





A Graph Convolutional Network Based on Sentiment Support for Aspect-Level Sentiment Analysis

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Abstract: Aspect-level sentiment analysis is a research focal point for natural language comprehension. An attention mechanism is a very important approach for aspect-level sentiment analysis, but it only fuses sentences from a semantic perspective and ignores grammatical information in the sentences. Graph convolutional networks (GCNs) are a better method for processing syntactic information; however, they still face problems in effectively combining semantic and syntactic information. This paper presents a sentiment-supported graph convolutional network (SSGCN). This SSGCN first obtains the semantic information of the text through aspect-aware attention and self-attention; then, a grammar mask matrix and a GCN are applied to preliminarily combine semantic information with grammatical information. Afterward, the processing of these information features is divided into three steps. To begin with, features related to the semantics and grammatical features of aspect words are extracted. The second step obtains the enhanced features of the semantic and grammatical information through sentiment support words. Finally, it concatenates the two features, thus enhancing the effectiveness of the attention mechanism formed from the combination of semantic and grammatical information. The experimental results show that compared with benchmark models, the SSGCN had an improved accuracy of 6.33–0.5%. In macro F1 evaluation, its improvement range was 11.68–0.5%.

Keywords: aspect-level sentiment analysis; graph convolutional network; attention mechanisms; sentiment support words



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1. Introduction

Sentiment analysis involves extracting viewpoints and judging emotional tendencies in subjective texts. Aspect-level sentiment analysis is more refined, particularly when judging the emotional polarity of texts in terms of given aspect words (e.g., positive, negative, and neutral) [1–3]. As shown in Figure 1, the sentence has two sides: “price” and “screen”. The emotional polarity of the sentence is negative with regard to “price” and positive in terms of “screen”. The main task of aspect-level sentiment analysis is to accurately find the opinions and emotional tendencies of sentences according to the identified aspects. In this way, the statement is partially understood. This is currently an important tool for online opinion gathering for governments and businesses concerning policies or business strategies [4]. For example, it can be used to analyze a company’s blockchain statements and obtain a short-term value evaluation of the company [5]. It can also be employed to analyze the behavior of users in the blockchain [6].

Attention mechanisms can improve the structure of deep learning by concentrating on the important points. Wang et al. [7] presented the application of attention mechanisms to long short-term memory (LSTM) [8]. They used an attention mechanism to acquire the semantic information between words in a text and aspect words, obtaining crucial parts of

the sentences to obtain a more accurate aspect sentiment analysis. Ma et al. [9] introduced interactive attention networks (IANs) based on LSTM and attention mechanisms to realize the interactive learning of attention based on goals and contexts. However, many studies have used attention mechanisms to obtain the relation between words and aspect words in sentences from a semantic perspective [10–12]. When a sentence has several aspect words and the emotional polarity of these words is different, the attention mechanism can easily focus on the wrong part or a part that is unrelated to the aspect words. As shown in Figure 1, if the attention mechanism mistakenly concentrates on the opinion word “good” for the aspect of “price”, it is likely to cause errors in the emotional polarity.

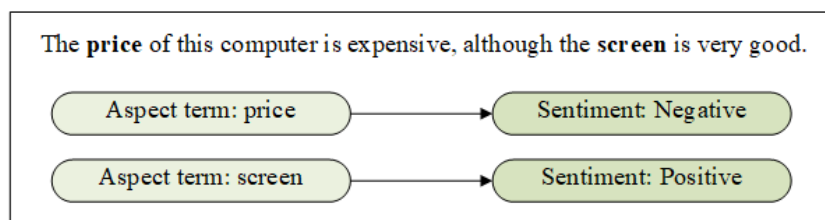


Figure 1. An example sentence of aspect-level sentiment analysis.

In order to enable the model to accurately concentrate on opinion words that correspond to the aspect words, it is important to introduce the grammatical relations between words in sentiment analysis. Graph convolutional networks (GCNs) [12] combined with syntactic dependency trees can better obtain grammatical features. Zhang C. et al. [10] employed graph convolutional networks in aspect-level sentiment analysis, and their results showed excellent model performance. In the following study, Zhang Z. et al. [11] joined the grammatical structure and semantic correlation of aspect words. They presented an aspect perception attention mechanism combined with a self-attention mechanism, and their work shows promising results.

It is evident that a sentence not only contains aspect words but also other types of words. If sentiment analysis was only performed with the combination of grammatical and semantic features of aspect words, some important information in the sentence would be lost. Therefore, we introduced sentiment support words (SSWs; proposed in our previous study [13]) to supplement a sentiment analysis in order to obtain more complete grammatical and semantic features of sentences. SSWs are words that influence an aspect word in a sentence, often supporting the emotional polarity of the whole sentence in one aspect. Through a grammatical dependency tree, we can obtain the aspect of sentiment support words. Figure 2 shows a concrete example of this. From the figure, we can see that the aspect words are attributes of the object entities in the sentence. For example, an aspect can be the price of computers or computer screens, while sentiment support words directly evaluate part of the target information. For example, when the aspect is the price of computers, sentiment support words evaluate the price of computers as “expensive”. The emotional polarity here is clearly negative. Therefore, combining aspect words with SSWs is beneficial for identifying the emotional polarity corresponding to certain aspect words. We can identify the SSWs corresponding to each aspect of a sentence by analyzing the parts of speech and applying fixed rules. This approach allows us to consider the grammatical and semantic information of emotive support words in the sentence.

Based on this idea, this paper presents a sentiment-supported graph conventional network (SSGCN). First, we used an aspect perception attention mechanism and a self-attention mechanism to obtain attention scores; then, we input these scores into the GCN through a syntactic mask matrix to obtain sentence features that initially combined semantic and grammatical information. Then, the semantic and grammatical information of the SSW combination was obtained. Finally, this was combined with the semantic and grammatical information of the aspect words to obtain the enhanced information of the combination of syntactic and semantic information. In this way, a more complete combination of semantic and grammatical information could be obtained. When evaluated on three publicly avail-

able datasets, the model presented in this paper demonstrated a greater efficiency than the eight comparison models.

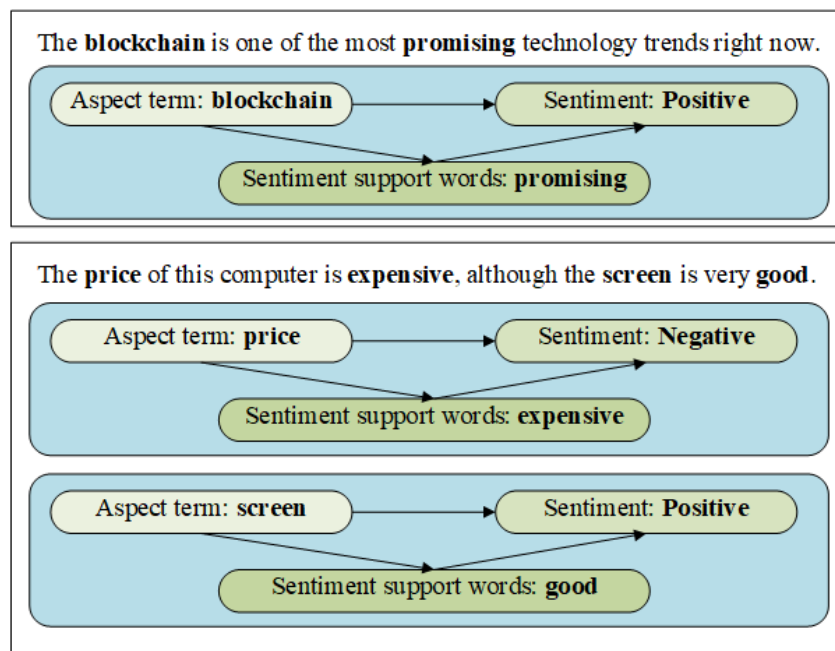


Figure 2. Examples of SSWs in aspect-level sentiment analysis sentences.

The main contributions of this paper are as follows:

- (1) A method of combining semantics and grammar using sentiment support words is presented. This method effectively captures the evaluation information of aspect words in sentences and assists the model in extracting the correct feature information.
- (2) A further combination method is presented. This method integrates syntactic and semantic information based on aspect and sentiment support words. It enhances the comprehensiveness of the constructed combined features by incorporating semantic and grammatical information.
- (3) Experiments on three public datasets demonstrated that the SSGCN was more effective than the benchmark models.

The remainder of this paper is organized as follows: Section 2 provides a review of the research associated with aspect-level sentiment analysis. Then, the proposed SSGCN model is introduced in detail in Section 3. The experiments and discussion are presented in Section 4. Finally, Section 5 provides our conclusions.

2. Related Work

Aspect-level sentiment analysis is a subtask of sentiment analysis. Compared with ordinary sentiment analysis tasks, it is a more refined emotional classification task aimed at discovering the emotional polarity of a sentence in a specific aspect.

Early sentiment analysis tasks mostly adopted machine learning methods [14]. Kiritchenko et al. [15] obtained a large number of analytical attributions for classification by manually constructing features. However, this method is labor-intensive, demands a lot of human resources and time, and loses the dependency between the aspect words and the context. Kim et al. [16] used neural networks to model text, concluding that convolutional neural networks (CNNs) perform well when extracting the local features of sentences in a text. Therefore, CNNs have begun to be widely used in sentiment analysis [17–19]. The variant model of the recurrent neural network (RNN) is also a common method used in sentiment analysis [20]. For instance, in the case of using aspect word information, Tang et al. [21] introduced target-dependent long short-term memory (TD-LSTM). This

approach employs two LSTMs to model the context before and after aspect words, utilizing the aspect words' semantic information to judge the emotional polarity. This method achieved good results in their experiments. In aspect-level sentiment analysis, an attention-mechanism-based approach [22,23] directs the model's increased attention toward the feature information of aspect words. For instance, Wang et al. [7] input the word vector of aspect words into the structure of an attention mechanism. The obtained attention score represents the weight of each word in this aspect of the sentence. The higher the score, the more important it becomes. Finally, the sentence features are obtained by weighted summation. Their experiments showed that this method is superior to its baseline methods. Similarly, Huang et al. [24] used BiLSTM-SNP to obtain the correlation between aspect words and content words, applying attention mechanisms to determine their weights. The experiments on multiple Chinese and English datasets showed that this method has significant advantages in terms of accuracy.

To a certain extent, the attention mechanism can find the semantic correlation between aspect words and other words in a sentence, but when the sentence composition is complex, the attention mechanism may make the model concentrate on the wrong part of the sentence [25]. Unlike traditional deep learning models, graph convolutional networks capture the relationships and feature information between nodes in a graph by defining the convolution operations on the graph structure [26]. Specifically, they first represent nodes in the graph as low-dimensional vectors and aggregate the information of adjacent nodes through matrix multiplication to obtain new feature representations for each node in the graph. Since GCNs address this deficiency better [27], it was used for the first time by Zhang et al. [10] for aspect-level sentiment analysis. Their proposed method was named the aspect-specific graph convolutional network (ASGCN). The model established the GCN on the syntactic dependency tree and acquired grammar-dependent information from a sentence. The dual graph convolutional network (DualGCN) [28] was proposed by Li et al. They also argued for the complementarity of grammatical structure and semantic relations, and combined an attention mechanism with a grammatical dependency tree. In this model, a GCN is employed to obtain the abundant syntactic information on the syntactic dependency tree, and another GCN is applied to obtain the semantic relations using a self-attention mechanism. Yang et al. [29] introduced tight connections into GCNs, enabling GCNs to obtain rich local and global information. A syntactic- and semantic-enhanced graph convolutional network (SSEGCN) was presented by Zhang et al. [11]. It initially integrates the syntactic and semantic information of sentences. In order to model the relevance of specific semantics of terms from different aspects, Zhang et al. also introduced the aspect-aware attention mechanism and combined it with the self-attention mechanism. In order to highlight the aspect-related semantic information, Zhang et al. also took the attention score as the initial adjacency matrix of the graph convolutional network, constructed a syntactic mask matrix calculated from the different distances between words with the syntactic information, and used the aspect word mask matrix corresponding to the position of the aspect word to highlight the features after the graph convolutional network. Current research focuses on the simultaneous use of attention mechanisms and GCNs, beginning attempts to combine semantic information obtained using attention mechanisms with grammatical information obtained using GCNs. Therefore, the current research is devoted to finding a more efficient way to combine semantic and grammatical information.

3. The Proposed SSGCN Model

In this section, we propose the sentiment-supported graph convolutional network (SSGCN) model, as shown in Figure 3.

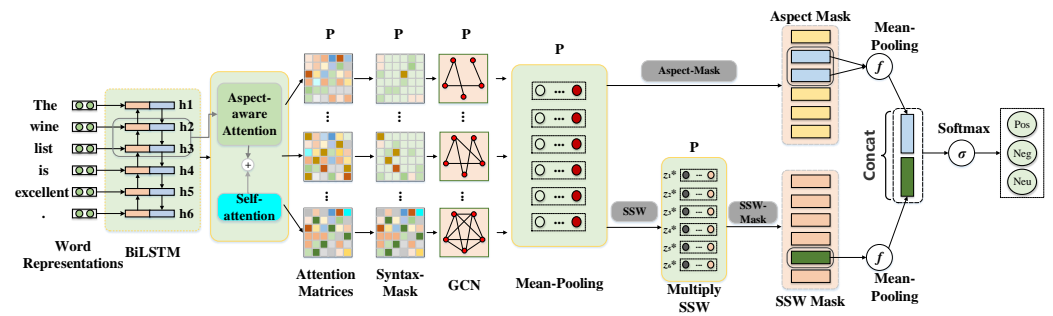


Figure 3. Architecture of the sentiment-supported graph convolutional network (SSGCN) model. Herein, * Represents multiplication.

3.1. Input and Coding Layers

We first used GloVe embedding [30] to obtain the word vector representation of each word, and then we used the Bi-LSTM network to learn the hidden representation H of each word in a sentence. Here, $H = \{h_1, h_2, h_3, \dots, h_N\}$ contains the hidden representation subsequence $h_a = \{h_{a1}, h_{a2}, h_{a3}, \dots, h_{am}\}$ corresponding to aspect A .

3.2. Attention Layer

We used an aspect-aware attention mechanism and a self-attention mechanism to form the attention layer. The aspect-aware attention mechanism mainly learns and obtains aspect-related features by calculating the attention of each aspect word. Simultaneously, information regarding the interaction between any two words in a sentence is obtained through the self-attention mechanism. We used the multi-head (P -head in Figure 3) aspect-perceived attention mechanism to obtain the attention score matrix of a sentence, and we also used the P -head self-attention mechanism to obtain a score matrix, finally combining the aspect-perceived attention score with the self-attention score, as shown in Equation (1).

$$A^i = A_{asp}^i + A_{self}^i \tag{1}$$

where A_{asp}^i and A_{self}^i represent the attention scores obtained from the i th aspect-perceived attention head and the i th aspect self-attention head, respectively.

3.3. Syntax Mask Layer

In this study, we used Stanford Parser 3.9.2 (Stanford NLP Group, Stanford, CA, USA) to obtain the syntactic parsing trees. In the syntax mask layer, some nodes in the parsing tree are masked based on different syntactic distances. The model takes the shortest path between nodes V_i and V_j in the parsing tree as the syntactic distance $D(i, j)$ and constructs P syntactic mask matrices based on the syntactic distance. Herein, according to Figure 3, we set $P = 5$. Then, the attention score matrix is combined with the syntactic mask matrix to obtain the syntactic mask matrix A_{mask} using Equation (2).

$$A_{mask}^i = Softmax(A^i + M^i) \tag{2}$$

where A_{mask}^i represents the syntactic mask matrix obtained by combining the i th attention score matrix with the i th syntactic mask matrix, and M^k represents the k th syntactic mask matrix.

3.4. Graph Convolutional Network Layer

Due to there being $P = 5$ different syntactic mask matrices, we performed the graph convolution operation 5 times. For graph convolutional networks, whether the nodes are connected depends upon the syntactic mask matrix A_{mask} . We updated the value of the

i th node in layer l , as shown in Equation (3). The final output of the GCN is shown in Equation (4).

$$h_i^l = \sigma\left(\sum_{j=1}^n A_{ij}W^l h_j^{l-1} + b^l\right) \quad (3)$$

$$H_l = \{h_1^l, h_2^l, h_3^l, \dots, h_n^l\} \quad (4)$$

where W^l and b^l are denoted as linear transformation weights and bias terms, respectively. σ represents the nonlinear functions. h^{l-1} is denoted as the input of layer l , and h^l represents the output of layer l . H^l indicates the final output of the GCN.

3.5. Semantic and Syntactic Layers of Sentiment Support

In this section, SSWs are used to achieve a preliminary combination of semantics and grammar. We obtained each word's part of speech in a sentence according to the dependency analysis tree, obtaining the semantic information of a sentence from the part of speech perspective. As shown in Figure 4, we conducted the part-of-speech analysis of the aspect words on a widely used dataset, namely, *Laptop*. In its training dataset, we found that among the 2914 pieces of data, 1074 of the aspect words were nouns (NNs), representing 37%. However, the proportion of nouns (NNs) or noun combination phrases (NN-NNs) and plural forms of nouns (NNSs) reached 90%, and the rest were adjectives (JJs) or combinations of adjectives and nouns (JJ-NNs). That is, the aspect terms were mostly noun phrases, nouns, or adjectives plus nouns. Consequently, we proposed three rules for the extraction of emotive support words to determine the emotive support words in specific aspects of sentences from the perspective of grammar, thus acquiring the grammatical information of SSWs in sentences.

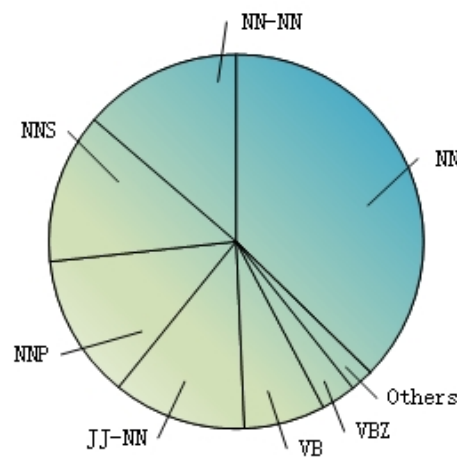


Figure 4. Part of speech statistics for aspect words in the Laptop dataset.

In the syntactic parsing tree, the rules of SSW extraction are as follows:

- (1) Noun type: when the part of speech of the aspect word is a noun or another form of a noun (such as a noun singular plural or a proper noun singular plural), we regarded the adjective or other form of the adjective closest to the aspect word in the sentence (such as the adjective comparative or adjective superlative) as the SSW for this aspect.
- (2) Combination: when an aspect word is a combination of an adjective or another form of an adjective with a noun or another form of a noun, we considered the adjective or other form of the adjective closest to the aspect word in the sentence as the SSW for that aspect.
- (3) Constraint rule: when the relative distance between the adverb and sentiment support word found in the noun and combined types do not exceed two words, we set the adverb as the SSW.

We then used the sentiment support weight z to combine the semantic and grammatical information of the SSW. The weight of the sentiment support is calculated using Equation (5).

$$z = \begin{cases} 2, & w_i \in \text{SSW} \\ 1, & \text{otherwise} \end{cases} \quad (5)$$

where z is the sentiment support weight of the word w_i , and SSW is denoted as the sentiment support word. After calculating the sentiment support weight, we used z to weigh the final output representation of the GCN, obtaining the weighted output representation of the GCN H^l .

$$h_i^l = z_i h_i^l \quad (6)$$

$$H^l = \{h_1^l, h_2^l, h_3^l, \dots, h_n^l\} \quad (7)$$

3.6. Semantic and Syntactic Information Enhancement Layer

In this section, we further describe the enhancement of the combination of semantic and grammatical information for aspect words with SSWs. Herein, the mask matrix of SSWs is employed to obtain the features of enhanced semantic and grammatical information of SSWs. Similarly, the mask matrix of aspect words is employed to obtain the features from the enhanced semantic and grammatical information of aspect words. For the semantic and grammatical information enhanced for SSWs, we masked the non-sentiment support words in the weighted representation H^l of the GCN output to obtain an SSW representation, retaining important information in the SSW representation through average pooling, as shown in Equation (8).

$$H_{SSW}^l = f(h_{SSW_1}^l, h_{SSW_2}^l, h_{SSW_3}^l, \dots, h_{SSW_r}^l) \quad (8)$$

For the semantic and grammatical information enhanced for aspect words, we masked the final output of the GCN to represent non-aspect words in H^l to obtain aspect word representations. Similarly, in Equation (9), we retained important information in each aspect word representation through average pooling.

$$H_{asp}^l = f(h_{a_1}^l, h_{a_2}^l, h_{a_3}^l, \dots, h_{a_r}^l) \quad (9)$$

where f represents the function of average pooling.

We then concatenated the SSW representation with the aspect word representation to obtain a more complete semantic and syntactic final feature representation. Finally, we represented the final feature by obtaining the probability distribution via the *Softmax* function, as shown in Equations (10) and (11).

$$H_{con}^l = \text{Concat}(H_{SSW}^l, H_{asp}^l) \quad (10)$$

$$y = \text{Softmax}(W_c H_{con}^l + b_c) \quad (11)$$

where *Concat* represents the concatenation operation, and W_c and b_c are linear transform weights and bias terms, respectively.

4. Experimental Analysis

4.1. Datasets

In this study, we used three public datasets to verify our proposed model. The datasets of *Restaurant* and *Laptop* were obtained from SemEval 2014 Task 4 [31], and the third dataset was *Twitter* [32]. Table 1 shows the number of sentences marked with positive, neutral, or negative emotional polarity in the training and test sets of the above datasets.

Table 1. Total number display table.

Dataset	Emotional Polarity	<i>Restaurant</i>	<i>Laptop</i>	<i>Twitter</i>
Training Set	Positive	2164	976	1507
	Neutral	807	851	1528
	Negative	637	455	3016
Test Set	Positive	727	337	172
	Neutral	196	128	169
	Negative	196	167	336

4.2. Parameter Settings

This study employed a 300-dimension pre-trained Glove as a word embedding. The hidden layer dimension of the Bi-LSTM was set to 50. The dropout rate was set to 0.3. The batch size was set to 16 for all models, and the learning rate was set to 0.002. We used Adam as the optimizer.

To ensure the model focused on SSWs, we conducted experiments on the sentiment support weight values of SSWs. We experimented with different weight values in the SSGCN, and the specific experimental results are shown in Table 2. Herein, the accuracy rate and macro F1 were used as evaluation indices.

Table 2. Sentiment support weight value.

<i>z</i>	<i>Restaurant</i>	
	Acc	Macro F1
1.1	83.65	76.25
1.2	82.57	75.04
1.5	83.02	75.91
1.7	84.18	76.94
2.0	84.36	77.67
2.2	83.11	75.85
2.5	83.20	74.87

We believe that the weight of the sentiment support should not be too large to highlight the sentiment support words or too small. From Table 2, it can be seen that when the sentiment support weight z was set to 2, using the accuracy and macro F1 as evaluation indicators, the sentiment analysis of the *Restaurant* dataset obtained the best results. Therefore, in this study, we set $z = 2$.

4.3. Baseline Models

In order to fully evaluate the proposed model, we used the following models as baseline methods:

- (1) IAN [9]: interactive attention networks are based on LSTM and attention mechanisms.
- (2) MGAN [33]: the combined coarse- and fine-grained attention mechanisms are used to create a multi-grained attention network.
- (3) MAN [34]: employs intra- and inter-level multi-attention networks.
- (4) KumaGCN [35]: a dynamic combination of word dependence graphs and latent infographs learned using self-attention networks.
- (5) DualGCN [28]: two GCNs designed to obtain syntactic and semantic information.
- (6) CNN-BiLSTM [36]: transfers the data learned from document- to aspect-level sentiment classification.
- (7) MIGCN [37]: multi-interaction GCNs that process the semantic and grammatical information between words.
- (8) SSEGCN [11]: a syntactic- and semantic-enhanced GCN in which the related feature information of aspect words is enhanced.

4.4. Experimental Results

As shown in Table 3, compared with the baseline models, we found that the accuracy improvement range of the SSGCN on *Restaurant* was 0.54–5.27%, and the improvement range of the macro F1 was 0.75–11.68%. The accuracy improvement range on *Laptop* was from 0.95% to 6.70%. The accuracy improvement range on *Twitter* was 0.10–3.43%, and its improvement range for the macro F1 was 0.32–4.04%. In summary, on all three datasets, the SSGCN showed better accuracy compared with the models based on attention structures or GCNs. In the *Restaurant* and *Twitter* datasets, the evaluated macro F1 results illustrate that the SSGCN was the best model. Our model achieved only a sub-optimal effect in terms of the macro F1 value on the *Laptop* dataset. This was because the syntax structure of the *Laptop* dataset was relatively chaotic, which increased the difficulty of obtaining syntactic information for certain samples. The experimental results demonstrate that our model achieved higher accuracy by incorporating the semantic and grammatical information of aspect words with SSWs.

Table 3. The results of the different comparison models. * indicates the results are directly cited from the original paper (%).

Model	<i>Restaurant</i>		<i>Laptop</i>		<i>Twitter</i>	
	Acc	Macro F1	Acc	Macro F1	Acc	Macro F1
IAN (2017)	79.09	65.99	72.63	67.52	72.50	70.81
MGAN (2018)	81.15	71.64	75.17	70.84	72.54	70.52
MAN (2020)	83.47	70.91	77.21	72.55	75.58	71.15
KumaGCN (2020)	81.43*	73.64*	76.12*	72.42*	72.45*	70.77*
DualGCN (2021)	83.02	76.07	76.58	73.11	75.18	74.06
CNN-BiLSTM (2022)	81.96*	74.16*	72.26*	68.95*	-	-
MIGCN (2022)	82.32*	74.31*	76.59*	72.44*	73.31*	72.12*
SSEGCN (2022)	83.82	76.92	78.01	75.35	73.31	72.12
SSGCN (textual model)	84.36	77.67	78.96	75.17	75.88	74.56

4.5. Fixed Random Seed

Since parameters in neural networks are randomly initialized by default, setting random seeds can enhance the neural network's fitting ability; however, the results are different each time. To illustrate the effectiveness of our model, we set random number seeds for the CPU, Numpy, and all GPUs to ensure that fixed random numbers were generated each time, ensuring that the experimental results of the same model structure were consistent each time. As shown in Table 4, we set the random number seed to 1000. The results show that our SSGCN was superior to the SSEGCN. Therefore, we argue that the model error in this study was not caused by random disturbances, but rather reflected the stable improvement resulting from model enhancements.

Table 4. Fixed randomized seed experiment results.

Model	<i>Restaurant</i>		<i>Laptop</i>		<i>Twitter</i>	
	Acc	Macro F1	Acc	Macro F1	Acc	Macro F1
SSEGCN	83.47	75.90	77.53	74.25	74.74	72.80
SSGCN	84.00	76.81	78.27	75.30	75.48	74.21

4.6. Comparison of Model Concatenation Methods

We used the concatenation operation to connect the feature representations of aspect words and SSWs, sending the final feature representations to Softmax for emotional classification. To illustrate why Concat was used, we applied the *Restaurant* dataset as an example to compare Concat with direct addition and multiplication operations. The experimental results are shown in Table 5. From this table, it can be seen that using the Concat operation yielded better results than other operations in terms of accuracy and macro F1.

Table 5. Concatenation method results.

Model Concatenation Methods	Acc	Macro F1
Concat	84.36	77.67
Add	83.47	76.71
Multiply	83.29	75.26

Through the experimental results, it can be seen that the operation of directly adding or multiplying the feature representations of aspect words and sentiment support words resulted in partially lost important information, which was inferior to the concatenation operation with regard to the accuracy and macro F1. Therefore, the concatenation operation was selected for the model in this section.

4.7. Significant Differences between the SSGCN and SSEGCN

Compared with the SSEGCN, the improvements in the proposed model proposed were relatively small. Therefore, in this study, we conducted a *t*-test to determine whether there was a significant difference in the results of our model compared with the SSEGCN, as shown in Table 6.

Table 6. *t*-test results.

Dataset	Acc		Macro F1	
	P	Significance	P	Significance
<i>Restaurant</i>	0.003	Remarkable	0.010	Remarkable
<i>Laptop</i>	0.0001	Remarkable	0.146	Not remarkable
<i>Twitter</i>	0.017	Remarkable	0.037	Remarkable

The null hypothesis was that there was no significant difference between the improved results of the SSGCN and the SSEGCN. The *t*-test showed that when the significance level is 0.05, the null hypothesis can be accepted if *p* is greater than 0.05; the null hypothesis is rejected if *p* is less than 0.05. As shown in Table 6, for the *Restaurant* and *Twitter* datasets, there were significant differences between our method and the SSEGCN. There were significant differences in accuracy on the *Laptop* dataset, and the macro F1 value was not significantly improved. The *t*-test generally showed that our model could effectively improve the results.

4.8. Ablation Experiments

In this study, the effectiveness of each module in the SSGCN was checked through ablation experiments. As shown in Table 7, the SSGCN was taken as the benchmark model. Without SSWs denotes that only the weight of the sentiment support was removed, while without SSWMask denotes that only the enhancement of the meaning of sentiment support words and grammatical information was removed. Without AspMask represents the enhancement of only removing aspect word meaning and grammatical information, while without SSWAspMask represents the enhancement of semantic and grammatical information and removing both sentiment support words and aspect words. The following conclusions can be drawn from the results in Table 7:

- (1) By comparing without SSWs with the SSGCN, we showed that the sentiment support weight obtained by combining the syntactic and semantic information of SSWs could improve the performance. Specifically, it improved the accuracy by 0.55–1.2% and macro F1 by 0.08–2.23%.
- (2) By comparing without SSWMask with the benchmark model, the validity of the enhancement module of the sentiment support word meaning and grammatical information was verified.

- (3) By comparing without AspMask with the benchmark model, the validity of the enhancement module of aspect word meaning and syntactic information was verified.
- (4) By comparing without SSWMask and without AspMask with the benchmark model, we demonstrated the effectiveness of the feature concatenation module.
- (5) According to the comparison between without SSWAspMask and the benchmark model, the accuracy and macro F1 of the model decreased when the semantic and grammatical information of aspect words and SSWs were not enhanced, further indicating the importance and effectiveness of the grammatical and semantic information of aspect words and SSWs.

Table 7. Ablation results.

Model	Restaurant		Laptop		Twitter	
	Acc	Macro F1	Acc	Macro F1	Acc	Macro F1
SSGCN	84.36	77.67	78.96	75.17	75.88	74.56
Without SSWs	83.56	75.46	78.32	74.41	75.33	74.48
Without SSWMask	83.36	76.96	77.06	73.43	75.04	73.43
Without AspMask	83.47	76.31	76.42	72.21	75.78	74.47
Without SSWAspMask	82.84	75.22	78.24	74.45	74.45	73.08

5. Conclusions

In this paper, we present the SSGCN by introducing a graph attention mechanism to obtain semantic and grammatical information about aspect words and SSWs. By constructing the model in this way, the combination of semantic and syntactic information obtained from the SSGCN is more complete. The experimental results illustrate that the accuracy and macro F1 of the proposed model on the open datasets were better than those of the comparison models. More precisely, the improvement in accuracy was 6.33–0.5%. When using macro F1 for evaluation, our method was only 0.18% worse than the SSEGCN, and the improvement range was 11.68–0.5%. We showed that the aspect-level sentiment information was more abundant and the results were more accurate when introducing the semantic and grammatical information of SSWs. However, we searched for SSWs at a relative distance of two words from the aspect word in the syntax analysis tree. This approach is suitable for declarative sentences, but it may not be as effective for other sentence structures. In the future, we will set rules for different sentence structures to improve the accuracy of identifying aspect words.

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References

1. Iglesias, C.A.; Moreno, A. Sentiment analysis for social media. *Appl. Sci.* **2019**, *9*, 5037. [[CrossRef](#)]
2. Tan, K.L.; Lee, C.P.; Lim, K.M. A survey of sentiment analysis: Approaches, datasets, and future research. *Appl. Sci.* **2023**, *13*, 4550. [[CrossRef](#)]

3. Jiang, L.; Li, Y.; Liao, J.; Zou, Z.; Jiang, C. Research on non-dependent aspect-level sentiment analysis. *Knowl.-Based Syst.* **2023**, *266*, 110419. [[CrossRef](#)]
4. Moreno, A.; Iglesias, C.A. Understanding Customers' Transport Services with Topic Clustering and Sentiment Analysis. *Appl. Sci.* **2021**, *11*, 10169. [[CrossRef](#)]
5. Cioroianu, I.; Corbet, S.; Larkin, C. The differential impact of corporate blockchain-development as conditioned by sentiment and financial desperation. *J. Corp. Financ.* **2021**, *66*, 101814. [[CrossRef](#)]
6. Risius, M.; Breidbach, C.F.; Chanson, M.; von Krannichfeldt, R.; Wortmann, F. On the performance of blockchain-based token offerings. *Electron. Mark.* **2023**, *33*, 32. [[CrossRef](#)]
7. Wang, Y.; Huang, M.; Zhu, X.; Zhao, L. Attention-based LSTM for aspect-level sentiment classification. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Austin, TX, USA, 1–6 November 2016; pp. 606–615.
8. Gers, F.A.; Schraudolph, N.N.; Schmidhuber, J. Learning precise timing with LSTM recurrent networks. *J. Mach. Learn. Res.* **2002**, *3*, 115–143.
9. Ma, D.; Li, S.; Zhang, X.; Wang, H. Interactive Attention Networks for Aspect-Level Sentiment Classification. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, Melbourne, Australia, 19–25 August 2017; pp. 4068–4074.
10. Zhang, C.; Li, Q.; Song, D. Aspect-based Sentiment Classification with Aspect-specific Graph Convolutional Networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, Hong Kong, China, 3–7 November 2019; pp. 4568–4578.
11. Zhang, Z.; Zhou, Z.; Wang, Y. SSEGCN: Syntactic and semantic enhanced graph convolutional network for aspect-based sentiment analysis. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Washington, DC, USA, 10–15 July 2022; pp. 4916–4925.
12. Kim, D.; Kim, Y.J.; Jeong, Y.S. Graph Convolutional Networks with POS Gate for Aspect-Based Sentiment Analysis. *Appl. Sci.* **2022**, *12*, 10134. [[CrossRef](#)]
13. Jiang, L.; Zou, Z.; Liao, J.; Li, Y. A Study on the Application of Sentiment-Support Words on Aspect-Based Sentiment Analysis. *Int. J. Pattern Recognit. Artif. Intell.* **2023**, *37*, 2357004. [[CrossRef](#)]
14. Sánchez-Rada, J.F.; Iglesias, C.A. Social context in sentiment analysis: Formal definition, overview of current trends and framework for comparison. *Inf. Fusion* **2019**, *52*, 344–356. [[CrossRef](#)]
15. Kiritchenko, S.; Zhu, X.; Cherry, C.; Mohammad, S. NRC-Canada-2014: Detecting aspects and sentiment in customer reviews. In Proceedings of the 8th International Workshop on Semantic Evaluation, Dublin, Ireland, 23–24 August 2014; pp. 437–442.
16. Kim, Y. Convolutional Neural Networks for Sentence Classification. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, Doha, Qatar, 25–29 October 2014; pp. 1746–1751.
17. Wang, J.; Yu, L.C.; Lai, K.R.; Zhang, X. Dimensional sentiment analysis using a regional CNN-LSTM model. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, Berlin, Germany, 7–12 August 2016; pp. 225–230.
18. Liao, S.; Wang, J.; Yu, R.; Sato, K.; Cheng, Z. CNN for situations understanding based on sentiment analysis of twitter data. *Procedia Comput. Sci.* **2017**, *111*, 376–381. [[CrossRef](#)]
19. Mutinda, J.; Mwangi, W.; Okeyo, G. Sentiment analysis of text reviews using lexicon-enhanced bert embedding (LeBERT) model with convolutional neural network. *Appl. Sci.* **2023**, *13*, 1445. [[CrossRef](#)]
20. Viadinugroho, R.A.A.; Rosadi, D. A Weighted Metric Scalarization Approach for Multiobjective BOHB Hyperparameter Optimization in LSTM Model for Sentiment Analysis. *Inf. Sci.* **2023**, *664*, 119282. [[CrossRef](#)]
21. Tang, D.; Qin, B.; Feng, X.; Liu, T. Effective LSTMs for Target-Dependent Sentiment Classification. In Proceedings of the 26th International Conference on Computational Linguistics, Osaka, Japan, 11–16 December 2016; pp. 3298–3307.
22. Gu, T.; Zhao, H.; Li, M. Effective inter-aspect words modeling for aspect-based sentiment analysis. *Appl. Intell.* **2023**, *53*, 4366–4379. [[CrossRef](#)]
23. Phan, H.T.; Nguyen, N.T.; Hwang, D. Aspect-level sentiment analysis: A survey of graph convolutional network methods. *Inf. Fusion* **2023**, *91*, 149–172. [[CrossRef](#)]
24. Huang, Y.; Liu, Q.; Peng, H.; Wang, J.; Yang, Q. Sentiment classification using bidirectional LSTM-SNP model and attention mechanism. *Expert Syst. Appl.* **2023**, *221*, 119730. [[CrossRef](#)]
25. Yadav, R.K.; Jiao, L.; Goodwin, M.; Granmo, O.C. Positionless aspect based sentiment analysis using attention mechanism. *Knowl.-Based Syst.* **2021**, *226*, 107136. [[CrossRef](#)]
26. Zhang, S.; Tong, H.; Xu, J.; Maciejewski, R. Graph convolutional networks: A comprehensive review. *Comput. Soc. Netw.* **2019**, *6*, 11. [[CrossRef](#)] [[PubMed](#)]
27. Yuan, P.; Jiang, L.; Liu, J.; Zhou, D.; Li, P.; Gao, Y. Dual-Level Attention Based on a Heterogeneous Graph Convolution Network for Aspect-Based Sentiment Classification. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 6625899. [[CrossRef](#)]
28. Li, R.; Chen, H.; Feng, F.; Ma, Z.; Wang, X.; Hovy, E. Dual graph convolutional networks for aspect-based sentiment analysis. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, Online, 11–6 August 2021; pp. 6319–6329.
29. Yang, C.; Song, J.; Yao, S. A Weighted Dependency Tree Convolutional Networks for Aspect-Based Sentiment Analysis. *J. Comput. Eng. Appl.* **2023**, *59*, 129–137.
30. Pennington, J.; Socher, R.; Manning, C.D. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Doha, Qatar, 25–29 October 2014; pp. 1532–1543.

31. Pontiki, M.; Galanis, D.; Papageorgiou, H.; Androutsopoulos, I.; Manhar, S.; Al-Smadi, M.; Al-Ayyoub, M.; Zhao, Y.; Qin, B.; De Clercq, O.; et al. Semeval-2014 task 4: Aspect based sentiment analysis. In Proceedings of the 8th International Workshop on Semantic Evaluation, Dublin, Ireland, 16–17 July 2014; pp. 27–35.
32. Dong, L.; Wei, F.; Tan, C.; Tang, D.; Zhou, M.; Xu, K. Adaptive recursive neural network for target-dependent twitter sentiment classification. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA, 22–27 June 2014; pp. 49–54.
33. Fan, F.; Feng, Y.; Zhao, D. Multi-grained attention network for aspect-level sentiment classification. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, 2–4 November 2018; pp. 3433–3442.
34. Xu, Q.; Zhu, L.; Dai, T.; Yan, C. Aspect-based sentiment classification with multi-attention network. *Neurocomputing* **2020**, *388*, 135–143. [[CrossRef](#)]
35. Chen, C.; Teng, Z.; Zhang, Y. Inducing target-specific latent structures for aspect sentiment classification. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, Online, 8–12 November 2020; pp. 5596–5607.
36. Ayetiran, E.F. Attention-based aspect sentiment classification using enhanced learning through CNN-BiLSTM networks. *Knowl.-Based Syst.* **2022**, *252*, 109409. [[CrossRef](#)]
37. Ruyan, W.; Zhongyuan, T.; Rongjian, Z.; Puning, Z.; Zhigang, Y. Multi-interaction Graph Convolutional Networks for Aspect-level Sentiment Analysis. *J. Electron. Inf. Technol.* **2022**, *44*, 1111–1118.

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