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Dual Graph Convolutional Networks with Semantic and Syntax Reinforcement for Aspect-based Sentiment Analysis

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Abstract. Aspect-based sentiment analysis (ABSA) aims to identify the sentiment polarity of the given aspect. Dependency trees contain different types of syntactic dependencies, but existing approaches do not consider the impact of different syntactic relations. Besides, how to efficiently capture the connection between aspects and context is also a challenge. Hence, we propose Dual Graph Convolutional Networks with Semantic and Syntax Reinforcement (SSRGCNs) for ABSA task. Specifically, we introduce a semantic context module using aspect-focused attention to capture aspect-related semantic context and self-attention to understand global information of the sentence. A weight allocation module is also proposed to assign different weights to different syntactic labels to fully consider the different influence. Then, we stack Graph Convolutional Networks (GCNs) layers over them to extract latent context representations. Finally, we propose a feature fusion mechanism to better integrate all features. Experiments on benchmark datasets demonstrate the effectiveness of our model.

Keywords: aspect-based sentiment analysis, semantic context, syntactic weight, feature fusion, graph convolutional net-works, attention mechanism, dependency tree

1 Introduction

Aspect-based sentiment analysis, also called aspect-based sentiment classification, seeks to determine the polarity of a given aspect within a certain context [1]. As shown in the example in Fig. 1, for the following sentence "*The environment is romantic, but the food is horrible…*", *environment* and *food* are the objects that the sentence describe, called aspects. *Romantic* and *horrible* are used to modify the aspects, called opinion items. The sentiment polarity of *environment* is *positive* but the polarity of the *food* is *negative*. Homoplastically, a sentence usually contains more than one aspect, detailed sentiment analysis across multiple aspects enables businesses to extract valuable insights from customer feedback, leading to more targeted improvements and strategies. Therefore, researchers began to conduct various researches on aspect-based sentiment analysis.

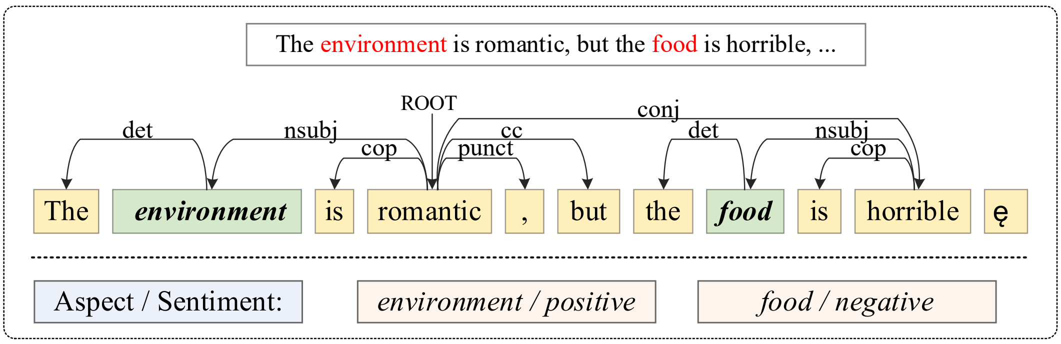

Fig. 1. A sentence from restaurant reviews with its dependency tree, containing two aspects with opposite sentiments

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Typically, the emotional orientation of an aspect is influenced by the opinion items expressed in association with it. So modelling the relationship between an aspect and opinion expression is the key to solving the ABSA task that allows us to more accurately capture subtle changes in emotion and discover the balance between subjective and objective in the text [1]. By deeply analyzing this association we can more accurately identify the emotional tendencies in various aspects of the text, thereby achieving more accurate sentiment analysis.

Existing methods typically employ self-attention mechanism to extract semantic contextual information. The self-attention mechanism allows our model to adaptively allocate attention across various sections of the text, allowing it to capture crucial semantic and emotional details. Nevertheless, it may focus excessively on the high-frequency words, while ignoring some words that are more important but appear less frequently in specific contexts. And merely using self-attention mechanisms may introduce unnecessary noise and capture context that is not targeted. In addition, the complexity and informal expression of online reviews also result in the inability to extract opinions related to aspects effectively. To address these issues, some studies are exploring the combination of other technologies to compensate for the shortcomings of self-attention mechanisms. For example, one kind of approach is to introduce external knowledge into the model to provide more plentiful semantic information and another is to introduce more complex attention mechanisms, such as positional attention or multi-head attention, to better capture the dependency relation between different words in the sentence. The comprehensive application of these methods is expected to improve the model's understanding of text semantics and emotions, thereby enhancing the effectiveness of aspect-level sentiment analysis.

Recently, more efforts have been devoted to graph neural networks over dependency trees to solve ABSA problems [2-5] which explicitly exploit the sentence's syntactic structure to analyze the close relationship between aspects and opinion items. As shown in Fig. 2, the GNN-based methods first generate a syntactic dependency tree of the comment context through a syntactic parser, obtaining the graph structure of the contextual sentence, and then uses a graph neural networks to encode the syntactic dependency tree. The syntactic dependency tree is a tree like structure that can establish the association between *aspect* and *emotional* viewpoint words. Each word is represented as a node in the tree, while syntactic relations are represented as edges between nodes. Through this analysis method based on syntactic structure, we can use syntactic information to guide sentiment analysis and make the model more capable of language understanding. In addition, one sentence encompasses various syntactic relationships, each with a different impact. For example, as in Fig. 1, *nsubj* between *environment* and *romantic*, *food* and *horrible* plays a decisive role in determining the polarity of aspect words *environment* and *food*. *Punct* has nothing to do with the results. So it is crucial to distinguish the importance of different dependency relationships. In addition, dependency parsers may generate incorrect or inaccurate dependency tree structures, resulting in incorrect results for subsequent analysis tasks. Therefore, we still need to comprehensively consider other semantic representation methods to obtain more accurate sentiment analysis results. In this paper, we propose a Semantic and Syntax Reinforcement based on Dual Graph Convolutional Networks architecture (SSRGCNs) that utilizes two GCNs to encode semantic and syntactic weights information to solve the aforementioned challenges.

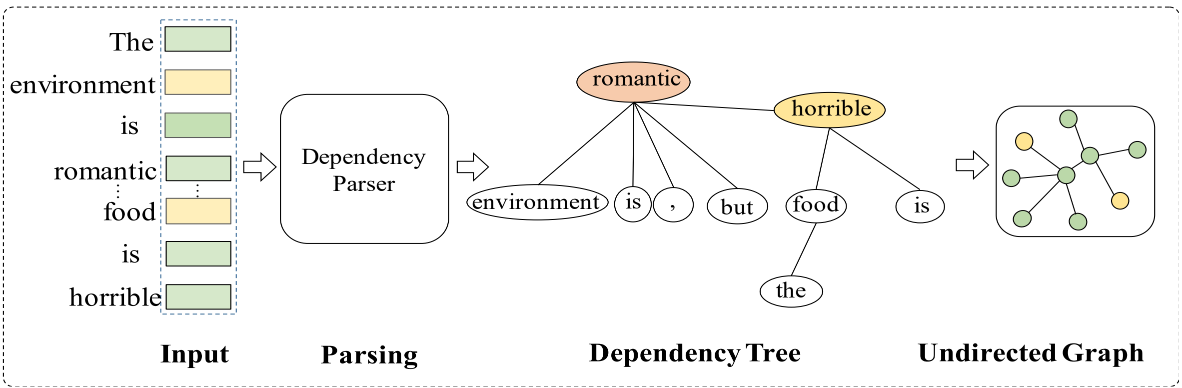


Fig. 2. The processing of GNNs over dependency trees. The sentence is initially parsed into a dependency tree and ultimately converted into an undirected graph

Fig. 3 shows the model architecture. Firstly, word embedding of the sentences are fed into a Bi-directional Long Short Term Memory (Bi-LSTM) network to obtain the hidden representation. In order to capture aspect related opinion items more comprehensively, we exploit aspect-focused attention to capture aspect related contextual information, while self-attention is used for capturing global context. Then, the syntactic weight matrix containing the dependencies between words assigns different weights to them according to the relevance of the syntactic relationships. Then, it is used as one of the initial adjacency matrixes for GCN encoding. Finally, we interact with the output features obtained from GCNs using a feature fusion mechanism. After a series of operations such as mean-pooling and aspect mask, the interaction result is utilized for the final sentiment classifier. The results of the classification show that our model outperforms various state-of-the-art models, and hence confirm the effectiveness of the semantic context and syntactic weight modules.

Our contributions can be summarized as follows:

- We introduce a Semantic Context Module that comprehensively considers the context information of aspects. Specifically, we exploit a multiple attention module containing aspect-focused attention and multi-head self-attention to extract the opinion items related to aspects.
- We propose a Syntactic Weight Module to discuss the impact of various dependency relationships on aspect sentiment polarity. It utilizes a syntactic weight matrix to analyze and quantify the significance of different dependency relationships within the text.
- We propose a feature fusion mechanism aimed at enhancing the integration of information encoded by GCNs from the two modules. It generates a fused representation that captures syntactic and semantic information for further analysis.
- We conduct extensive experiments on SemEval 2014 and the Twitter dataset. Experimental outcomes demonstrate that our model attains state-of-the-art performances.

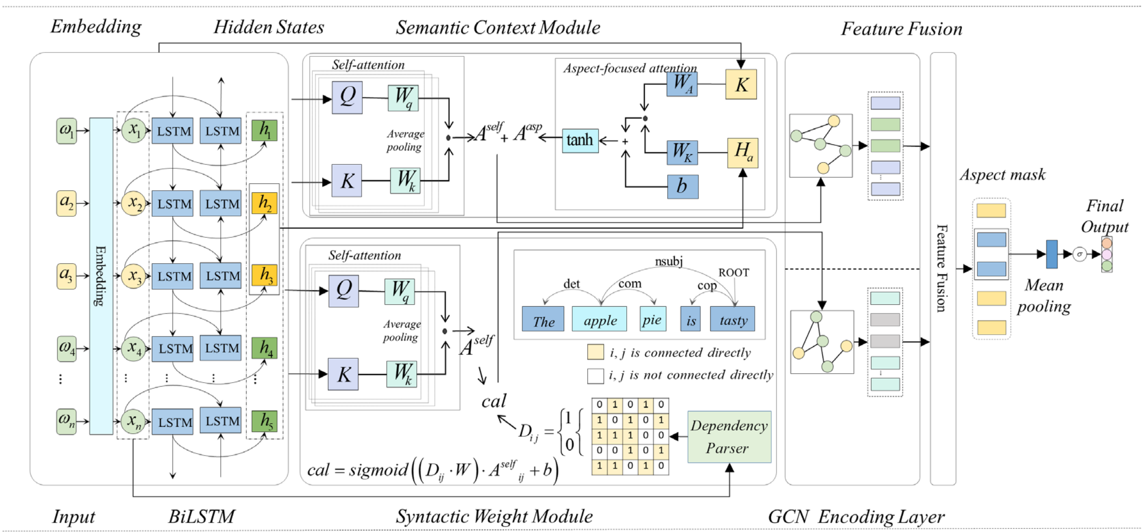


Fig. 3. The overall architecture of SSRGCNs

2 Related Work

Sentiment analysis plays an important role in the domain of natural language processing [6, 7], it can not only help understand and analyze emotional information in text, but also provide support for various downstream tasks such as recommendation systems [8, 9], question answering systems [10], and emotional chatbots [11-14]. Traditional sentiment analysis is conducted at the sentence or discourse level, focusing on the overall emotional orientation of the text. However, with the development of the information age, people's demand for emotional expression has become increasingly refined, resulting in a more fine-grained emotional analysis task - ABSA. ABSA not only considers the overall sentiment polarity, but also focuses on analyzing emotional information related to specific aspects in the text. By conducting aspect-level sentiment analysis on text, we can more comprehensively understand people's attitudes and emotional tendencies towards specific aspects, so as to provide more accurate sentiment analysis services for various practical application scenarios. Hence, in this paper, we expand our research on this more granular sentiment analysis task.

CNN & RNN. Prior studies utilize neural network such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models to extract semantic information between the target aspect and its contextual words [15-19]. CNN are capable of capturing the local dependencies within the text, while the RNN excels at capturing temporal dependencies and understanding contextual connections between words. RNN processes the input sequence by continuously updating the hidden state recursively, thus modelling the temporal dependence in the sequence data. Specifically, the RNN takes into account the hidden state of the previous time step when processing each input and combines it with the current input to update the current time step's hidden state. This recursively updated approach enables RNNS to efficiently capture long-term dependencies in sequence data. CNN uses convolutional layers and pooling layers to extract features, and convolutional operations are performed on the input by sliding convolutional kernels to capture the local dependencies therein. Convolution operation can effectively capture the spatial information in the image, and because of the characteristics of weight sharing, CNN has fewer parameters and is easier to train and optimize.

In natural language processing, sentences often represented through word embedding matrices. After applying convolutional operations to these matrices, local features are extracted, enabling the capture of semantic nuances and syntactic structures within the sentences. In these related works, Tang et al. introduced recurrent neural networks to retrieve the aspect-related information by fusing the aspect with its contextualized information in the sentence [15]. Huang et al. utilized parameterized filters and gates for integrating aspect information into CNN [18]. Li et al. proposed Tnet which contains a novel target-specific transformation component and forward the context information into a deep transformation architecture [19]. Gu et al. proposed a cascaded CNN containing two levels of convolutional networks [16]. Cahyadi et al. utilized a feedforward neural network with a one-vs-all strategy, incorporating the probability output from CNN as a feature [17]. Although CNN and RNN have performed well in ABSA, they lack explicit attention ability when processing sequence data, and cannot effectively capture the importance of different parts in the sequence.

Attention mechanism & Memory Networks. In sentiment analysis, one sentence often has complex structure, and these long-term dependencies are essential for comprehending the emotions in the text. The memory network and attention mechanism enable the model to selectively focus on various sentence segments and effectively capture long-term dependencies. Recently, numerous methods based on attention mechanism and memory modelling are believed to implicitly identify the semantic relationship between an aspect and its context for opinion expression extraction [20-28]. Zeng et al. proposed PosATT-LSTM, which incorporates both The significance of every context word and position-aware vectors [25]. Wang et al. proposed Long Short-Term Memory based on attention concatenating the aspect vector with the sentence hidden representations to compute attention weights [21]. Kumar and Ma combined BiLSTM with aspect attention module to effectively extract deep information from text [24, 27]. Chen and Wang designed models based on a combination of attention mechanism and recurrent neural networks [22, 28]. Lin et al. proposed Deep Selective Memory Network dynamically selects context memory to better enhance the multi-hop attention mechanism's guidance [26]. Tang et al. introduced a hierarchical attention network to pinpoint essential sentiment information linked to the specified aspect [20]. He et al. proposed an Attentional Encoder Network using attention-based encoders to encode the relationship between context and target [23].

While attention-based models show promise, they may not fully capture syntactic relations between contextual words and aspects in a sentence. Thus, merely using the attention mechanisms may lead to syntactically irrelevant contextual words as opinion items. Take Fig. 4 as an example, "*like*" is used as a preposition in this sentence, but the attention mechanism still assigns it a high weight, which may lead to the model mistakenly judging the aspect word as positive rather than neutral. To address the issue mentioned above, He et al. introduced an attention mechanism incorporating syntactic information into the attention model [23]. Another trend to address the above issues explicitly utilizes the syntactic information of dependency trees. Jia et al. proposed a neural network using dependency relations and structured attention to fuse multiple semantic segments and dependency features [29]. Zhang et al. leveraged syntactic relations between aspects and contexts, aggregating features at the n-gram level [30].

GCN over dependency tree. Recent ABSA researches utilize GCNs on sentence dependency trees to exploit syntactic structure. An example of GCN encoding is shown in Fig. 5. The core idea of GCNs is to use adjacency matrices to describe the topological structure of graphs, and then use these matrices to gradually propagate and aggregate node information through multi graph convolution operations. During this process, each layer's graph convolution updates the features of the current node by weighting and summing the features of neighboring nodes, where the weights depend on the adjacency matrix of the graph. Through multi-layer graph convolution operations, GCN can gradually capture local and global relationships between nodes, thereby obtaining richer and more accurate feature representations. This methodology facilitates a more thorough examination of syntactic relationships within text, enhancing the overall effectiveness of sentiment analysis tasks. In existing works, Marcheggiani et al. introduced a GCN variant for modelling representations in dependency graphs for semantic role labelling tasks [31]. Li et al. proposed DualGCN, which considers both syntactic structure and semantic correlation within sentences [32]. Xiao et al. proposed an attention-based graph convolutional network model to consider semantic and syntactic information [33]. Chen et al. connected linguistic dependency trees with aspect specific graphs which are automatically induced [34]. Yi et al. proposed a context-guided and syntactic augmented dual GCN [35]. Zhang et al. proposed a novel syntactic and semantic enhanced GCN model [36]. Tian et al. utilized dependency types with type-aware GCN, where attention distinguishes among different graph edges [37].

However, existing GCN-based methods have not exploited the distinctions in syntactic dependencies. And the semantic context related to the aspect was not well captured. Moreover, considering the crucial role of semantic and syntactic information in discriminating the polarity of aspect, it is necessary to allocate different weights to the output of GCN. Hence, we propose SSRGCNs to solve the deficiencies of the previous model.

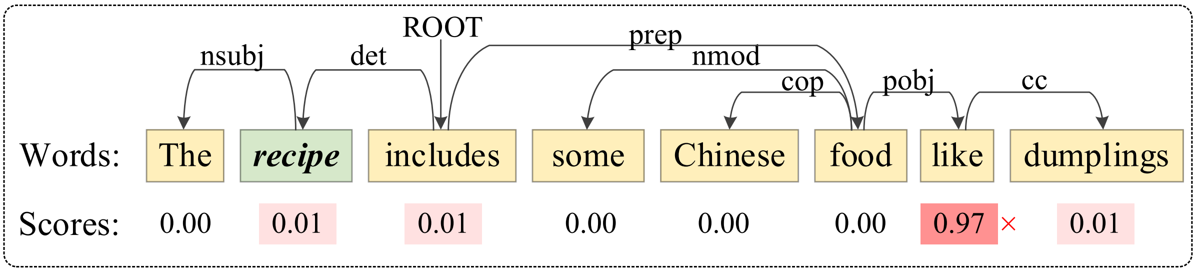


Fig. 4. An example from restaurant reviews. The scores under the words represent attention weights assigned by attention

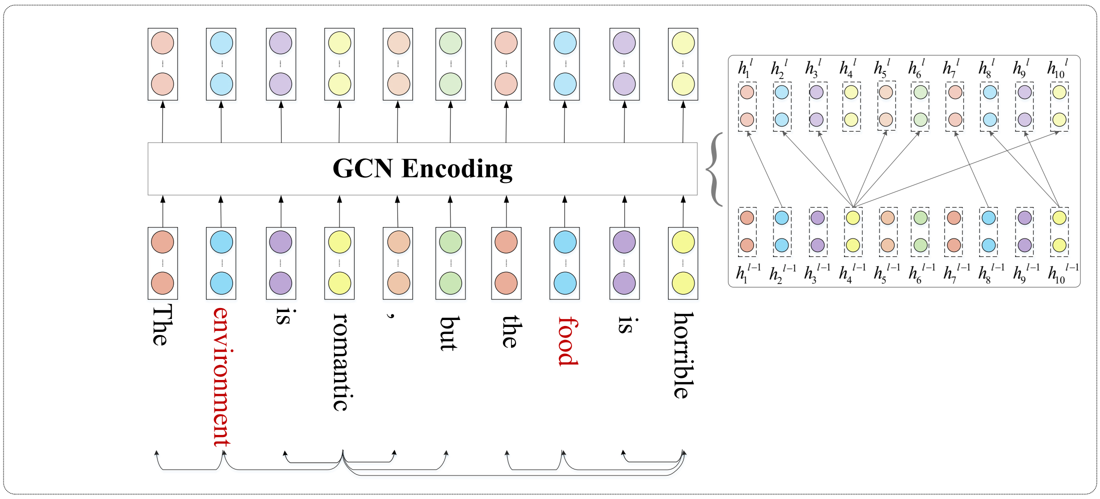


Fig. 5. An example of GCN layer

3 Proposed Methodology

In ABSA task, given a sentence-aspect pair (s, a), where $s= \{\omega_1, ..., \omega_n\}$ represents the whole sentence and $a= \{a_1, ..., a_m\}$ represents the aspect item. n and m respectively represent the length of the sentence and aspect. The objective of this task is to predict the polarity of aspect *a* in the sentence *s*. Fig. 3 provides an overview of our proposed model.

3.1 Embedding Layer

Initially, each word is mapped to a low-dimensional, real-valued vector using embedding matrices $E = \mathbb{R}^{|V| \times de}$, where $|V|$ is the size of lexicon and de denotes the dimensionality of word embedding. Here we obtain the embedding of the sentence $x = \{x_1, \ldots, x_n\}$. Then, we utilize BiLSTM as sentence encoder to employ hidden contextual representations $H = \{h_1, \ldots, h_n\}$, where $h_i \in \mathbb{R}^{2d}$. In particular, hi is formed by merging the hidden states from the forward and backward LSTMs, where d denotes the size of hidden state vectors in a unidirectional LSTM.

3.2 Semantic Context Module

In this paper, we propose a semantic context module, which comprehensively considers the contextual information of aspects, and extracts the opinion items related to aspects by using aspect-focused attention and multi-head self-attention. Fig. 6 shows the architecture.

The multi-head attention mechanism is employed to compute the attention scores between words in a sentence and multiple attention heads are used in parallel to identify the interrelationships and overall context between words in the sentence, and the outputs of each head are averaged and pooled to obtain the final output representation, helping the model to comprehensively understand and process the overall semantic structure of the sentence.

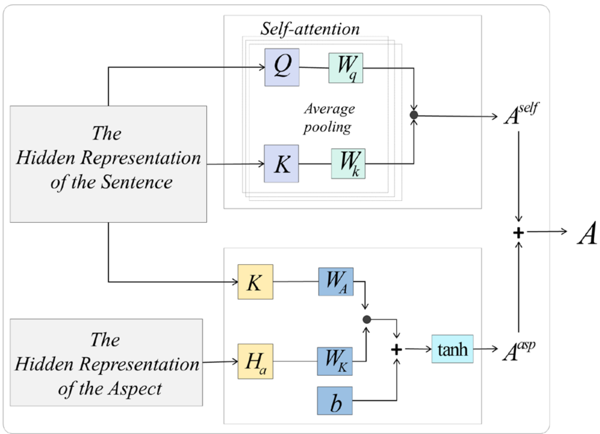


Fig. 6. The architecture of semantic context module

The calculation process is shown in the following equation:

$$A^{self} = \frac{QW_q \times (KW_k)^T}{\sqrt{d}} \tag{1}$$

where both Q and K are equal to H, W_q and W_k are both learnable weights.

As aspect sentiment analysis seeks to determine the sentiment of a specific aspect term within a context, it is essential to model semantic relations for different aspect terms. The global information of a sentence extracted by self-attention mechanism may contain some features that are irrelevant to the aspect sentiment and the noise introduced by self-attention will degrade the sentiment analysis performance. Therefore, we further exploit the aspect-focused attention which does not broadly consider the relationship between any two words in sentences, but rather measures the importance of contextual information centered on specific aspect words. It takes the hidden representations of aspect words and the hidden representation of the input sequence as input, and uses the learnable weight matrix to continuously optimize and adjust these representations. It is formulated as follows:

$$A^{asp\_a} = H_a W_A \tag{2}$$

$$A^{asp\_c} = KW_K \tag{3}$$

$$A^{asp} = \tanh\left(A^{asp\_a} \times \left(A^{asp\_c}\right)^T + b\right) \tag{4}$$

where H_a is obtained by transforming the embedding representation of the aspect.

For the single-word aspect, we copy it n times to obtain H_a. For the multi-word aspect, we first perform average pooling on it and then copy it n times. K represents the embedding representation of the input sentence. W and b are the learnable weight matrix and bias respectively. The aspect-focused attention is centered on the aspect and considers the components of the context that have more influence on the polarity judgment of the aspect emotion. After that, the aspect-related context information is assigned with different weights, with higher weights for those with higher association and vice versa, low weights.

Finally, we combine the global context A^{self} with the aspect-focused context A^{asp} as the ultimate output of the semantic context module.

$$A_{ij} = A_{ij}^{self} + A_{ij}^{asp} \tag{5}$$

3.3 Syntactic Weight Module

The semantic analysis above is not enough to accurately extract crucial information in sentences due to the complexity of the components in comments and the irregularity of expression. However, syntactic analysis can identify the relationship between modifiers and aspect words by analyzing the structure of a sentence. Moreover, considering that different syntactic relations can affect the emotional orientation of aspects, we introduce a syntactic weight module. The architecture is shown in Fig. 7.

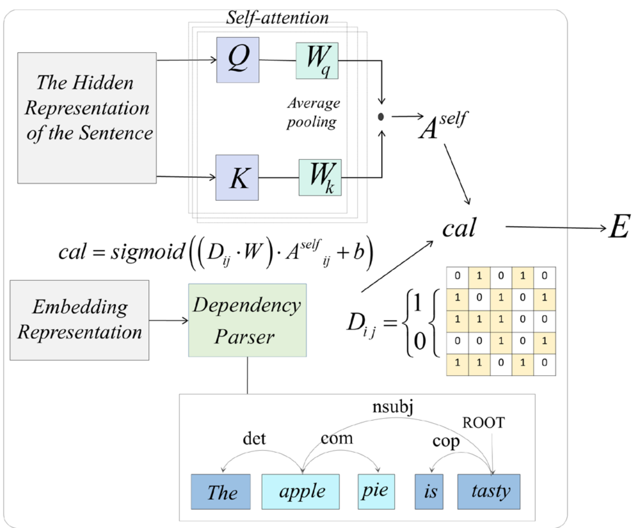


Fig. 7. The architecture of semantic context module

Initially, the matrix is built based on the syntactic relationships between words in the dependency tree. If two words exhibit a direct syntactic connection within a sentence, the corresponding element in the adjacency matrix is assigned a value of 1; otherwise, it is set to 0. As shown in Fig. 1, there is a direct syntactic relation-*nsubj* between environment and romantic, then the value of their corresponding position in the adjacency matrix will be 1, while there is no direct connection between but and the, the corresponding value will be 0. The construction process is as follows:

$$D_{ij} = \begin{cases} 1, & if\ \ i, j\ is\ connected\ directly \\ 0, & else \end{cases} \tag{6}$$

Then, the attention score and learnable weight matrix W are used to dynamically learn and constantly adjust parameters, and then assign different weights to various syntactic relations in the initial matrix, emphasizing or highlighting syntactic dependencies that are more crucial to the sentence's overall meaning so as to more effectively capture and understand the contribution of different dependencies in the text to the semantic and structure of the sentence The syntactic weight matrix is computed by the formula below:

$$E_{ij} = sigmoid\left(\left(D_{ij} \cdot W\right) \cdot A^{self}{}_{ij} + b\right) \tag{7}$$

where A represents the attention score matrix, D represents the initial syntactic matrix composed of 0/1 elements, ij denotes the element located in the i-th row and j-th column. W is the learnable weight, and b represents the bias term. An element E_{ij} indicates not only a directly connected syntactic relationship between i and j, but also indicates the importance of the connecting syntactic relationship. The syntactic weight matrix can effectively mitigate the errors caused by dependency parsing.

The visualization of the effect of the syntactic weight module is shown in the Fig. 8. The absolute values of 0 and 1 are used in the left image to indicate the existence of syntactic relations between words. The right image uses the value between 0 and 1 to distinguish the scores of different syntactic relationships, reducing the error caused by the dependency trees' own parsing errors. Through the right image, the strength difference between different dependencies can be seen more clearly, and this refined representation helps to understand the complex relationships at the sentence structure and semantic level more accurately.

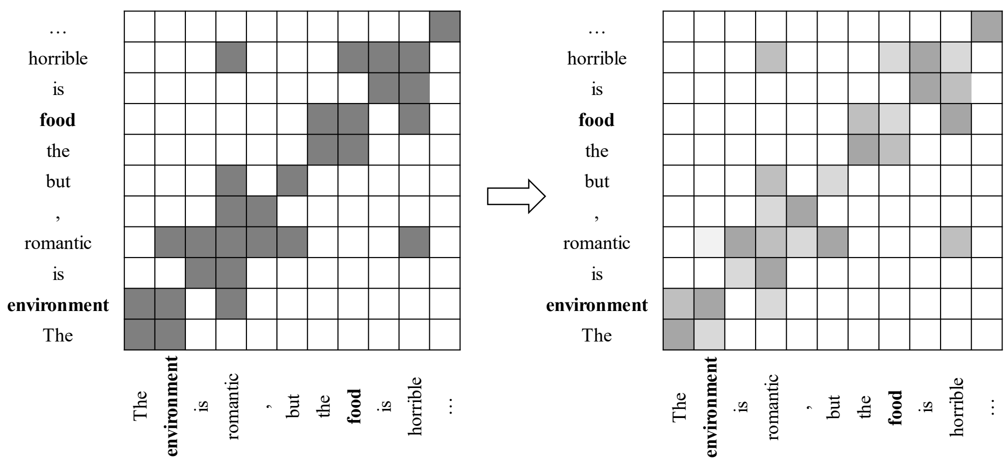


Fig. 8. Visualization of syntactic adjacency matrix (darker color blocks represent larger values)

3.4 GCN Encoding Layer

GCN updates and aggregates the features of a node by considering the weights of its neighbors and the edges between them. Through multi-layer graph convolution operations, each node can leverage the information from its neighboring nodes for feature extraction. This iterative updating and aggregation process enables each node to acquire richer contextual information, thereby enhancing feature extraction and representation learning capabilities. The node updating process of GCN is illustrated in Fig. 5. For the *i-th* node in the *l-th* layer in GCN, the hidden state representation is updated by the following equation：

For semantic context module:

$$h_{Ai}^{l} = selu\left(\sum_{j=1}^{n} A_{ij} W^{l} h_{j}^{l-1} + b^{l}\right) \quad \textbf{(8)}$$

$$H_{A} = \{h_{A1}{}^{l}, ..., h_{An}{}^{l}\} \quad \textbf{(9)}$$

For syntactic context module:

$$h_{Ai}^{l} = selu\left(\sum_{j=1}^{n} E_{ij} W^{l} h_{j}^{l-1} + b^{l}\right) \quad \textbf{(10)}$$

$$H_{E} = \{h_{E1}{}^{l}, ..., h_{En}{}^{l}\} \quad \textbf{(11)}$$

where b^l is a bias term, W^l is a weight matrix. A_{ij} and E_{ij} are the score matrices obtained by the syntactic weight module and the semantic context module respectively.

3.5 Feature Fusion

After obtaining the output representations $H_A = \{h_{A1}{}^{l}, ..., h_{An}{}^{l}\}$, $H_E = \{h_{E1}{}^{l}, ..., h_{En}{}^{l}\}$ encoded by GCNs, we perform a feature fusion operation on them to automatically assign different importance to the two types of information and get the final sentence representation:

$$H^{l} = \alpha H_{A} + \beta H_{E} \quad \textbf{(12)}$$

where α and β are learnable arguments.

3.6 Aspect Mask

After obtaining the final sentence representation, the aspect mask operation is applied to enhance the model's focus on aspect words: the vector representation of non-aspect words is set to zero, and the vector representation of aspect words is kept unchanged. Specifically, we set the vector representations of non-aspect words to zero, while preserving the original representations of the aspect words unaffected. The formula is expressed as follows:

$$h_{t}^{l} = \begin{cases} h_{t}^{l}, & \tau \le t < \tau + m \\ 0, & 1 \le t < \tau, \tau + m \le t < n \end{cases} \quad \textbf{(13)}$$

where τ represents the starting index of aspect words, and m represents the length of the aspect. At this point, we have acquired the final representation of aspect $H_a^l = \{h_{a1}{}^{l}, ..., h_{am}{}^{l}\}$.

3.7 Output

Then, we apply average pooling on the aspect representation to retain most of the information:

$$h_{a}^{l} = f_{pool}\left(h_{a_1}^{l}, ..., h_{a_m}^{l}\right) \quad \textbf{(14)}$$

where f_{pool} is an average pooling operation. we input h_l into a softmax function to obtain the probability distribution for the sentiment decision space:

$$p_a = softmax\left(W_p h_a^l + b_p\right) \tag{15}$$

where W_p is the learnable weight and b_p is the the bias of the fully connected layer.

4 Training

Our model is trained with standard gradient descent using cross-entropy loss and L2 regularization.

$$L = -\sum_{(s,a)\in D}\sum_{C}\hat{p}_a \log p_a + \lambda\left\|\Theta\right\|_2 \tag{16}$$

Here, $\hat{p}_a$ represents the golden polarity of aspect a, D and C are the set of all the sentence-aspect pairs (s,a), and all the sentiment polarities respectively, Θ indicates all trainable parameters, λ represents the coefficient of L_2 regularization.

5 Experiments

We performed a series of experiments to showcase the effectiveness of our proposed model in aspect-level sentiment analysis.

5.1 Datasets

We conduct experiments on three benchmark datasets for aspect-based sentiment analysis: Rest14, Laptop14 [38] and Twitter [39].

Table 1. Detailed statistics of three datasets in our experiments

Datasets	Division	#Positive	#Negative	#Neutral
Rest14	Training	2164	807	637
	Testing	727	196	196
Laptop14	Training	976	851	455
	Testing	337	128	167
Twitter	Training	1507	1528	3016
	Testing	172	169	336

The first two datasets respectively contain comments on restaurants and laptops. Twitter contains tweets expressing emotions towards specific brands or products, and due to its use of informal language, this dataset is particularly challenging. The statistics for three datasets are reported in Table 1.

5.2 Implementation Details

We use Stanford Parser as the sentence parser and Adam [40] as the optimizer for our model with the learning rate initialized by 0.001. We use the pretrained 300-dimensional word embedding of GloVe [41] to initialize the word embedding. We concatenate the position, part-of-speech and word embedding to enrich the sentence representation and then feed them into a BiLSTM model. The dimensionality of each of the three is set to 30 and the hidden size of BiLSTM is set to 60. The GCN model consists of 2 layers, with a dropout rate of 0.3 in the input layer. It is trained for 20 epochs using a batch size of 8. We use the Macro-F1 (F1) and Accuracy (Acc) metrics to assess the model's performance.

5.3 Baseline Methods

To demonstrate the effectiveness of our model, we choose several models as baselines to compare against the results of our model. The selected baselines are primarily categorized into attention-based and graph-based approaches. Our chosen baselines are described as follows:

1) **TNet-AS** [19] uses a CNN layer to extract key features from word representations transformed by a bi-directional RNN layer.

2) **AEN-GloVe** [42] avoids recurrence and instead uses attention-based encoders for modeling the relationship between context and target.

3) **CDT** [43] uses GCN to model sentence structure via its dependency tree.

4) **ASGCN** [44] utilizes syntactic dependencies in sentences to address long-distance multi-word dependency issues.

5) **R-GAT** [1] proposes a relational graph attention network for encoding the tree reshaped by an regular dependency parse tree.

6) **BiGCN** [45] introduces a bi-level interactive graph convolution network to leverage both syntactic and lexical graphs adequately.

7) **KumaGCN** [34] suggests gating mechanisms to dynamically integrate information from latent graphs and word dependency graphs.

8) **MAN** [7] suggests employing multi-attention networks within and across hierarchical levels.

9) **Inter-**GCN [46] utilizes an interactive approach to identify aspect-specific sentiment characteristics by exploring sentiment connections within and across different aspects in the given context.

10) **DRSAN** [47] proposes semantic distance attention for obtaining high-quality word vectors and semantic coding, calculating SDA values, and extracting aspect semantic features.

11) **BE-GCN** [48] proposes a bidirectional edge-enhanced GCN that effectively combines syntactic structure and dependency label information.

12) **DRGCN** [49] utilizes two GCNs to encode the dependency edge and tag, followed by a bi-affine module for their interaction.

13) **IMA** [50] proposes a model that utilizes an interaction matrix and global attention mechanism to improve aspect-based sentiment analysis.

5.4 Main Results

The results of our proposed model compared with the baseline models are shown in Table 2. All baseline models perform relatively poorly on the Twitter dataset, as the text often contains a large number of abbreviations and informal language, which increases the complexity of analysis. Tnet-AS and AEN-GloVe used attention mechanism and RNN, their overall performance on the dataset is less than satisfactory. Conversely, other models incorporating GNNs outperform these two models, consequently confirming the effectiveness of GNNs in aspect sentiment classification. For example, CDT encoded the dependency tree of sentences and obtained improved results. Further, Inter-GCN prunes dependency trees to retain only directly connected dependency relations, and achieves superb results on three datasets, validating that the noise caused by long-distance syntactic relationships would reduce the model performance.

Compared to the state-of-the-art graph-based model R-GAT, our model achieves an accuracy improvement of 1.26% on the Rest14 dataset and 1.35% on the Laptop dataset. In particular, our model makes especially 2.45% improvements in terms of F1 on Laptop dataset compared to R-GAT. Besides, our SSRGCNs also performed better than other advanced models on Acc. Our SSRGCNs achieved optimal performance on all metrics, thus confirming the efficacy of extracting context for specific aspects and assigning different weights to different syntactic relationships.

Table 2. Experimental results comparison on three public datasets

Model	Rest14		Laptop		Twitter	
	Acc.	F1.	Acc.	F1.	Acc.	F1.
TNet-AS	80.69	71.27	76.54	71.75	74.97	73.60
AEN-GloVe	80.98	72.14	73.51	69.04	72.83	69.81
ASGCN	80.77	72.02	75.55	71.05	72.15	70.40
BE-GCN	80.86	72.18	75.70	71.82	72.01	70.55
KumaGCN	81.43	73.64	76.12	72.42	72.45	70.77
BiGCN	81.97	73.48	74.59	71.84	74.16	73.35
Inter-GCN	82.23	74.01	77.86	74.32	-	-
CDT	82.30	74.02	77.19	72.99	74.66	73.66
DRSAN	82.78	73.67	76.39	72.96	75.64	74.12
IMA	82.81	73.66	77.44	73.48	-	-
DRGCN	83.10	73.58	77.01	73.74	75.68	74.03
R-GAT	83.30	76.08	77.42	73.76	75.57	73.82
MAN	83.47	70.91	77.21	72.55	75.58	71.15
Our SSRGCNs	**84.56**	**76.23**	**78.80**	**76.21**	**76.07**	**74.89**

5.5 Ablation Study

We performed ablation studies to evaluate the contribution of each component in our SSRGCNs, with the results presented in Table 3. We set the SSRGCNs as the baseline model. In Semantic Context Module, aspect-focused attention can capture contextual information that is strongly associated with aspect words. Self-attention mechanism can capture global information in sentences. The former is an enhancement of the latter, while the latter is a supplement to the former. In Syntactic Context Module, the syntactic weight matrix assigns different weights to the impact of different syntactic relationships. We first remove the self-attention of the semantic context model and observe that the model demonstrates lower performance, indicating that global context information plays a crucial role in the ABSA task

Removing the aspect-focused attention reduce the performances as well, confirming that the model we proposed can capture the most correlated semantic information between aspect and opinion words. We also observe that the removal of the both parts simultaneously leads to a significant performance degradation, which further indicates that semantic information indeed contributes to the model performance. Besides, we remove the whole syntactic context module and the model ranges a lower accuracy on three datasets, which demonstrates that it can effectively capture the various features in dependency parsing and obviously reduce the noise. All incomplete models did not achieve the best results, the ablation experiments reveal that each module contributes to the sentiment analysis task from different perspectives, collectively enhancing the overall performance of the SSRGCNs.

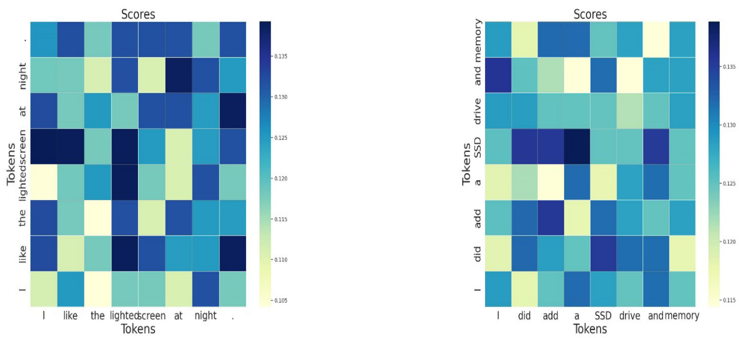
Table 3. Experimental results of ablation study on three public datasets

Model	Rest14		Laptop		Twitter	
	Acc.	F1.	Acc.	F1.	Acc.	F1.
SSRGCNs	84.56	76.23	78.80	76.21	76.07	74.89
w/o aspect-attention	81.41	71.05	76.58	72.73	74.74	73.36
w/o self-attention	81.50	73.18	77.53	73.51	74.30	72.71
w/o semantic context	81.59	72.40	76.74	73.43	73.86	72.54
w/o syntactic weight	81.95	72.85	77.22	74.24	74.89	73.30

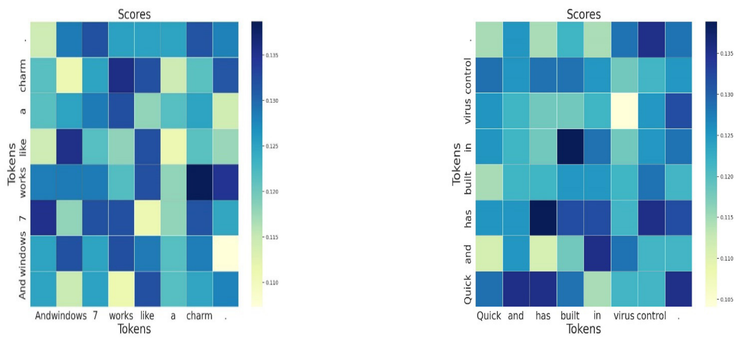
5.6 Attention Visualization

Attention weight visualization can visually show the focus of the model when processing input data. To further evaluate the effectiveness of our model across the three datasets, we visualize the attention scores on four test examples, each channel in the adjacency tensor precisely describe the semantic relations between words. In the sentence "*I like the lighted screen at night*", for the aspect *lighted screen*, our model gives a higher weight to *like* and it does play a decisive role in the polarity discrimination of the aspect. For the harder example of the sentence "*And windows 7 works like a charm*", as shown in Fig. 9(c), our SSRGCNs correctly assigns high weights between *windows 7* and *works*, *works* and *charm*, achieving the correct judgment results. The sentence “*I did add a SSD drive and memory*” does not show a strong emotional bias, so our model judges the emotional polarity of *SSD drive* and *memory* as neutral. In the sentence “*Quick and has built in virus control*”, our SSRGCNs comprehensively considers syntactic and semantic information by introducing aspect-focused attention and syntactic weight modules.

From the four examples above, it can be seen that SSRGCNs is capable of achieving the correct polarity discrimination through the reinforcement of syntactic and semantic information.



(a) The attention score matrix of *“I like the lighted screen at night”* (b) The attention score matrix of *“I did add a SSD drive and memory”*



(c) The attention score matrix of *“And windows 7 works like a charm”* (d) The attention score matrix of “Quick and has built in virus control”

Fig. 9. Attention visualization of learned latent weights by SSRGCNs

5.7 Case Study

Table 4 shows some sample cases. The red markings indicate aspect words. The notations Pos., Neu. and Neg. in the table represent positive, neutral and negative respectively. Taking the second sample as an example, *highly recommend*, which is an extremely optimistic description, is used to modify the aspect term *Samsung 830 SSD*. *R-GAT* did not fully capture this crucial information, resulting in incorrect judgment results. However, our model fully considers the overall syntactic structure information of the sentence and makes correct judgments on the polarity of aspect words. In the third sample, *R-GAT* mistakenly assumed that the negative expression of *can’t believe* and *making the same mistake* were offset, leading to its erroneous judgment that the polarity of *USB ports* was positive. Our model obtains accurate polarity discrimination results by comprehensively capturing semantic contextual information and correctly assigning different weights to different components in the sentence. In the fourth sample, our SSRGCNs comprehensively considers the dual effects of *Needs* and *bigger*, understanding the semantic information that the *power switch* is not large enough and identifying its polarity as negative. To sum up, our SSRGCNs have the ability to parse the overall syntactic structure and capture the semantic contextual information of sentences to achieve accurate aspect sentiment classification.

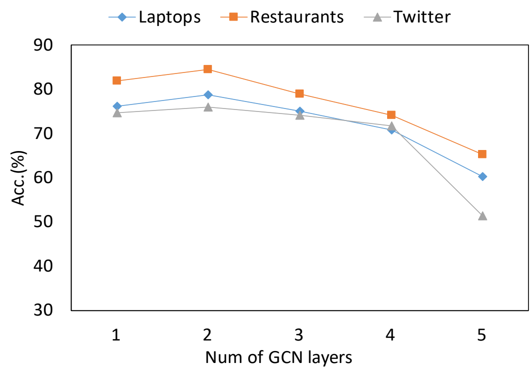
5.8 Impact of GCN Layers

When performing deep syntactic and semantic feature extraction, too many GCN layers may lead to too smooth node feature representation and loss of discrimination, while increasing computational complexity and memory requirements, and leading to gradient disappearance and overfitting problems. Too few layers may limit the ability of the model to aggregate neighbor information and not fully capture the hidden information in the graph. Therefore, it is necessary to select the appropriate number of layers to balance the expressive power and computational efficiency of the model, so as to achieve the best performance.

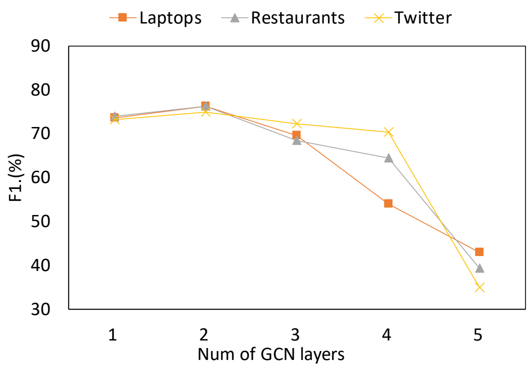
To examine the effect of the number L of GCN layers, we vary it from 1 to 5, shown in Fig. 10. From (a), we can see that our model first shows an upward trend, reaching the best performance at L=2 (especially achieving 84.56% accuracy on the Restaurant dataset), and then begins to decline. Similarly, when the GCN layer is 2, the model achieves the best F1 score on all three datasets. The above results indicate that under appropriate layers, GCN can effectively capture the complex relationships between nodes in the graph structure, thereby improving the predictive ability of the model. When L is too small, GCN only learns local information of nodes and cannot fully utilize the broader contextual information in the graph, resulting in the model being unable to fully understand the structure and features of the graph, thereby limiting its performance. While for large L, the model may obtain redundant information, leading to gradient explosion, which makes it difficult for the model to converge to the optimal solution during the training process, resulting in the degradation of model performance.

Table 4. Case study of our SSRGCNs compared with advanced baselines

Review	Golden	RGAT	SynWeght	SemWeight	SSRGCNs
I am still in the process of learning about its features	**Neu**	Pos	Neu	Neu	Neu
I did swap out the hard drive for a Samsung 830 SSD which I highly recommend	**Neu/Pos**	Neu/Neu	Neu/Neu	Neu/Pos	Neu/ Pos
I can't believe Apple keeps making the same mistake with regard to USB ports	**Neg**	Neu	Neg	Neg	Neg
Needs a CD/DVD drive and a bigger power switch	**Neu**	Neg	Neu	Neu	Neu



(a) The impact of layers on accuracy



(b) The impact of layers on F1 score

Fig. 10. Impact of GCN layers

6 Conclusion

In this paper, we proposed Dual Graph Convolutional Networks with Semantic and Syntax Reinforcement for ABSA. We proposed two contextual modules and encode the matrices of them with two separate GCNs, followed by aggregating their respective outputs to generate a fused representation that captures syntactic and semantic information for further analysis. Specifically, we use aspect-focused attention combined with self attention to extract contextual information related to aspects. And we construct a syntactic weight matrix to incorporate syntactic information into the model. To the best of our knowledge, it is the first work to integrate the attention mechanism with syntactic matrix for the ABSA task. We have learned how the syntactic structure and semantic information of a sentence affect specific aspects of emotional orientation. Therefore, we adopted a fusion mechanism to integrate syntactic and semantic information to extract more precise representations of contextual information. We conducted experiments on three different datasets, and the experimental results reveal that our model outperforms the state-of-the-art models in all evaluation metrics on each dataset. We also performed ablation experiments to validate the individual contributions of each module to the model. Experimental results with case studies and visualizations further support the effectiveness of our model in extracting the final embedding.

7 Acknowledgement

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