not considered, since the entity pair, which is composed of an aspect entity and sentiment entity, is the basic unit of emotion expression, which can be used to obtain the view of people toward a certain aspect. However, a commenter may give different evaluations on different aspects of the same object in a piece of comment. In future work, we wish to explore the guiding relation between different emotions to analyze the overall emotion of a sentence. Secondly, SKG-Learning depends on the detailed degree of classification of a dataset. In this paper, experiments were carried out on common datasets of fine-grained sentiment classification, and emotion was divided into six kinds of attribute categories. Actually, emotions can be classified in more detail. Therefore, model performance should be verified on different datasets. Finally, the results of the automatic parameter adjustment method of deep learning are inferior to manual adjustment since insufficient samples. In future work, we will improve the performance of deep learning tuning.

Acknowledgements This work was supported in part by the National Natural Science Foundation of China under Grant 61802258, Grant 61572326, in part by the Natural Science Foundation of Shanghai under Grant 18ZR1428300.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relations that could have appeared to influence the work reported in this paper.

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