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Aspect-Level Sentiment Analysis of Bi-Graph Convolutional Networks Based on Enhanced Syntactic Structural Information

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Abstract

Aspect-oriented sentiment analysis is a meticulous sentiment analysis task that aims to analyse the sentiment polarity of specific aspects. Most of the current research builds graph convolutional networks based on dependent syntactic trees, which improves the classification performance of the models to some extent. However, the technical limitations of dependent syntactic trees can introduce considerable noise into the model. Meanwhile, it is difficult for a single graph convolutional network to aggregate both semantic and syntactic structural information of nodes, which affects the final sentence classification. To cope with the above problems, this paper proposes a bi-channel graph convolutional network model. The model introduces a phrase structure tree and transforms it into a hierarchical phrase matrix. The adjacency matrix of the dependent syntactic tree and the hierarchical phrase matrix are combined as the initial matrix of the graph convolutional network to enhance the syntactic information. The semantic information feature representations of the sentences are obtained by the graph convolutional network with a multi-head attention mechanism and fused to achieve complementary learning of dual-channel features. Experimental results show that the model performs well and improves the accuracy of sentiment classification on three public benchmark datasets, namely Rest14, Lap14 and Twitter.

Keywords

Aspect-Level Sentiment Analysis, Sentiment Knowledge, Multi-Head Attention Mechanism, Graph Convolutional Networks

1. Introduction

Aspect-based Sentiment analysis (ABSA) is a fine-grained field of emotion analysis. Its main task is to identify and analyze the emotional polarity expressed in a given text, such as positive, negative or neutral, for a specific aspect or entity. This kind of analysis method can let us understand the feelings expressed in the text more deeply, especially when dealing with complex text containing multiple aspects or entities, such as product reviews, restaurant reviews, etc. Taking "the waiter was attentive, the food is unpleasant" as an example, the sentence contains two aspects of "waiter" and "food", and the corresponding emotional polarity is positive and negative respectively. The goal of the ABSA task is to establish the relationship between the aspect item and the opinion item, so as to judge that the emotional polarity of the two aspects is positive and negative respectively.

Aspect level emotion analysis methods can be divided into two types: machine learning based methods and deep learning based methods [1]. The method based on machine learning relies on rich and correct feature representation and an emotional dictionary that needs to be updated at any time, which is more expensive and difficult. With the rise of deep learning, attention mechanisms have become widely used in aspect-level emotion analysis tasks [2]-[4]. Although the attention mechanism is widely used in aspect level tasks and has achieved some results, it cannot obtain the syntactic relationship between specific aspect words and contexts. Many scholars have applied Graph Convolutional Networks (GCN) [5] to aspect level emotion analysis tasks to solve this problem. GCN can effectively process the dependency tree or syntactic structure of a sentence, where nodes represent words and edges represent the grammatical relationship between words. By applying convolution operations on such a graph structure, GCN can capture the dependencies between words and help the model better understand the semantic content of sentences. Although GCN can obtain syntactic information in sentences, it is insufficient to obtain information, and it also brings a lot of noise. External emotional knowledge is also needed to enhance the syntactic features of sentences. In existing research, emotional features are usually enhanced by establishing an emotional knowledge map, introducing emotional dictionary knowledge and introducing common sense knowledge into external emotional knowledge, and many scholars have proved that emotional knowledge plays a positive role in emotional classification. And has a positive impact on emotional classification. How to effectively use deep semantic information and refined syntactic structure information to effectively fuse them to enhance graph neural networks and extract emotional features more fully has become a problem worth exploring.

Therefore, this paper proposes a two-channel graph convolutional network model that introduces emotional knowledge. The main contributions are as follows:

(1) Strengthen the relevance of syntactic information, associate syntactic dependency matrix and phrase matrix, and combine graph convolution neural network to extract more accurate feature information.

(2) The syntactic structure information and semantic information are dynamically updated through the dual channel graph convolution network. In order to

fully integrate the syntactic information and semantic information, the importance of different representations is adaptively learned using the trainable parameter matrix.

(3) The performance of the model is evaluated on three public data sets. The experimental results show that the accuracy and macro F1 value of the model are improved for different data sets.

2. Related Work

In recent years, more and more deep learning methods have been applied to aspect level emotion analysis tasks, which can be roughly divided into two categories in existing work. The first type is to obtain the semantic information of sentences through the attention mechanism. Tang *et al.* [6] proposed a long-term and short-term memory network model based on goal dependency. Long Short Term Memory (LSTM) is used to obtain the feature information of target words and contexts, and effectively identify the corresponding emotional polarity. ATAT-LSTM [7] is an LSTM model based on attention. It uses the context and aspect word information in sentences to splice and model through the attention mechanism. Ma *et al.* [2] proposed that the Interactive Attention Network (IAN) can effectively model the relationship between the target word composed of multiple words and the context, focusing on the parts with higher relevance to the target word. Xu *et al.* proposed the Multi Attention Network (MAN), which uses the global attention module and the local attention module to capture the global semantic information and the semantic information between the context of the aspect words respectively. The combination of the two improves the accuracy of the model. However, such attention mechanism based methods only focus on the characteristics of aspect words and context in sentences, and cannot capture the syntactic dependency between context words in sentences.

The second type is to obtain syntactic structure information through dependency resolution. The syntactic structure information can obtain words that are dependent on aspect words, which greatly shortens the distance between aspect words and opinion words. Modeling through GCN can make up for the deficiency of attention mechanisms in aspect-level emotion analysis tasks. CDT [8] uses Bi LSTM to learn the feature representation of sentences, and GCN convolution based on syntactic dependency tree to learn the feature representation of sentences. TD-GAT [9] directly conveys emotional features from the context of the syntactic structure of aspect words, making the opinion words closer to aspect words, and resolving potential syntactic ambiguity, so that the model can obtain more accurate syntactic information. Most of the above GCN models based on dependency syntax trees ignore the emotional information between aspect words and contexts. In order to add emotional knowledge to aspect level emotion analysis tasks, Zhou *et al.* [10] proposed a graph convolution network model based on syntactic dependency and emotional knowledge modeling. This model is composed of two graph convolution neural networks, which construct syntactic dependency graphs and emotional knowledge graphs respectively and apply the multi head attention mechanism. Liang *et al.* [11] proposed a graph convolution network model for emotional knowledge enhancement, which complements a single syntactic dependency by introducing emotional knowledge in SenticNet, while constructing the adjacency matrix for emotional enhancement to extract the syntactic structure features of strong dependency.

Based on the above observations, this paper proposes to extract more accurate emotional information through the dual channel graph convolution neural network (BiC-GCN) to help find aspect words, opinion words and their emotional polarity.

3. Binary Channels Graph Convolution Model (BiC-GCN)

As shown in **Figure 1**, the BiC-GCN model proposed in this paper consists of six parts: embedding layer, Bi LSTM layer, feature extraction layer, graph convolution layer, aspect word masking layer, interaction layer, and classification layer.

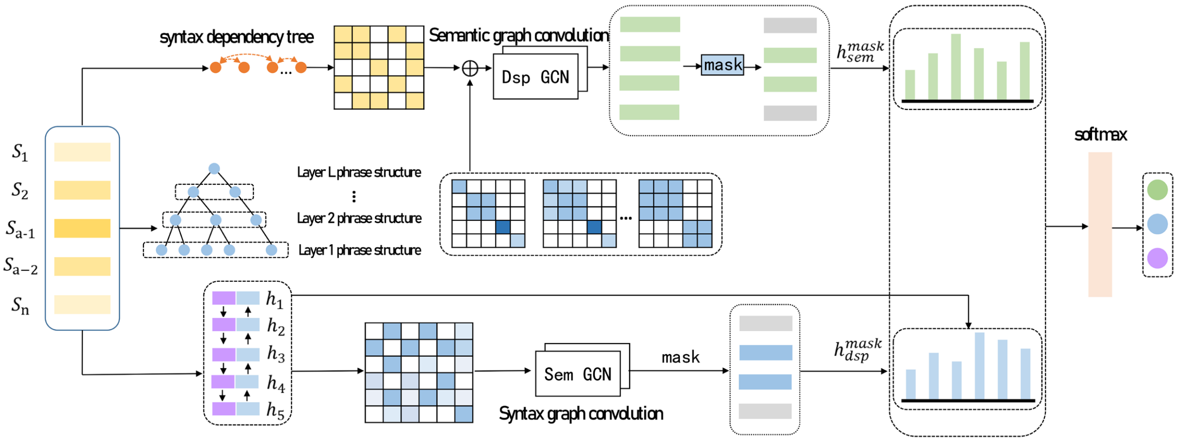

Figure 1. BiC-GCN model architecture.

3.1. Embedded Layer

Assume that the sentence is $S=\{s_1,s_2,\cdots,s_{a+1},s_{a+2},\cdots,s_{a+k},\cdots,s_n\}$ consists of n words, Where s_i denotes the ith word and s_{a+i} denotes the ith aspect word, set of aspect words $A=\{s_{a+1},s_{a+2},\cdots,s_{a+k}\}$. Use pre pre-trained GloVe word vector [12] map each word in the input statement to a vector with low dimensional real value to obtain the embedding matrix $E\in\mathbb{R}^{|V|\times d_{\text{emb}}}$, $|V|$ is the size of vocabulary, d_{emb} denotes the dimension of each word vector. Therefore, the sentence has corresponding word embedding $x=\{x_1,x_2,\cdots,x_n\}$.

3.2. Bi-LSTM Layer

LSTM can learn the information of sentences from front to back during training, but cannot encode the information from back to front. Therefore, Bi-LSTM is used to learn the hidden information in the context. Bi LSTM is a combination of forward and backward LSTM. The forward LSTM of sentence S is expressed as:

$\overrightarrow{H^F} = \{\overrightarrow{h_1}, \overrightarrow{h_2}, \cdots, \overrightarrow{h_n}\}$, the backward LSTM of sentence S is expressed as $\overleftarrow{H^B} = \{\overleftarrow{h_1}, \overleftarrow{h_2}, \cdots, \overleftarrow{h_n}\}$, the hidden state vector $\mathrm{H} = \{h_1, h_2, \cdots, h_n\}$ finally generated by Bi LSTM is spliced with the vectors corresponding to $\overrightarrow{H^F}$ and $\overleftarrow{H^B}$, where $h_i \in \mathrm{H}^{2d}$, using H as the initial input for the model.

3.3. Feature Extraction Layer

Build an enhanced emotional dependency matrix for feature extraction. In aspect level sentiment analysis tasks, phrase structure tree and dependency syntax tree are two syntactic structures used to capture the collocation relationships between words in a sentence. Essentially, it is to represent each word in a sentence as a node in a tree, with dependency relationships represented as directed edges. This article uses the Stanford NLP tool for syntactic analysis and constructs a dependency syntactic tree. The dependency syntactic tree can be interpreted as a graph with nodes, where nodes represent words in the sentence and edges represent syntactic dependency paths between words in the graph. The dependency tree G of any sentence can be expressed as the adjacency matrix D of $n \times n$, If node i is connected to node j through a single dependent path in tree G, Then $D_{ij} = 1$, otherwise $D_{ij} = 0$, as shown in Formula (1):

$$D_{ij} = \begin{cases} 1 & s_i, s_j \ \text{Dependency} \\ 0 & s_i, s_j \ \text{No dependency} \end{cases} \tag{1}$$

In the ASGCN model, we believe that the dependency between words is mutual, so we can build an undirected graph, where $D_{ij} = D_{ji}$.

The phrase structure tree is a grammatical structure that helps to understand the text structure and capture the phrase level relationship, and can reflect the hierarchical relationship between sentence phrases [6]. The construction of the phrase structure tree usually involves phrase structure analysis. The nodes of the phrase structure tree represent phrases, and the phrases at each level can contain all the words of the sentence. As shown in the **Figure 2**:

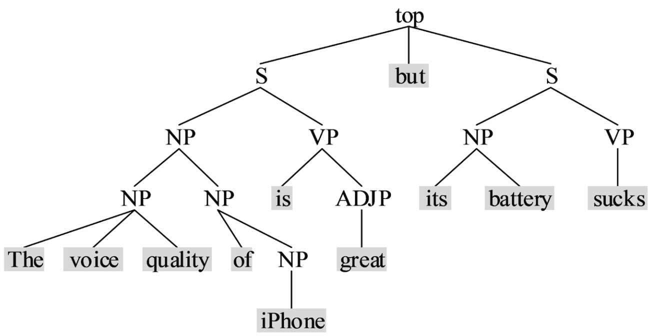

Figure 2. The phrase structure tree.

The method of this paper is to give a sentence and use the natural language processing tool Stanford Consistency Parser developed by Stanford University to generate the phrase structure tree. Different from the dependency syntax tree, the phrase structure tree shows the organizational structure between words in the sentence. This paper uses each node in the phrase structure tree to segment the sentence. Each node in the phrase structure tree can be understood as a phrase, E.g. sentence “The voice quality of iPhone is great but its battery sucks”, the L-layer structure will be analyzed in the structural analysis, the topmost layer is broken down into [“The voice quality of iPhone is great”, “but”, “its battery sucks”], according to the phrase structure tree, the phrase structure at the next level can be expressed as [“The voice quality of iPhone”, “is great”, “but”, “its battery sucks”], Up to the bottom, so you can get the phrase list of each layer h_p^l, the phrase list of each layer can contain all the words of the sentence. Because the phrase structure has multiple layers, the phrase set of L layer can be obtained $\left\{h_p^1, h_p^2, \cdots, h_p^l\right\}$, and the set is transformed into a multi-level phrase matrix $P_{i,j}^l$ by formula (2):

$$P_{i,j}^l = \begin{cases} 1 & \text{If } w_i, w_j \text{ are in the same phrase} \\ 0 & \text{Other situations} \end{cases} \tag{2}$$

where h_p^l is the vector representation of phrases at each level, l is the number of levels of phrase set, and p is the number of phrases at that level. If only syntactic dependency trees are used, the association between great and socks will lead to noise problems, which is not conducive to capturing the emotional context of each aspect, thus leading to the misjudgment of emotional polarity. Therefore, phrase structure is added to the traditional syntactic dependency matrix to make it more closely related to the context. Because the subtree in the phrase structure governs all words appearing in the syntactic dependency subtree [7]. So, the dependency tree has the same words in its corresponding phrase subtree. From the perspective of these subtrees, the association between the transformed syntactic dependency matrix and the phrase matrix at each level can be established. Therefore, this paper combines the syntactic dependency matrix and the phrase matrix, as shown in Formula (3):

$$PD^l = P^l \oplus \mathrm{D} \tag{3}$$

The information of the two is integrated into a common representation, including the internal context information and syntax information. By deleting the edges that may cause noise, the remaining dependent edge positions are added, and the edge merging is completed by matching the dependency type or phrase structure type. As shown in **Figure 3**:

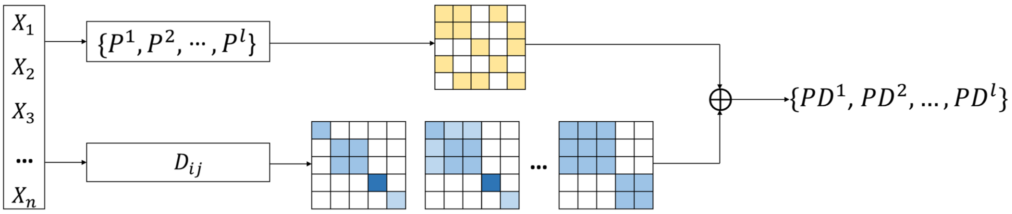

Figure 3. Dependency matrix and phrase matrix fusion.

P^l refers to the phrase matrix at each level, while D refers to the syntactic dependency matrix generated by the syntactic dependency tree.

The adjacency matrix obtained through the fusion of phrase matrix and syntactic dependency matrix contains both phrase and sentence information. The phrase level grammatical information and sentence level grammatical information are fused to obtain the set of adjacency matrix of $\left\{PD^1, PD^2, \cdots, PD^l\right\}$, which is used as the input of GCN. Since there are multiple adjacency matrices in the set, multiple outputs G are obtained through formula (4), and the final GCN output $\left\{h_{D1}^1, h_{D2}^2, \cdots, h_{Di}^l\right\}$ is obtained by averaging the output hidden vectors of each layer, where $\left\{h_{D1}, h_{D2}, \cdots, h_{Di}\right\}$ represents the feature output from the first node to the ith node. The syntactic feature information is enhanced after the fused adjacency matrix passes through the GCN layer.

$$h_{Di}^{(l)} = \rho\left(\sum_{j=1}^{n} PD_{ij} W^{(l)} h_j^{(l-1)} + b^{(l)}\right) \tag{4}$$

where, $h_{Di}^{(l)}$ refers to multiple GCN outputs after fusion, PD_{ij} refers to the adjacency matrix of a fused layer, i and j represent the relationship between words, $W^{(l)}$ refers to the weight matrix, $b^{(l)}$ refers to the deviation vector, ρ refers to the activation function, and h refers to the initial hidden vector input.

3.4. SemGCN

Inspired by the work of Huang [12] *et al.* and He [13] *et al.*, semantic graph convolution is introduced to distinguish the importance of different contexts. Its process is shown in **Figure 2**. The semantic map convolution is mainly divided into two parts, one is the initialization part, and the other is the update part.

The initialization part H^0 is used as the initialization input, and self attention operation is carried out on the initialized input to construct k weight matrices based on H^0. Summing k weight matrices and applying top-k function to retain t important context words, we can get the initial adjacency matrix A^0 of semantic map convolution by this method, and extract the preliminary semantic information by graph convolution operation.

$$A_i^0 = \frac{\left(H^0 W_k^0\right)\left(H^0 W_q^0\right)^{\mathrm{T}}}{\sqrt{d_k}} \tag{5}$$

$$A^0 = \text{top-k}\left(\sum_{i=0}^{k} A_i^0\right) \tag{6}$$

In formula (5), H^0 is the hidden state H generated by the coding layer Bi-LSTM, and A_i^0 is the ith adjacency matrix, $W_k^0, W_q^0 \in \mathbb{R}^{d_{\text{lstm}} \times d_k}$ is a trainable weight parameter, d_k is the dimension of attention, k is the number of attention heads.

For the update part, in the initialization semantic map A^0, the update formula is as follows:

$$H^l = \left[H^0; H^1; \cdots; H^{l-1}\right] \tag{7}$$

$$A_i^l = \frac{\left(H^l W_k^l\right)\left(H^l W_q^l\right)^{\mathrm{T}}}{\sqrt{d_k}} \tag{8}$$

$$A^l = \text{softmax}\left(A_1^l, A_2^l, \cdots, A_k^l\right) \tag{9}$$

$$A^l = \text{top-k}\left(A^l\right) \tag{10}$$

$$h_i^{l+1} = \text{ReLU}\left(\sum\nolimits_{j=1}^{n}\left(A_{ij}^l W^{l+1} h_j^l + b^{l+1}\right)\right) \tag{11}$$

The difference between the update part and the initialization part lies in the input. The input H^l of the update part is obtained from the convolution training of the previous $l-1$ layer graph. The softmax function operation of the weight matrix A^l can obtain the probability matrix that is most closely related to the maximum probability in the current semantic map. Finally, the top-k selection of multi-layer graph convolution is used to obtain deeper semantic information, and the final output is H_{sem} and H_{dsp}.

3.5. Covering Layer of Aspect Words

In order to highlight the important features of aspect words, mask the output of L layer graph convolution before information fusion, and reserve the vector of aspect words, that is, the vector corresponding to aspect words is set to 1, the vector of non-aspect words is set to 0, and the output after setting is $h_{\text{dsp}}^{\text{mask}}$ and $h_{\text{sem}}^{\text{mask}}$.

$$M_i^{\text{mask}} = [0, \cdots, 1, \cdots 1, \cdots, 0]^{\text{T}} \tag{12}$$

$$h_{\text{dsp},i}^{\text{mask}} = M_i^{\text{mask}} H_{\text{dsp},i} \tag{13}$$

$$h_{\text{sem},i}^{\text{mask}} = M_i^{\text{mask}} H_{\text{sem},i} \tag{14}$$

3.6. Interaction Layer

The syntactic structure information and semantic information of a sentence are inseparable. If a certain kind of information is calculated separately, the effect of the model will be poor. Therefore, the interaction layer is designed so that the model can extract the feature information of the sentence from different perspectives. Specifically, the text feature information H obtained from the coding layer Bi-LSTM interacts with the enhanced dependency feature $h_{\text{dsp}}^{\text{mask}}$ after masking and the aspect word feature $h_{\text{sem}}^{\text{mask}}$ after masking the aspect feature.

$$\text{Similarity}\ \left(H, h_{\text{dsp,sem}}^{\text{mask}}\right) = \sum\nolimits_{i=1}^{n} H^{\text{T}} h_i^{\text{mask}} \tag{15}$$

$$\eta = \frac{\exp\left(\text{Similarity}\left(H, h_{\text{dsp,sem}}^{\text{mask}}\right)\right)}{\sum_{i=1}^{n}\exp\left(\text{Similarity}_i\left(H, h_{\text{dsp,sem}}^{\text{mask}}\right)\right)} \tag{16}$$

$$h_{\text{dsp,sem}} = \sum\nolimits_{j=1}^{n} \eta_j H_j \tag{17}$$

The interactive h_{dsp} and h_{sem} are fused and learned by using the trainable parameter matrix, so that the appropriate weight coefficient can be found in the continuous iterative training, and the final representation H' of the text vector under this model can be obtained.

$$\mathrm{H}' = \frac{\alpha h_{\mathrm{dsp}} + \beta h_{\mathrm{sem}}}{2} \tag{18}$$

3.7. Classification Layer

Take the final output H' of the model as the input of the full connection layer, and determine the final emotional polarity through the softmax function.

$$y = \mathrm{softmax}\left(W_i \mathrm{H}' + b_i\right) \tag{19}$$

H' is the final output of the fusion layer, and W_i and b_i are the weights and bias terms of the full connection layer. Gradient descent algorithm is used to train the model during training to achieve the final classification purpose.

3.8. Loss Function

$$\mathrm{loss} = -\sum_{i=1}^{S} \sum_{j=1}^{C} y_i^j \cdot \log\left(\hat{y}_i^j\right) + \lambda \left\|\theta\right\|_2 \tag{20}$$

In formula (20), S represents the number of training samples, C represents the number of categories, and y_i^j represents the real label of the training set, $\hat{y}_i^j$ represents the prediction label of the model, θ represents all parameters that can be trained, and λ represents the coefficient of L_2 regularization term.

4. Experiment and Analysis

4.1. Data Set

This paper conducted experiments on three publicly available fine-grained emotion analysis based datasets, including restaurant comment dataset Rest14 [2], laptop comment dataset Lap14, and Twitter tweet comment dataset [3]. Each dataset is composed of real comments, and each comment has its corresponding emotional polarity, including positive, neutral and negative. This paper adopts Sun *et al.*'s pretreatment method to process data sets, and the statistical results of each data set after processing are shown in **Table 1**.

Table 1. Statistics for the three experimental datasets.

data set	grouping	positive	neutral	negative
Rest14	Train	2164	637	807
	Test	727	196	196
Laptop	Train	976	455	851
	Test	337	167	128
Twitter	Train	1507	3016	1528
	Test	172	336	169

4.2. Hyperparameter Setting

The BiC-GCN model was tested with the parameters used, Glove [7] word vector dimensions were used with 300 dimensions, the number of graph convolution layers was tested to be optimal at 2, and the optimiser used Adam, which performs well in many deep learning tasks as it is able to adaptively adjust the learning rate for each parameter. The specific hyperparameter settings are shown in **Table 2**:

Table 2. Model parameter settings.

Parameter	parameter value	Parameter	parameter value
Glove [19] Word vector dimension	300	optimizer	Adam
Learning rate	0.001	Batch size	16
Training Iterations	100	dropout	0.3
GCN Number of layers	2	L2 Regularization coefficient	0.00001

The model uses accuracy and F1 value as indicators to evaluate whether the model is effective.

4.3. Comparative Experiment

In order to verify the effectiveness of the model, it will be compared with a series of benchmark models on three data sets. The following is a brief introduction of each model:

LSTM [14]: LSTM processes sequential data through a unique gate mechanism that effectively captures and preserves long-term dependencies and contextual information in text. Its output is a hidden state vector that contains a comprehensive feature representation of the text, incorporating important information about specific aspect words and their context.

ASGCN: A model that combines Graph Convolutional Networks (GCN) and Attention Mechanisms has been developed to model the syntactic information of a sentence by constructing a graph structure based on dependency trees and learning the dependencies between words. ASGCN has been shown to be capable of more accurately identifying and understanding the sentiment tendency of a sentence, thus enabling effective sentiment classification.

DGCN [15]: The integration of Bi-LSTM networks, syntactic dependency trees and graph convolutional networks is intended to facilitate the extraction of contextual information and features from text at multiple levels for the purpose of efficient sentiment analysis and related NLP tasks.

TD-GAT [12]: Graph Attention Networks are utilised for the purpose of aggregating aspect-related feature information. By means of this process, the model is capable of focusing on key information that is closely related to a particular aspect, while simultaneously ignoring irrelevant contextual information. This enables more accurate understanding and analysis of emotional tendencies or aspect-specific information in a text.

BiGCN [16]: The model has been designed as a two-layer interactive graph convolutional network. It is capable of interacting and fusing information between two graphs (grammatical and lexical) to extract a deeper and more comprehensive representation of features.

MIGCN [17]: A multi-interaction attention layer is utilised to capture semantic and syntactic information in the text. The integration of information from disparate layers enables the model to comprehend the underlying structure and relationships in the text more effectively.

MSD-GCN [18]: This paper introduces a novel fusion of the cross-attention mechanism with graph convolutional neural networks. The cross-attention mechanism enables the model to process text by focusing on key parts that are relevant to a particular task or goal while ignoring other irrelevant information. This approach enables the model to comprehend text in a multi-granular manner, thereby capturing rich syntactic information.

SGAN [17]: A syntactic graph attention network is proposed with the objective of incorporating syntactic dependency knowledge into graph attention networks to facilitate more efficient processing of text data. When processing text, the network is able to identify and focus on keywords or phrases based on the syntactic structure of the sentence and associate them with specific aspect terms.

R-GAT [12]: The information concerning dependency labels in the syntactic dependency tree is introduced as features in order to construct the relationship graph. Consequently, R-GAT is capable of capturing complex dependencies between words in a text and modelling them effectively.

DGEDT [1]: A combination of Transformer and Graph Convolutional Networks (GCN) has been designed to learn semantic features and graph representations of sentences. The model processes textual and graphical information through different modules and combines them through an interaction mechanism. The Transformer module is used to learn semantic features of sentences. The Graph Convolutional Network (GCN) is employed to learn graph representation. The employment of bi-affine transformations facilitates the interaction of features, thereby ensuring the capture of richer textual information.

As demonstrated in **Table 3**, the Glove word embedding-based model demonstrates significantly superior outcomes in comparison to the LSTM baseline model on the same dataset when employing BiC-GCN. Furthermore, a comparison of the latest GCN model reveals that all models exhibit varying degrees of enhancement. Among them, BiGCN and MIGCN, which employ semantic syntax interaction, exhibit an enhancement in model accuracy by 3.46% and 2.21%, respectively, on average, when compared to ASGCN. However, these models are limited to shallow semantic syntax interaction, which results in a deficiency in context and aspectual word information, consequently leading to a decline in model accuracy. In contrast, the GCN-based models (MSD-GCN, R-GAT, DGEDT) exhibited an enhancement in model accuracy by an average of 1.35%, 0.64%, and 1.12%, respectively. R-GAT emerged as the most effective model among the baseline models. It incorporated the label information of the dependencies in the syntactic dependency tree as a feature into the model to construct the relational graphical attention network. However, it did not utilise syntactic parsing to obtain the complete dependency tree. The complete dependency tree obtained leads to ignoring part of the syntactic information, resulting in limited model enhancement.

Table 3. Experimental results.

Models	Res14		Laptop		Twitter	
	Acc	F1	Acc	F1	Acc	F1
LSTM	78.13	67.47	69.28	63.09	69.56	67.70
ASGCN	80.77	72.02	75.55	71.05	72.15	70.40
TD-GAT	81.32	71.72	75.63	70.64	72.70	70.45
BiGCN	81.97	73.48	74.59	71.84	74.16	73.35
MIGCN	82.32	74.31	76.59	72.44	73.31	72.12
MSD-GCN	82.67	75.44	77.59	74.18	74.52	73.68
R-GAT	83.55	75.99	78.02	74.00	75.36	74.15
DualGCN	87.13	81.16	81.80	78.10	77.40	76.02
BiC-GCN	**87.16**	**81.24**	**81.70**	**78.45**	**78.27**	**77.29**

4.4. Ablation Experiment

In order to demonstrate the significance of each module in DS-GCN, this paper conducts an experimental study on the model. The results of these experiments are presented in Table 4. The baseline model is represented by DS-GCN, with the semantic branch and syntactic branch modules removed, respectively.

The notations "w/o dsp" and "w/o sem" in Table 4 denote the removal of the semantic branching module and the removal of the syntactic branching module respectively. The notations "w/o dsp-ren" denote the removal of dependency information, with the retention of phrase structure information.

Table 4. Experimental results of ablation study.

Models	Res14		Laptop		Twitter	
	Acc	F1	Acc	F1	Acc	F1
w/o dsp	85.71	78.32	79.57	75.25	75.47	74.66
w/o sem	86.16	79.94	80.62	77.10	76.45	75.42
w/o dsp-ren	86.45	80.28	79.59	76.93	76.52	76.07
BiC-GCN	**87.16**	**81.24**	**81.70**	**78.45**	**78.27**	**77.29**

A series of ablation experiments were conducted to ascertain the impact of employing distinct modules for modelling. Utilising solely the semantic module resulted in a diminished capacity to acquire information and exhibited suboptimal generalisation capabilities, consequently leading to a decline in accuracy of 1.61%, 1.49%, and 1.30% for Res14, Laptop, and Twitter, respectively. This finding signifies that the structural information inherent within a sentence constitutes an indispensable component of the model. In contrast, when the syntactic module is used alone, there is a decline in accuracy of 1.83%, 1.80%, and 1.73% for Res14, Laptop, and Twitter, respectively. This suggests that incorporating semantic information enhances the classification accuracy of the model. However, when the model removes the sentiment node and retains only sentence dependency and semantic information, the accuracy of the model is observed to decrease on all three datasets. This finding indicates that the sentiment node plays a positive role in enhancing the syntactic information. Furthermore, the w/o dsp-ren reflects that the syntactic and semantic information can be complementary to each other, which further underscores the importance of integrating semantic information with syntactic information. In conclusion, it can be stated that the sentence representations obtained from different branches of the model all have an important impact on the model of this paper.

4.5. hyperparametric Analysis

4.5.1. GCN Layer Analysis

In order to verify the effect of the number of GCN layers on the model, the number of GCN layers was set to 1 - 5, respectively. Following experimentation on three datasets, changes in accuracy and F1 value were analysed for different layers. The experimental results are shown in Figure 4 and Figure 5:

As demonstrated in Figure 1, the model achieves optimal performance when the number of GCN layers is set at 2. However, as the number of GCN layers increases, the model's overall performance exhibits a decline. This phenomenon can be attributed to the fact that, with an augmented number of GCN layers, the model's parameters also rise, consequently hindering its capacity to learn effectively, leading to convergence difficulties or even the disappearance of the gradient. This, in turn, results in a decline in model accuracy.

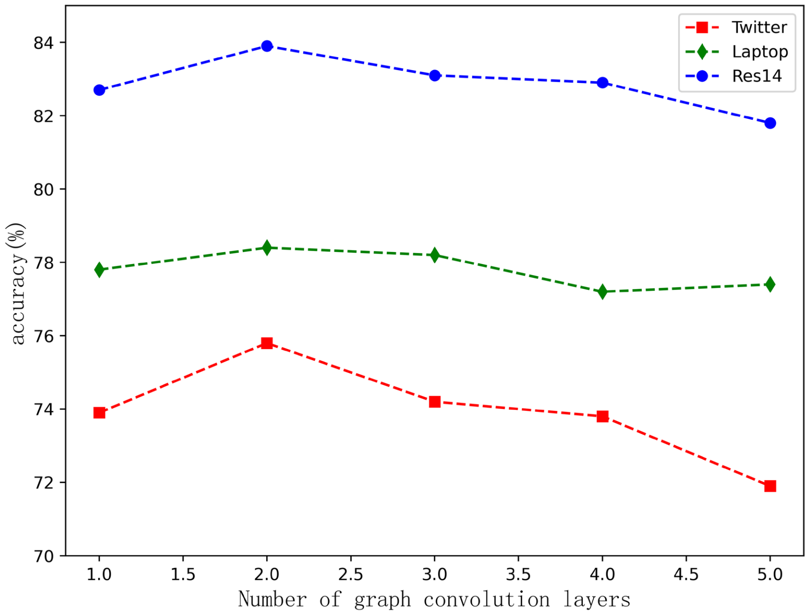

Figure 4. Effect of number of GCN layers on model accuracy.

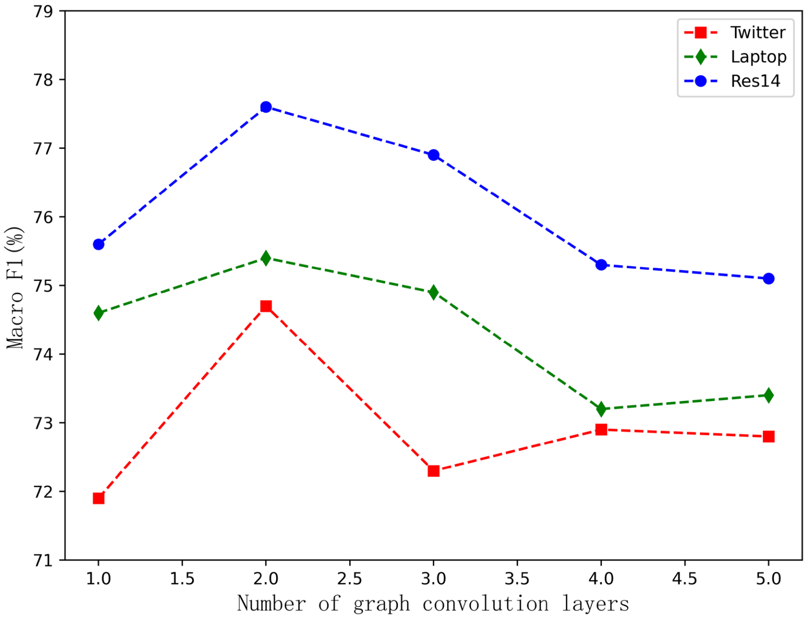

Figure 5. Effect of number of GCN layers on F1 values.

4.5.2. Top_k Value Analysis

In the semantic analysis module, the top_k function is utilised to identify and retain significant contextual words, whilst also conducting a comprehensive analysis of the impact of these words on the model's final outcomes. The experimental results are illustrated in **Figure 6** and **Figure 7**:

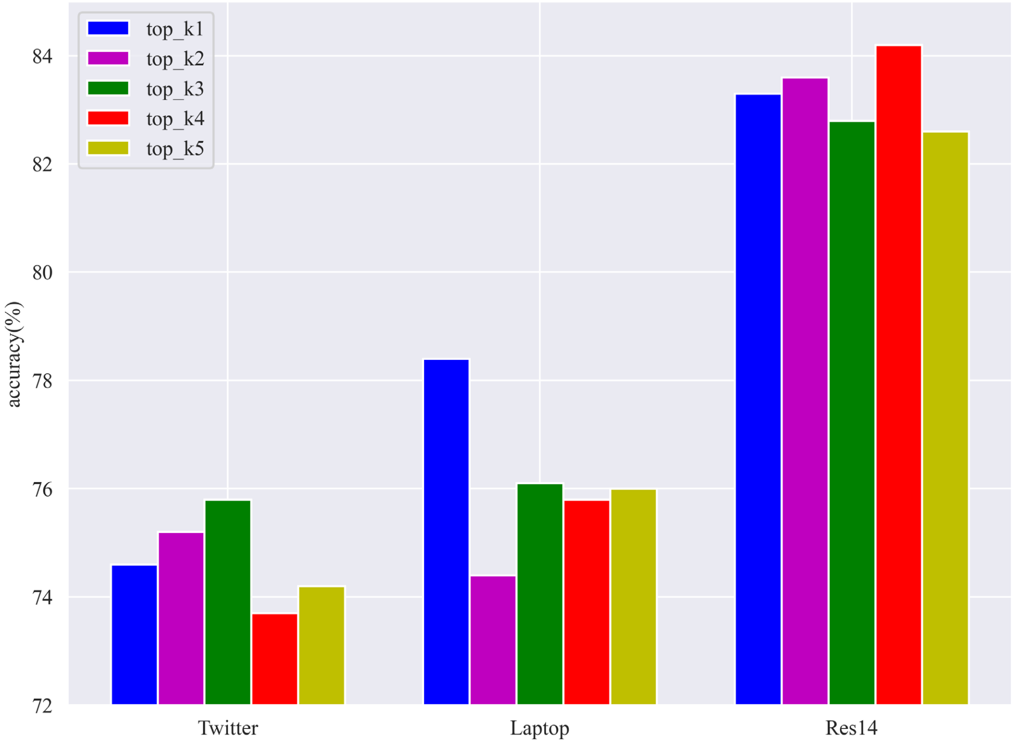

Figure 6. Effect of the value of top_k on accuracy.

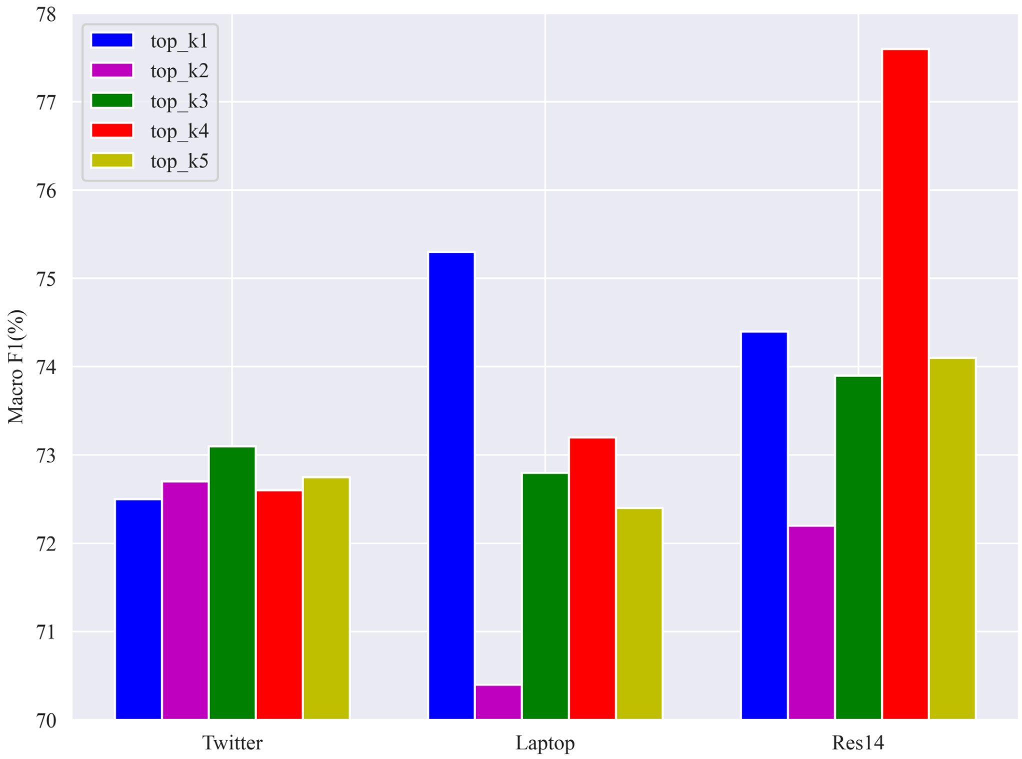

Figure 7. Effect of the value of top_k on the value of F1.

It is evident that the number of keywords selected by the model with the best results, top_k, varies for different datasets, primarily due to the varying number of aspect words across different datasets of differing data lengths. The model's overall performance is optimised when 1 - 4 high-scoring words are selected. However, as the number of selected keywords increases, the introduction of irrelevant words becomes more prevalent, thereby introducing noise that interferes with the model's ability to accurately discern sentiment polarity.

4.5.3. Case Studies

A case study was conducted, with several examples categorised using different models. The results are shown in Table 5. P, N and O are used to denote positive, negative and neutral, respectively, and Label represents the true affective polarity of the aspect word.

Table 5. Case study.

example sentence	Label	R-GAT	DualGCN	our
(a) The menu is limited but the dishes are excellent.	(N, P)	(N, P)	(N, P)	(N, P)
(b) The menu is limited but the dishes are excellent.	(P, N)	(P, P)	(P, N)	(P, N)
(c) I hand great interest in this restaurant due to its atmosphere, but the service was disappointing.	(P, N)	(N, N)	(O, N)	(P, N)

Despite the close proximity of both "speed" and "battery life" to the opinion word "better", an analysis of the data reveals a slight disparity between the two. Specifically, "battery life" exhibits a marginally greater distance from the opinion word "speed" compared to "battery life". Despite the proximity of both "speed" and "battery life" to the opinion word "better", the analysis demonstrates that "battery life" is marginally more distant from the opinion word "speed". This finding underscores the limitations of the R-GAT model in accurately extracting dependency information, consequently leading to prediction errors.

In the third sentence, the opinion expression corresponding to the "atmosphere" aspect is "great interest", which is actually the same as the opinion expression "appointing". "Appointing" is closer to the expression of opinion. Consequently, the R-GAT and DualGCN models demonstrate a tendency towards bias in their predictions. However, the model proposed in this paper is able to more accurately capture the emotional cues in real opinion expressions by introducing emotional knowledge, which improves the accuracy of prediction. The enhanced ability to manage intricate emotional interrelationships ensures a more precise evaluation of products or services.

5. Conclusions

In this paper, we propose a two-channel graph convolution neural network model based on increasing sentiment knowledge for aspect-level sentiment analysis tasks. Initially, the syntactic dependency graph, augmented with sentiment knowledge, undergoes a graph convolution operation. Concurrently, the semantic features of the entire text are obtained through the utilisation of a multi-head attention mechanism. Thereafter, an adaptive learning process occurs, whereby the semantic and syntactic features are integrated. The efficacy of the model is validated through experiments on three datasets, which demonstrate that the model outperforms the benchmark model in terms of accuracy and F1 values. Furthermore, the individual modules of the model are demonstrated to contribute to improved classification results through a series of ablation experiments.

The proposed BiC-GCN model in this paper has achieved positive research results in fine-grained sentiment analysis tasks, but there are still some limitations and directions worth further exploring: firstly, the experimental validation of this paper has been carried out in Res14, Laptop, and Twitter, and the dataset has limited domain diversity. In the future, we can consider expanding the domain coverage of the dataset to further validate the generalisation and robustness of the proposed method. Secondly, issues such as emoji usage and character expression in the task of fine-grained sentiment analysis of comment text increase the difficulty of the task, and the accuracy needs to be improved. However, these limitations also point to the direction of future research in this study. Future research can further improve the accuracy of fine-grained sentiment analysis by increasing the dataset domain coverage and enhancing emoji and symbol sentiment representation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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