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Integrating external knowledge into aspect-based sentiment analysis using graph neural network

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A B S T R A C T

Aspect-based sentiment analysis aims to analyze the sentiment polarity of a given aspect. The graph convolutional neural network model is widely used. However, most existing research focuses on mining the context-word-to-aspect-word dependencies of dependency trees based on the sentence itself without using much text-related external knowledge. In addition, the problem of reasonably capturing words outside the multihop grammatical distance and edge label hinders the effect of GCN. This paper proposes a graph convolutional network that fuses external knowledge (sentiment lexicon and part-of-speech information) (EK-GCN). Specifically, we conduct a statistical study on part-of-speech and construct a part-of-speech matrix to fully consider the influence of denying words, degree words, and other words that affect sentiment expression in sentences on sentiment classification. Then, an external sentiment lexicon is used to assign sentiment scores to each word in the sentence to construct a sentiment score matrix to highlight the weight of sentiment words, which to a certain extent, compensates for the fact that the syntactic dependency tree cannot capture edge labels. In addition, we design a Word–Sentence Interaction Network (WSIN), which can fully consider the information of the current aspect word and interact with the context information of the reviews to filter useful sentence information. We conduct experiments on four benchmark datasets, and the excellent experimental results demonstrate the effectiveness of our model. The results also verify that fully integrating external knowledge can assist in completing aspect-based sentiment analysis tasks.

1. Introduction

With the development of the internet and e-commerce platforms, an increasing number of users share their shopping experiences online. However, the complex structure of these opinions makes it difficult to deal with them. Traditional sentiment analysis methods could not meet growing demands of individuals, who could not obtain accurate and concise information in time. Therefore, sentiment analysis methods based on deep learning have emerged. Among them, sentiment analysis is essential to natural language processing [1]. Unlike document-level sentiment analysis, it considers the interaction information between a given aspect word and the context. It determines the sentiment polarity (positive, neutral, and negative) of a particular aspect word in a review sentence [2,3]. As shown in Fig. 1, the aspect words of the review are "food" and "service", and their corresponding sentiment words are "delicious" and "poor". Therefore, we identify their corresponding emotions as "positive" and "negative".

In recent years, with the continuous development of deep learning methods, neural network methods have been continuously applied to natural language processing tasks. These methods can effectively learn the semantics of the data and its feature representation from the original review text. For example, convolutional neural networks (CNNs) [4,5] and recurrent neural networks (RNNs) [6,7] also suffer from vanishing gradients and the inability to resolve long-range word dependencies. Therefore, LSTM [8,9] and its variants (Bi-LSTM, GRU) have been proposed, which can not only obtain the contextual information of the text but also solve the above problems.

For aspect-based sentiment analysis, it is crucial to mine the word dependencies between words from the original reviews, capture the emotional and structural clues implicit in the sentences, and then guide the completion of aspect-based sentiment analysis tasks. Dependency tree-based graph convolutional neural networks (GCNs) [10,11] are widely used in sentiment analysis . These approaches can better capture the grammatical information and global dependencies of remote words, and generate more accurate sentence representations for complex sentence structures, which allows the model to more accurately analyze the sentiment of aspect words, making it easy to judge polarity in sentences.

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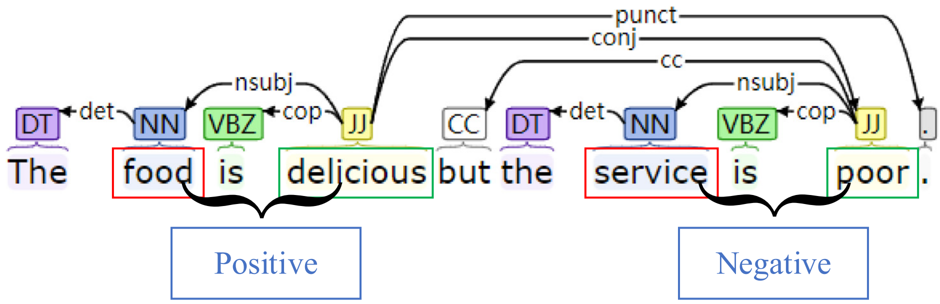

Fig. 1. An example of aspect-based sentiment analysis for the review "The food is delicious but the service is poor".

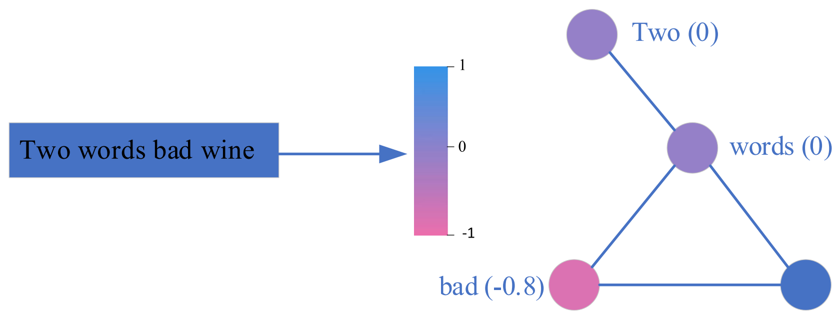

Fig. 2. Schematic diagram of assigning sentiment scores to each word in a review using a sentiment lexicon.

Most research focuses on the learning of context-word-to-aspect-word dependencies based on sentence dependency trees. In addition, there is considerable underutilized external knowledge related to the text, which can help the model better understand the structural information of the text [12–15]. Therefore, we decided to add part-of-speech information [16–18] and external knowledge of the sentiment lexicon [19,20] to reconstruct the syntactic dependency tree. First, we used the sentiment lexicon to assign sentiment scores in the interval [−1, 1] to each word in the review sentence. A sentiment value close to 1 is positive, close to −1 is negative, and 0 is neutral. For the example "The fried rice is amazing here", we can each word a sentiment score [0, 0, 0, 0, 0.956, 0] according to the sentiment lexicon. Therefore, with external knowledge of the sentiment lexicon, we can assign a high score to the word "amazing" and assign a higher weight when building the syntactic dependency tree. Therefore, we can better sentence representation by rationally utilizing external knowledge. At the same time, some noise is introduced, as shown in Fig. 2. For the sentence "Two words bad wine", the sentiment polarity of the aspect word "wine" should be "negative". However, the external sentiment lexicon knowledge assigns each word a sentiment score of [0, 0, −0.8, 0.921]. The sentiment lexicon gives "bad" a sentiment score of −0.8 but assigns "wine" a high positive sentiment score of 0.921, which will generate noise and inhibit model learning.

In addition, considering the influence of denying words, degree words, and other words that affect the emotional expression of aspect words in the review, we decided to add an external part-of-speech matrix to address the insufficient construction of dependency syntax trees. Specifically, we sample 100 reviews from four public datasets and conduct a statistical study of the part-of-speech of the opinion words in each review. The part-of-speech statistics are shown in Table 1.

According to the statistical analysis of part-of-speech, we can conclude that most opinion words are adjectives, adverbs, and verbs. By using fine-grained part-of-speech analysis, we can obtain the part-of-speech set of opinion words as P = [adjectives (JJ, JJR, JJS), verbs (VB, VBD, VBG, VBN, VBP, VBZ), adverbs (RB, RBR, RBS)]. Our statistical results are consistent with those of [21]. Next, we create a part-of-speech matrix based on the sentiment scores of the words and the preset part-of-speech set. The detailed construction process of words is shown in Algorithm 1. In the part-of-speech matrix, we mark the row and column with the part-of-speech set as 1 or −1 and the other positions as zero. Through external knowledge, the influence of negative words, degree words and other emotional expression words in sentences on sentiment classification is fully considered. To a certain extent, this feature compensates for the fact that the syntactic dependency tree cannot capture the edge labels and for the lack of sentiment dictionary data.

An aspect-based sentiment analysis error study found that 40% of prediction errors were caused by not considering the aspect word itself [22]. Therefore, it is imperative to correctly mine the aspect word and the information concerning its interaction with the context. In addition, this paper considers the complexity of the text structure and the situation in which that there are multiple aspect words in a sentence. Therefore, we decided to add a WSIN, which can fully consider the information of the current aspect word and interact with the context information of the reviews to filter useful sentence information. We also add position information to the reviews. The relative position relationship provided by the position information has been proven to facilitate the model classification [23,24]. A better sentence representation can be obtained to guide the completion of aspect-based sentiment analysis tasks. Finally, the proposed EK-GCN model is tested on four benchmark datasets, and the experimental results demonstrate the effectiveness of our model. In summary, the main contributions of this paper are as follows:

- This paper is not limited to the text information of the comment itself but fully considers a large number of external knowledge related to the text (sentiment lexicon and part-of-speech information) and reconstructs the dependency tree by introducing external knowledge.
- A novel model EK-GCN is designed to integrate external knowledge into aspect-based sentiment analysis using graph neural networks.

Table 1
Random selection of 100 reviews from each of four public datasets for fine-grained part-of-speech statistics.

	JJ	JJR	JJS	RB	RBR	RBS	NN	NNS	NNP	VB	VBD	VBG	VBN	VBP	VBZ	CD	DT
Restaurants14	147	7	5	47	6	2	1	0	0	7	11	3	4	1	1	1	3
Laptop14	133	14	3	35	3	1	1	1	1	16	22	4	1	0	3	0	2
Twitter	112	12	3	38	3	0	9	3	5	34	15	18	5	9	5	5	6
Restaurants16	155	4	6	53	1	0	2	1	0	10	10	4	6	3	2	2	5

• We conduct experiments on four benchmark public datasets, and the experimental results demonstrate the effectiveness of our model in introducing external knowledge.

The main structure of this paper is as follows:

We review previous work on aspect-based sentiment analysis in Section 2. Section 3 gives a detailed description of the proposed EK-GCN model. In Section 4, we conduct comparisons, ablation experiments, visualization studies, and case studies on four public datasets. The last section summarizes the shortcomings and future research directions regarding the model.

2. Related work

In an era of information explosion, aspect-based sentiment analysis methods are indispensable. They are designed to analyze and process subjective reviews so that people can obtain important comment information. Next, we introduce related work on aspect-based sentiment analysis. We divide the methods used in previous work into four categories: Traditional machine learning methods, Neural network methods, Methods based on external knowledge, and Methods based on graph convolutional neural networks.

Traditional machine learning models

Traditional machine learning methods require a lot of manual work to annotate the feature information in sentences, such as sentiment lexicon, bag of words (Bow), TF-IDF, support vector machine (SVM), and naive Bayesian model (NBM) [25–27]. Due to a large amount of manual design and the influence of knowledge reserve of annotation personnel, this method has many problems, such as high cost, poor generalization, and annotation quality. To address this issue, Cambria et al. [19] integrate logical reasoning using the deep learning architecture LSTM and BERT [28], thereby constructing a new version of the lexicon SenticNet with both symbolic and sub-symbolic approaches.

Neural Network methods

Many neural network-based methods are widely used in natural language processing tasks and have achieved satisfactory results. The neural network can focus on the text and capture emotion-related clues from the original comment corpus without requiring a large number of manual annotation features, which significantly improves the efficiency of the work. Tang et al. [9] proposed the TD-LSTM and TC-LSTM algorithms, which model context information in the left and right directions with the aspect word as the axis. Fan et al. [29] proposed a combined coarse- and fine-grained attention method (MGAN) to address the loss of coarse-grained attention information. It presents a multiaspect word-aligned loss function to interact aspect words with the same context. Huang et al. [30] automatically paid attention to critical emotional cues in sentences in a familiar way to further mine the interaction between aspect words and context. Li et al. [31] focused on the attention mechanism and the features that hinder the CNN, adopting a new module (TNet) represented by word vectors generated by the CNN and bidirectional RNN. Li et al. [32] integrated the CNN and LSTM in a parallel manner and proposed a new method of sentiment filling to develop a method more suitable for sentiment analysis.

Methods based on external knowledge

External knowledge has been widely used in many NLP tasks. On the one hand, Feng et al. [33] fused large-scale commonsense knowledge with dialog sentences to create a novel heterogeneous graph network (DHGN) to guide the generation of dialog summaries. In addition, Feng et al. [34] introduced 16 external dialog relationships into the dialog summary task and proposed a dialog discourse-aware conference summary generator (DDAMS). When conducting sentiment analysis, the external sentiment knowledge provided by an excellent external sentiment lexicon can make our work more effective. External emotional common sense knowledge is often used as a source to enhance the expression of emotional features in sentiment analysis tasks [35–37]. Baccianella et al. [38] designed a lexical resource SentiWordNet, explicitly designed to support sentiment classification and opinion mining applications. Deng et al. [39] introduced entity and event target concepts into the database MPQA for entity-event-level sentiment analysis tasks. MPQA is a multispan annotation dataset based on news articles using manually annotated statuses of others. Cambria et al. [19] combine common sense reasoning, psychology, linguistics, and machine learning to create a sentiment analysis tool and technology: SenticNet. Liang et al. [40] created a graph convolutional network based on the aforementioned SenticNet, which can fully exploit the emotional dependencies between words in a sentence according to different aspect words. To solve the problem of insufficient training data, Ayetiran [41] proposed a novel attention-based joint learning method. This method can use the learned document-level sentiment data features to implement aspect-level sentiment classification. On the other hand, part-of-speech, as the basis of grammar, play an instructive role in understanding sentences. The statistical rules of opinion words show that some part-of-speech contribute significantly to sentiment analysis. Adding part-of-speech information to the syntactic dependency tree can give more weight to emotional words to better complete ABSA tasks.

Methods based on graph convolutional neural networks

Since their introduction, graph convolutional neural networks have been widely applied in natural language processing tasks. In the aspect-based sentiment analysis task, for a given review, the GCN can capture words that are relatively far away from the previous aspect word according to the grammatical distance. Kipf et al. [42] proposed a GCN that performs convolution operations on raw graph-structured data to obtain hidden layer vector representations. Beck et al. [43] considered the importance of the information on nodes and edges. They fused the gated graph neural network with the input transformation information, which can effectively solve the problem of too many parameters. Veličković et al. [44] adopted the attention mechanism to obtain the attention weight of each word to solve the problem of the dependence matrix of the previous graph convolutional neural network and its approximation method. Wang et al. [45] focused on the complexity of the sentence structure and the problem of multiple aspects of a word, reconstructed and pruned the dependency tree, and established a dependency tree structure with the target word as the root node.

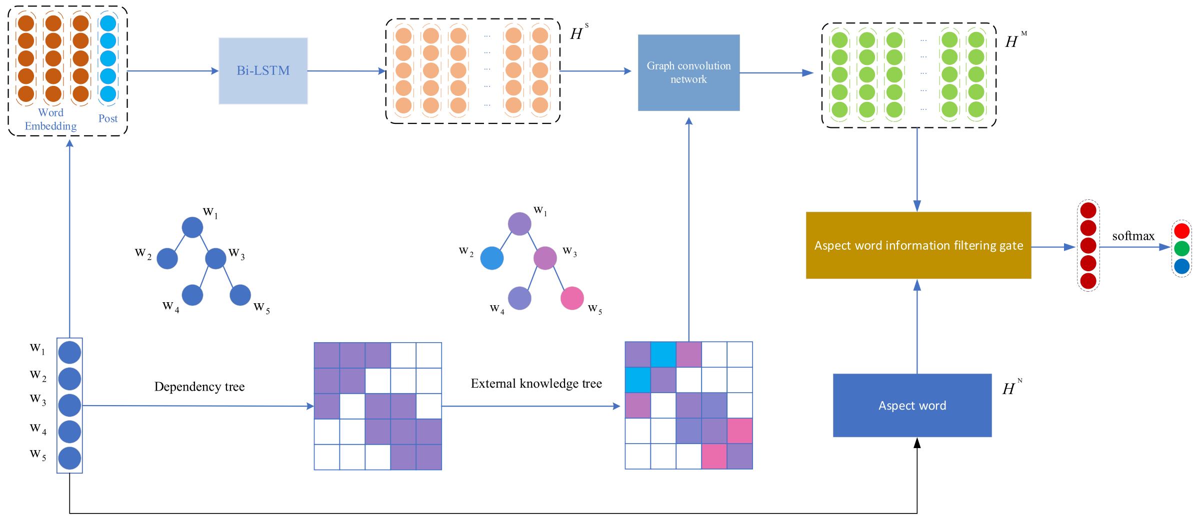

Fig. 3. The overall architecture of our proposed EK-GCN model.

Table 2
Symbols used in the EK-GCN model.

Notation	Description
a_i	The *i* th word of a sentence
x_i	Embedding vector of the *i* th word of a sentence
l_i	Position embedding vector of the *i* th word in the sentence
H^S	Hidden layer vector of Bi-LSTM
A_{ij}	Original dependency matrix
P_{ij}	Part of speech matrix
L_{ij}	Emotional lexicon matrix
D_{ij}	External knowledge matrix
Δ	Is the supplementary matrix.
H^M	Sentence embedding vector of graph convolution network
H^N	Aspect word embedding vector

3. Model description

In this section, we will introduce our proposed model (EK-GCN). This chapter is divided into the problem definition, input layer, matrix reconstruction, graph convolution neural network, Word–Sentence Interaction Network (WSIN), and output layer. A diagram of the model is shown in Fig. 3.

3.1. Problem definition

Given a sentence S containing n context words and m aspect words, we denote the context and aspect as $[a_1, a_2, \ldots, a_n]$ and $[a_i, a_{i+1}, \ldots, a_{i+m-1}]$, respectively. Aspect words are subset sequences of context words, which can be single words or phrases. The purpose of our study is to determine the sentiment polarity of a given aspect word in a review. Set of emotional polarities Y $\in$ {positive, neutral, and negative}. The symbols used in our model are shown in Table 2.

3.2. Input layer

We use the GloVe vector to initialize mapping for each word. For a given review S, we can obtain the word embedding X $= \{x_1, x_2, \ldots, x_n\}, x_i \in R^{n*dim_x}$, and relative position embedding L $= \{l_1, l_2, \ldots, l_n\}, l_i \in R^{n*dim_l}$. Here, dim_x and dim_l are the dimensions of word embedding, and position embedding, respectively. We concatenate the word embedding X and the relative position embedding L as the input $H^S = \{w_1, w_2, \ldots, w_n\}, w_i \in R^{n*dim_w}$ in the Bi-LSTM model, $dim_w = dim_x + dim_l$.

3.3. Dependency matrix reconstruction

For aspect-based sentiment analysis, it is crucial to capture the word-to-word interdependence features in a sentence and infer the sentiment polarity of a given aspect word. Inspired by predecessors [46], for the review S $= \{a_1, a_2, \ldots, a_n\}$, we first create a dependency matrix A_{ij} based on the dependencies between words:

$$A_{ij} = \begin{cases} 1, & if\ a_i\ and\ a_j\ have\ dependences \\ 0, & other \end{cases} \quad (1)$$

In addition, there is considerable underutilized external knowledge related to the text, which can help the model better understand the structural information of the text. Therefore, we decide to reconstruct the syntactic dependency matrix by adding part-of-speech information and external knowledge of the sentiment lexicon. Specifically, we first use a sentiment lexicon to assign a corresponding sentiment score S_{a_i} to each word a_i in the sentence to create a sentiment score matrix:

$$L_{ij} = S_{a_i} + S_{a_j} \quad (2)$$

where, L_{ij} is the sentiment lexicon matrix we created. a_i and a_j represent the words in a review, i and j $\in$ [1, n]. S_{a_i} and S_{a_j} are the sentiment scores assigned to words a_i and a_j by the sentiment lexicon, respectively. The sentiment lexicon we use here is SenticNet5. It is a knowledge base and a collection of sentiment analysis tools and techniques that combine common sense reasoning, psychology, linguistics, and machine learning. In SenticNet5, the affective value is very close to 1 for vital positive concepts, while it is close to -1 for strong negative concepts. SenticNet5 has shown remarkable performance in enhancing affective representation learning as a multifunctional affective knowledge base.

At the same time, considering the influence of denying words, degree words, and other words that affect the emotional expression of aspect words in the review and the insufficient number of words in the emotional lexicon, we decided to add an external part-of-speech matrix to help address the insufficient construction of the dependency syntax tree. Based on our part-of-speech statistical research, we determined the part-of-speech set P= [adjectives (JJ, JJR, JJS), verbs (VB, VBD, VBG, VBN, VBP, VBZ), adverbs (RB, RBR, RBS)]. The specific part-of-speech matrix determination process is shown in Algorithm 1.

Here, P_{ij} the part-of-speech matrix is created for us. C_{a_i} and C_{a_j} represent the part-of-speech category of the words a_i and

Algorithm 1 The construction process for the part-of-speech matrix

Input: A reviews $S = \{a_1, a_2, \ldots, a_n\}$; Preset part of speech set P; C_{a_i} is the part of speech of the word a_i; S_{a_i} is the emotion score calculated by the emotion lexicon for word a_i; Part-of-speech matrix is P_{ij}.

Output: dependency matrix P_{ij}

```
for i = 1 → n do
  for j = 1 → n do
    Generated by emotion lexicon L_ij = S_ai + S_aj
      if C_ai or C_aj ∈ P:
        if S_ai > 0 and S_aj > 0:
          P_ij = 1
        if S_ai < 0 and S_aj < 0:
          P_ij = −1
        else:
          M = MAX(|S_ai| ≥ |S_aj|)
          P_ij = sign(M)
      end if
  end for
end for
```

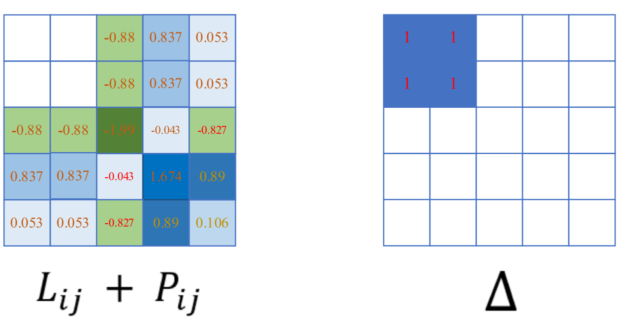

Fig. 4. The construction process of matrix Δ.

a_j respectively. P represents our predetermined set of part-of-speech. Finally, we combine the dependency matrix obtained above to obtain the external knowledge matrix D_{ij} as:

$$D_{ij} = A_{ij} * \left(L_{ij} + P_{ij} + \Delta\right) \tag{3}$$

Here, $*$ is the bitwise multiplication, and Δ is the supplementary matrix, which to ensure that the matrix does not obtain a digital zero when the matrix is multiplied by bit, so that the structure of the original dependency matrix A changes. The construction process for matrix A is shown in Fig. 4. The specific steps for generating a dependency matrix for each sentence are shown in Algorithm 2.

3.4. Graph convolutional networks

We adopt a graph convolutional neural network based on a dependency tree [11]. Given that a given review S contains N words, we can construct an original dependency tree G containing k nodes. Here the number of nodes is the word number, and the edge is the dependency between any two words in the reviews. Then we can obtain the original dependency matrix $A_{ij} \in R^{k*k}$. We mark the position with the dependency as 1 or 0 without it. For the ith node, we mark the input of the 1th layer as h_i^{l-1} and the output as h_i^l. The calculation process for the graph convolutional neural network is as follows:

$$h_i^l = \sigma\left(\sum_{j=1}^{n} A_{ij} W^l \mathrm{h}_i^{l-1} + b^l\right) \tag{4}$$

The weights W^l and bias b^l are trainable parameters. Here, we replace A_{ij} with the dependency matrix D_{ij} obtained by Algorithm 2. The matrix D_{ij} incorporates external knowledge (part-of-speech information, sentiment lexicon). It can solve the problem of difficulty in capturing edge labels, strengthen the weight of deny words, degree words and other words that affect sentiment polarity, and better guide the completion of aspect-based sentiment analysis tasks. We obtain the final hidden layer representation H^M of the sentence:

$$H^M = \sigma\left(\sum_{j=1}^{n} D_{ij} W^l \mathrm{h}_i^{l-1} + b^l\right) \tag{5}$$

3.5. Word-Sentence Interaction Network (WSIN)

Considering the complexity of the text structure and the presence of multiple aspect words in a sentence, fusing the information of current aspect words is critical for aspect-based sentiment analysis. Inspired by [30], a WSIN is added. It can fully consider the information of the current aspect word and the context information of the reviews through the linear interaction of the aspect word reviews to filter useful sentence information. The

Algorithm 2 The process of constructing a dependency matrix for each review

Input: A reviews $S = \{a_1, a_2, \ldots, a_n\}$; Preset part of speech set P; C_{a_i} is the part of speech of the word a_i; S_{a_i} is the emotion score calculated by the emotion lexicon for word a_i; Dependency set M between words; Part-of-speech matrix is P_{ij}; Sentiment score matrix is L_{ij}; External knowledge matrix is D_{ij}.

Output: dependency matrix D_{ij}

for $i = 1 \rightarrow n$ do
  for $j = 1 \rightarrow n$ do
    if dependency$(a_i, a_j) \in$ M or i = j then
      Generated by dependency tree $A_{ij} \leftarrow 1$
      Generated by emotion lexicon $L_{ij} = S_{a_i} + S_{a_j}$
      $if\ C_{a_i}\ or\ C_{a_j} \in P$:
        $if\ S_{a_i} > 0\ and\ S_{a_j} > 0$:
          $P_{ij} = 1$
        $if\ S_{a_i} < 0\ and\ S_{a_j} < 0$:
          $P_{ij} = -1$
        else:
          $M = MAX(|S_{a_i}| \geq |S_{a_j}|)$
          $P_{ij} = \mathrm{sign(M)}$
      end if
    end if
    $D_{ij} \leftarrow A_{ij} * (L_{ij} + P_{ij} + \Delta)$
  end for
end for

calculation process is as follows:

$$\mathrm{M} = \mathrm{relu}\left(H^M W^b + b_m\right) \tag{6}$$

$$N = sigmoid\left(H^M W^n + H^N W_n' + b_n\right) \tag{7}$$

$$S = M * N \tag{8}$$

where W^b, W^n and W_n' are learnable weight parameters, and bm and bn are biases. Here, H^M represents the review information obtained by the graph convolutional neural network (EK-GCN) incorporating external knowledge, and H^N represents current aspect word information to judge the emotion. Through the linear interaction of the two, the model can fully consider the information of the present aspect word, capture the relevant emotional clues in the review information, and generate a review representation based on the aspect word.

3.6. Output layer

We employ the obtained review representation based on the aspect word S as input. The final sentiment polarity $y \in (1, 0, -1)$ is obtained using *softmax* as the activation function.

$$y(a) = softmax\,(W_0 S + b_0) \tag{9}$$

where $y(a)$ is the probability of aspect a belonging to sentiment polarity. After backpropagation, the model is trained and calculated. Our goal is to optimize all parameters to minimize the loss function as much as possible. We use cross-entropy as the loss function. The formula is as follows:

$$L_\theta = -\sum_{(S,A)\in D}\sum_{a\in A} log\ y\,(a) \tag{10}$$

where A represents the aspects that appear in sentence S, D represents the aspect-sentiment pairs contained in sentence S, and θ denotes all trainable parameters of the EK-GCN model.

Table 3
Statistics of the four datasets for the ABSA task.

Dataset	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
Restaurant14	2164	727	637	196	807	196
Laptop14	976	337	455	167	851	128
Twitter	1507	1507	172	336	1528	169
Restaurant16	1620	597	88	38	709	190

4. Experiment

4.1. Datasets

In this section, we evaluate our EK-GCN model on four open datasets (Restaurant14, Laptop14, Tweets, and Restaurants16). The first two datasets (Restaurant14 and Laptop14) are from the semeval-2014 task [47], the Twitter dataset is from the Twitter collection collated by [48], and the last dataset is from semeval-2016 [49]. Table 3 shows some information about these datasets.

4.2. Relevant parameters

We use the GloVe vectors [50] to initialize the mapping of each word, and the vector dimension is 300 dimensions. We set the GCN to two layers; and the dimension to 50 dimensions. We use the Adam [51] model to optimize the initial update of the parameters and set the learning rate to 0.001, and the batch size to 32. The weights and parameters used in the neural network are initialized according to a uniform distribution. To highlight the universality of our model, we also replace the language model with BERT [27]. We set the dimension of the BERT-based model to 768 and the learning rate to 0.00002. The accuracy and F1 value as are used evaluation indicators.

4.3. Baseline model

We introduce some excellent baselines to compare the performance of our models. We classify the models into four categories: Semantics and Attention Based Models, Models based on graph convolutional neural networks, Models with BERT as the main framework, and our proposed model.

• **Semantics and Attention Based Models:**

ATAE-LSTM [52]: Aiming at the complexity of sentence structure, the model can pay attention to different sentence context information according to the input of different aspect words.

IAN [53]: The model focuses on interactive modeling of aspect words and context, enabling better target representation generation.

RAM [54]: The model combines attention-based Bi-LSTM learning sentence representation and position information nonlinearly with recurrent neural networks to improve the performance of the model.

LSTM+SynATT [55]: The model employs an attention mechanism to model sentences and uses the weighted summation of aspect words as the target representation.

MAN [56]: The model employs intra- and inter-level attention mechanisms. First, the transformer encoder is used for encoding, and second, global and local attention mechanisms focus on the entire sentence and inter-word interactions, respectively.

PBAN [57]: The model adopts a GRU module to sense position information, and a bidirectional attention mechanism to model sentence and aspect word information.

MenNet [58]: The model explicitly captures the importance of contextual words in aspect terms through multiple layers of computation. The number of calculation layers is set to 9 layers.

IPAN [59]: The model uses the part-of-speech information POS as a guide to assign different weight ratios to different part-of-speech so that the model pays more attention to words related to emotional expressions. At the same time, a mechanism to highlight aspect words is also designed, which can fully interact between aspect words and context.

CPA-SA [60]: The model adopts two context weighting mechanisms to assign different positional weights according to the position of the aspect word in the reviews. It can effectively alleviate the interference of the number of words in the context of the aspect word to the model. In addition, a completely new loss function is created based on the class imbalance problem.

• **Models based on graph convolutional neural networks:**

ASGCN [61]: This model proposes a graph convolutional neural network model based on dependency trees, which can fully utilize syntactic information and word dependencies.

CDT [11]: This model applies a graph convolutional neural network to a sentence dependency tree for the first time so that contextual information and dependency information are propagated from opinion words to aspect words.

DGEDT [62]: The model combines the sentence representation learned by the transformer and the graph representation learned by the dependency tree through iterative interaction. The two reinforce each other and improve the model performance.

GAT [44]: The model adopts the attention mechanism to obtain the attention weight of each word to solve the problem of the dependence matrix of the previous graph convolutional neural network and its approximation method.

CNN-BiLSTM [41]: The model proposed a novel attention-based joint learning approach to address the lack of training data. This method can use the learned document-level sentiment data features to achieve aspect-level sentiment classification.

R-GAT [45]: The model pays attention to the complexity of the sentence structure and the problems of many aspects of the word, reconstructs and prunes the dependency tree, and establishes a dependency tree structure with the target word as the root node.

• **Models with BERT as the main framework:**

BERT [28]: fine-tuned BERT

BERT-SPC [63]: The model is a variant of transformers that converts raw reviews into sentence pairs and fine-tunes them for aspect-based sentiment analysis tasks.

BAT [64]: This paper proposes a novel architecture called BERT Adversarial Training (BAT) to utilize adversarial training for the two significant tasks of Aspect Extraction and Aspect Sentiment Classification in sentiment analysis.

AEN-BERT [63]: The model focuses on the time-consuming and labor-intensive problem of labeling datasets, introducing adversarial networks into aspect-based sentiment analysis tasks. The model performs a malicious process to generate comment text similar to the real-world dataset, increasing the number of training datasets and making the neural network model more robust.

R-GAT-BERT [45]: R-GAT-BERT is the model R-GAT with the Bi-LSTM replaced by BERT.

DualGCN+BERT [65]: This model considers both the complementarity and semantic correlation of grammatical structures and proposes a Dual Graph Convolutional Network (DualGCN) model to address dependency parsing inaccuracy as well as the complexity of reviews.

Sentic GCN-BERT [40]: The model created a graph convolutional network based on the SenticNet, which can fully exploit the emotional dependencies between words in a sentence according to different aspect words.

• **Our proposed model:**

EK-GCN: EK-GCN is the network model we propose.

EK-GCN-BERT: EK-GCN-BERT is our EK-GCN with the Bi-LSTM replaced by BERT.

4.4. Experimental results and analysis

To verify the effectiveness of our proposed EK-GCN model, we conduct comparative experiments on four benchmark datasets. Different language models (Bi-LSTM, BERT) are used for comparative experiments, and the ACC and F1 values of other methods are shown in Tables 4 and 5, respectively. Through comparative experiments, we find the following:

(1) Compared with models based on attention mechanisms and semantics, GCN-based models achieve better results. The GCN network can better capture the dependencies between words.

(2) Compared with the CDT model, our model does not simply concatenate part-of-speech information at the vector input layer. We statistically integrated the part-of-speech information, preset the part-of-speech matrix, and fused it into the syntactic dependency matrix as external information. The results show the effectiveness of the part-of-speech matrix.

(3) Compared with GCN-based models (GAT and R-GAT), our EK-GCN achieves better performance on four benchmark datasets. Our model is not limited to mining latent information of the

Table 4
Performance comparison on different models on the benchmark datasets. We use accuracy and F1 as evaluation criteria. The best results are in bold, and the second-best are underlined.

Models		Twitter		Restaurant14		Laptop14		Restaurant16	
		Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
Syn.+Att	ATAE-LSTM	–	–	77.20	–	68.70	–	–	–
	IAN	–	–	78.60	–	72.10	–	84.74	55.21
	RAM	69.36	67.30	80.23	70.80	74.49	71.35	83.88	62.14
	LSTM+SynATT	–	–	80.45	71.26	72.57	69.13	84.61	67.45
	MAN	**76.70**	72.41	84.29	71.36	78.21	72.98	–	–
	PBAN	–	–	81.16	–	74.12	–	–	–
	MenNet	69.65	67.68	78.16	65.83	70.33	64.09	85.44	65.99
	IPAN	74.30	72.50	82.80	73.80	77.20	73.50	–	–
	CPA-SA	–	–	82.64	73.38	75.18	71.50	89.02	72.43
GCN	ASGCN	72.15	70.40	80.77	72.2	75.55	71.05	88.69	66.64
	CDT	74.66	73.66	82.30	74.02	77.19	72.99	85.58	69.93
	DGEDT	–	–	83.90	75.10	76.80	72.30	–	–
	GAT	71.67	70.13	78.21	67.17	73.04	68.11	–	–
	R-GAT	75.51	73.80	83.29	**77.33**	73.74	75.56	88.92	70.89
	CNN-BiLSTM	–	–	81.96	74.16	72.26	68.95	87.27	**74.44**
Our model	EK-GCN	75.84	**74.57**	**83.96**	74.93	**78.46**	**76.54**	**89.36**	69.32

Table 5
Performance comparison of different models with BERT as the language model on benchmark datasets. The best results are in bold, and the second-best are underlined.

Models		Twitter		Restaurant14		Laptop14	
		Acc.	F1	Acc.	F1	Acc.	F1
BERT-BASE	BERT	75.28	74.11	85.62	78.28	77.58	72.38
	BERT-SPC	73.55	72.14	84.32	77.15	78.54	75.26
	BAT	–	–	86.03	79.24	79.35	76.50
	AEN-BERT	74.71	73.13	83.12	73.76	79.93	76.31
	R-GAT-BERT	76.15	74.88	86.60	81.35	78.21	74.07
	Sentic GCN-BERT	-	–	86.92	81.03	**82.12**	79.05
	DualGCN+BERT	**77.40**	**76.02**	87.13	81.16	81.80	78.10
	EK-GCN-BERT	75.89	75.16	**87.65**	**82.55**	81.30	**79.19**

dependency tree but incorporates external knowledge to assist in mining emotional cues and better accomplish aspect-based emotional subtasks.

(4) Compared to the ASGCN, ASEGCN, and CDT models, our model does not involve a simple average pooling operation on aspect words. This feature proves the effectiveness of the WSIN we designed, which can filter sentence information irrelevant to the current aspect word.

(5) The performance of models using traditional GloVe embedding vectors is generally inferior to BERT-based models. The shortcomings of conventional word embedding vectors limit the performance of complex feature extraction modules. Therefore, we also transformed the language model and adopted the EK-GCN-BERT model with BERT as the main framework. Compared to BERT-based models, our model considers external knowledge and the importance of WSIN to capture aspect-specific sentiment cues. It can highlight the weight ratio of the sentiment words of specific aspect words and has an important guiding role in sentiment classification. The experimental results show that our model is highly competitive, as shown in Table 5.

(6) The performance of our model on the dataset Tweets is not outstanding. There may be too many other characters in the dataset, most of which are words outside the sentiment lexicon. Therefore, the sentiment lexicon cannot determine the sentiment scores of these words, making the sentiment word matrix relatively sparse, and the model cannot fully utilize the indications provided by external knowledge.

4.5. Ablation experiment

We conduct the following ablation experiments to further demonstrate the effectiveness of each component of our proposed model. The experimental results are shown in Table 6, where "w/o" means "none". We cancel the part-of-speech matrix, sentiment score matrix, and WSIN to verify their effectiveness.

The results show that all these components contribute to the excellent performance of EK-GCN. The part-of-speech matrix and sentiment lexicon score matrix are important external parts that can solve the problem of complex capture edge labels, enhance the weight of words that affect sentiment polarity, such as deny words and degree words, and generate more accurate sentence representations. The F1 score of Restaurant14 is better without this component. We hypothesize that sentiment lexicons are sentiment analysis tools and techniques that combine a range of common sense reasoning, psychology, linguistics, and machine learning. When using sentiment lexicons, a certain amount of noise may be introduced due to differences in data. However, in most datasets, the modular sentiment score matrix still shows positive effects. Inspired by [62,66], in future research, we will seek to comprehensively understand the external knowledge of parsers and sentiment dictionaries from a cognitive perspective. We will design multiple rounds of deductive modules to simulate the extraordinary learning ability of human beings. The deductive module balances external knowledge with the flat representation of the text through continuous deductive reasoning. The ultimate goal is to reduce the noise of the parser and the inaccurate score of sentimental lexicons. At the same time, it shows the critical role of the WSIN in the sentence. It can fully consider information on the current aspect word and filter out sentence information irrelevant to the present aspect word to better guide the completion of the aspect-based sentiment analysis task.

4.6. Parameter research

To verify the validity and rationality of our model, we conduct a parametric study. We explored the number of layers of graph convolutional neural networks, the directed edge and undirected edge exploration of dependency trees, and the size of dropout and word vector dimensions.

4.6.1. Analysis of the number of GCN layers

To verify the influence of the number of GCN network layers on the model effect, we conducted experiments on the Restaurants14 and Laptop14datasets. We separately counted the accuracy and F1 values of the GCN layers in the interval [1,11], and the experimental results are shown in Fig. 5. We found that the EK-GCN model works best when the number of GCN layers is 2. We believe that when the graph convolutional neural network is iterated once, the model may not convolve enough information

Table 6
The ablation experiment of our proposed EK-GCN model.

Models	Twitter		Restaurant14		Laptop14		Restaurant16	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
EK-GCN w/o pos matrix	74.58	73.37	82.16	74.28	77.64	75.44	87.64	68.87
EK-GCN w/o sentiment score matrix	75.04	74.18	83.19	**75.26**	78.11	75.59	88.17	68.59
EK-GCN w/o WSIN	75.26	73.94	83.57	74.68	78.10	75.93	88.28	68.91
EK-GCN	**76.84**	**74.57**	**83.96**	74.93	**78.46**	**76.54**	**89.36**	**69.32**

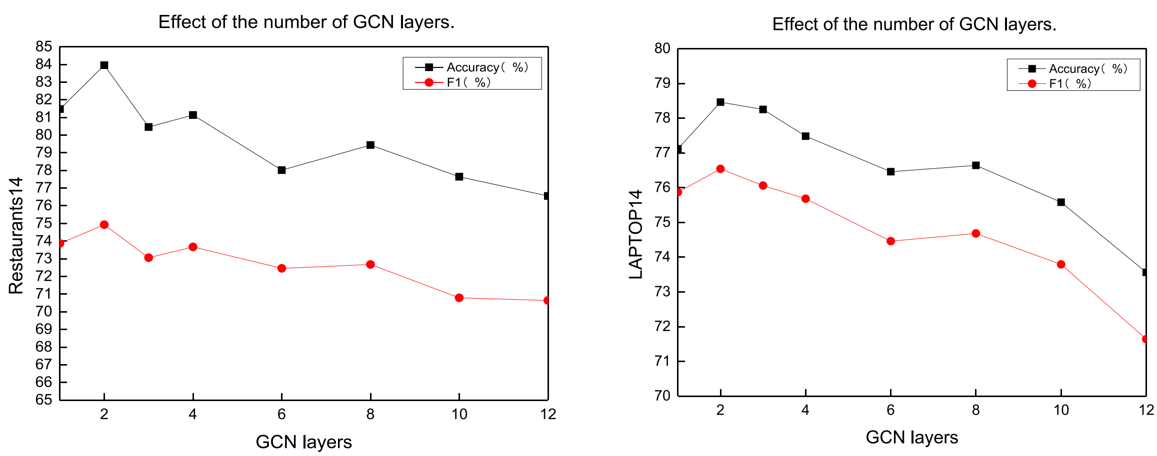

Fig. 5. Accuracy and F1 value of EK-GCN model on the dataset and laptop with different numbers of GCN layers.

to produce a more informative sentence representation, and the model does not learn well. When the number of GCN layers is greater than 2, the word represents the information of adjacent words through continuous convolution grammar. The embedding of each word vector gradually tends to be consistent, negatively impacting subsequent classification. When the number of network layers keeps increasing, too many training parameters will be generated, making the model more difficult to train.

For better illustration, we counted the sentences with only one aspect word in the Restaurants14 and Laptop14 datasets. The results are shown in Table 7. Hops represent the position of the aspect word in relation to the sentiment word in the sentence. The table shows that most sentiment words are distributed within two hops of the aspect words, so the model performance is best when the number of GCN layers is two.

4.6.2. Directed edge and undirected edge exploration of dependency trees

The dependencies between words in the dependency tree are classified as either directed or undirected. This section investigates the effect of using directed and undirected dependency trees in GCN models incorporating external knowledge. The directed dependency tree model is labeled EK-GCN-D, and the undirected dependency tree model is EK-GCN. The experimental results are shown in Table 8, which shows that the results for undirected graphs are better than those for directed graphs.

Here, we consider two dependency trees: dependency trees with directed edges and dependency trees with undirected edges. An example is shown in Fig. 6.

We believe that the parent node and its child nodes influence each other. However, the directed dependency tree considers only that the parent node can affect the child node, weakening this mutual relationship. A parent node of an undirected dependency graph can be influenced by its children. An undirected dependency graph can make a word fully consider the information of its adjacent word nodes.

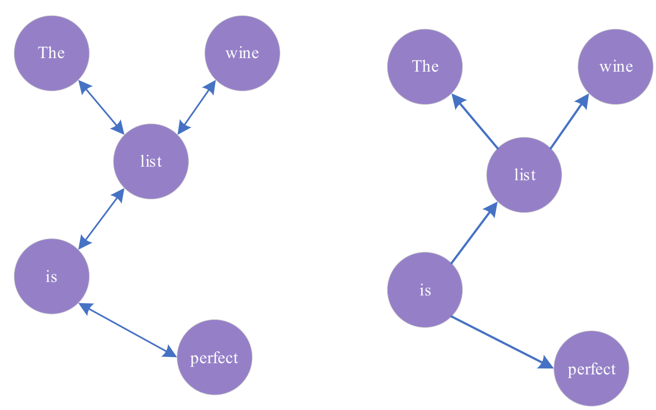

Fig. 6. An example graph of the directed edge and undirected edge dependency tree for the review "The wine list is prefect".

4.6.3. Size of dropout and word vector dimensions

To explore the optimal setting of the model EK-GCN parameters and then obtain the optimal effect of the model, we conducted experiments on input_dropout, rnn_dropout, and dimension. For the parameter input_dropout, we performed an analysis on three datasets. The results are shown in Fig. 7. When the parameter input_dropout is 0.7, the model achieves the best effect, which is consistent with the analysis of Wang et al. [45]. If the input_dropout is too small, the model may learn too many useless features in the training set, making the model overfit and fail to capture vital emotional cues correctly. When the input_dropout is too large, the model will discard most of the learned text features, leading to the insufficient model learning and underfitting. The model is undertrained to make correct judgments about the data in the test set. Furthermore, when we fixed input_dropout to 0.7, we experimented with the parameter rnn_dropout. The results are shown in Fig. 8, which shows that the model works best when the rnn_dropout decay is 0.2. Furthermore, we investigated the dimensionality of Bi-LSTM and GCN on the dataset Laptop14. The results are shown

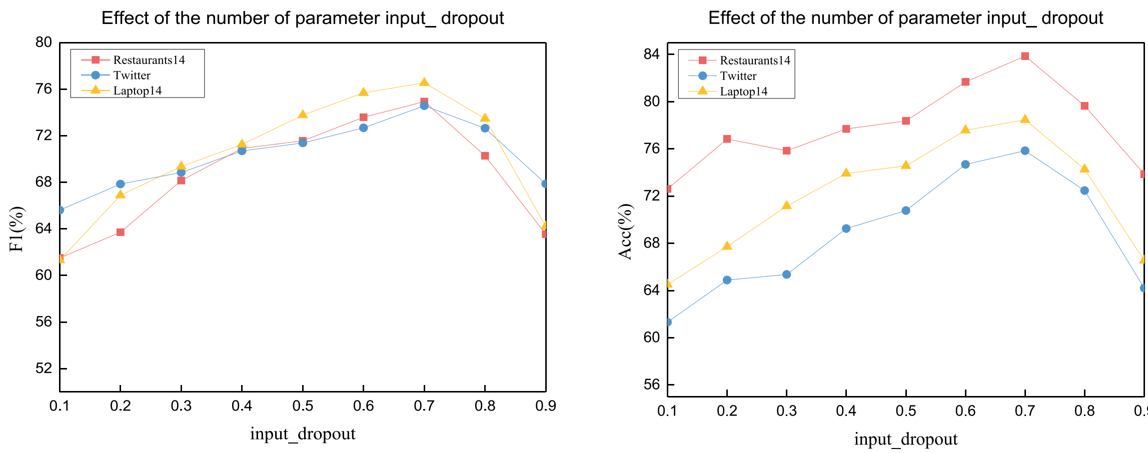

Fig. 7. Accuracy and F1 value of EK-GCN model on three datasets using different input_dropout values.

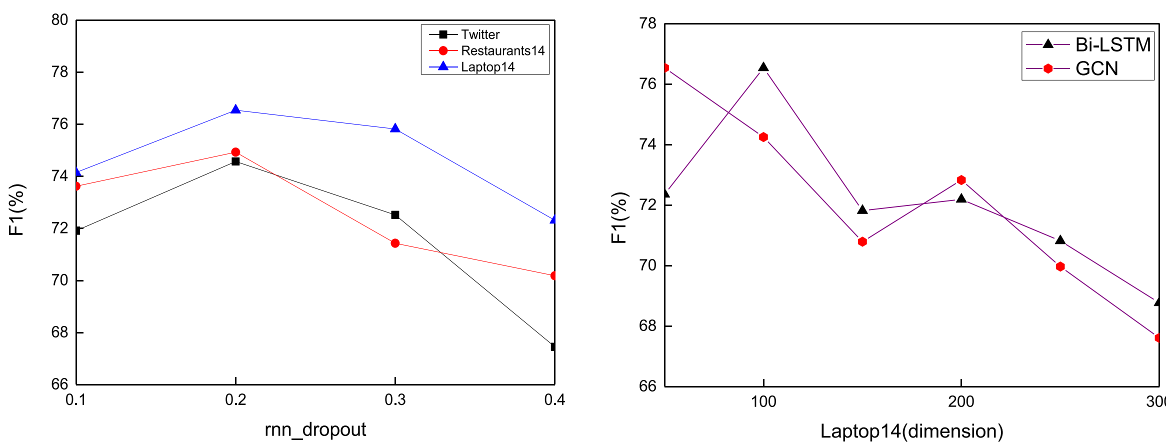

Fig. 8. Experimental results of EK-GCN model on datasets with different rnn_dropout and dimensions.

Table 7
The experimental results of the model when using a directed dependency tree and an undirected dependency tree, respectively.

Hops	1	2	3	4	5	6	7
Restaurants14	224	91	38	13	6	5	2
Laptop14	181	29	16	9	8	2	2

Table 8
The experimental results of the model when using a directed dependency tree and an undirected dependency tree, respectively.

Models	Twitter		Restaurant14		Laptop14	
	Acc.	F1	Acc.	F1	Acc.	F1
EK-GCN-D	75.58	74.29	**83.97**	74.67	78.43	76.18
EK-GCN	**76.84**	**74.57**	83.96	**74.93**	**78.46**	**76.54**

in Fig. 8. When the dimensions of Bi-LSTM and GCN are 100 and 50, respectively, the model performs best. The results of this study are the same as the dimension settings of most previous models [59].

4.7. Case study and visual analysis

In this section, we take the comment "The menu is slightly above average" as an example to simulate the process of constructing an external knowledge matrix with our EK-GCN model. The details are shown in Fig. 9. The darker the color in the figure is, the more the model pays attention to it. For example, the aspect word is "menu" and the sentiment polarity is negative. As shown in the figure, the original dependency matrix assigns the same weight to each word and cannot highlight the weight of words contributing to sentiment analysis. The model tends to assign a positive sentiment to the aspect word "menu" based on the meaning of the word "above". However, our EK-GCN gives greater weight to the word "slightly" after fully introducing external knowledge and reconstructing the dependency matrix. This approach can strengthen the weight of negative words, degree words, and other words that affect sentiment polarity, and to a certain extent solves the problem that graph convolutional neural networks cannot capture edge labels. The model can thus generate better sentence representations to guide aspect-based sentiment analysis.

At the same time, to verify the effect of the EK-GCN matrix and the WSIN on the EK-GCN model, we test an example, as shown in Figs. 10 and 11. In both instances, we used the shades of heatmap colors to highlight the level of word attention, with darker colors representing higher attention scores.

From Fig. 10, we can see that for the review "This laptop has only 2 USB ports.", the model containing the external knowledge matrix can capture the negative sentiment word "only" of the aspect word "laptop" well. Conversely, in the absence of the external knowledge matrix, the model does not extract the negative sentiment words of the aspect "only", but only mines the noun phrase "2 USB ports". However, in contrast to the original aspect, the noun phrase has no obvious sentiment feature The word "laptop" has a different meaning.

The example sentence in Fig. 11, "After replacing the hard drive, the battery stopped working, which was frustrating." is

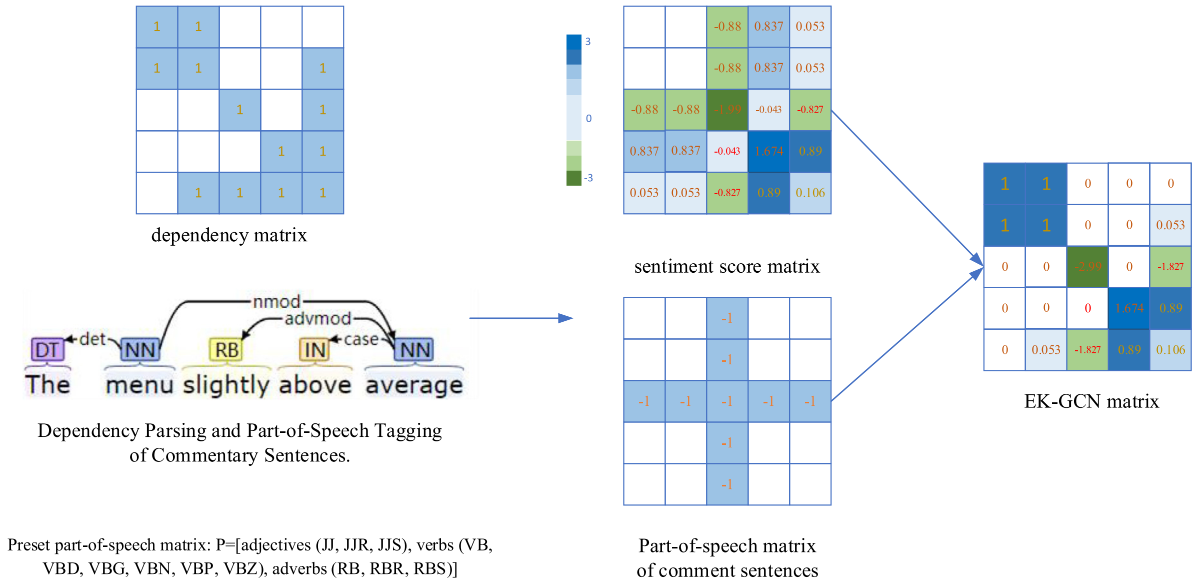

Fig. 9. The process of our EK-GCN model generating the final matrix for the example "The menu slightly above average",.

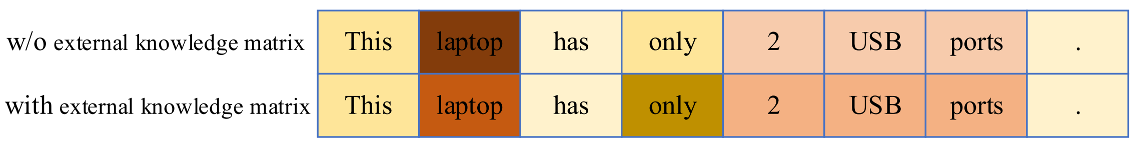

Fig. 10. An example of the attention weights of the model with or without the external knowledge matrix.

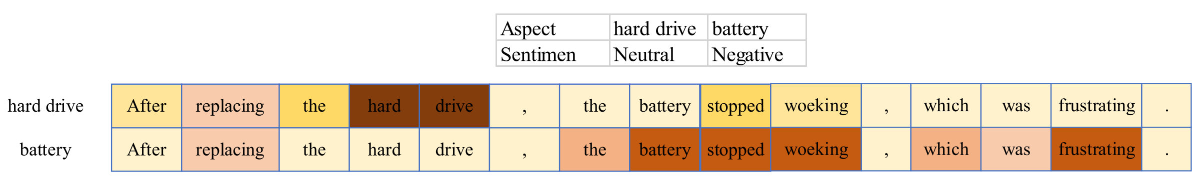

Fig. 11. An example of the attention weight of the model with or without WSIN.

used to illustrate the importance of the WSIN. When multiple aspect words and multiple emotions are mixed occur in a sentence, the greatest challenge of aspect-based sentiment classification is to obtain the correct sentiment information for a specific aspect. The EK-GCN model with the WSIN can accurately capture the sentiment polarity of the specific aspect in the sentence instead of relying on the sentiment of the entire review. The aspect word "hard drive" is not affected by the emotional polarity (negative) of the entire review and interacts with the context information of the review to filter out valuable sentence information to obtain the correct sentiment polarity. For the aspect word "battery", the model can also capture the sentiment word cues related to it, and obtain the negative sentiment polarity.

5. Conclusion

This work proposes a graph convolutional neural network EK-GCN that incorporates external knowledge. It reconstructs the dependency matrix and enhances word embeddings by introducing external knowledge. Specifically, we construct an external knowledge matrix that contains a sentiment lexicon score matrix and a part-of-speech information matrix. This approach can address the difficulty in capturing edge labels, strengthen the weight of denying words, degree words, and other words that affect sentiment polarity, and better guide the completion of aspect-based sentiment analysis tasks. In future work, we will consider designing multiple rounds of deductive modules to balance external knowledge with the flat representation of the text through a continuous process of deductive reasoning. The ultimate goal is to reduce the noise of the parser and the negative impact of inaccurate scores in sentiment lexicons. Furthermore, the original dependency tree building relies on external dependency parsers, which may not be available for low-resource languages, or may perform worse in low-resource domains. In the future, we will try to induce a dependency tree from the review and integrate external commonsense knowledge and reference relations. Finally, we will apply our EK-GCN model to implicit sentiment analysis and many more NLP tasks.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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