GCNet: Global-and-Context Collaborative Learning for Aspect-Based Sentiment Analysis

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Abstract

Aspect-Based Sentiment Analysis (ABSA) aims to determine the sentiment polarities of specified aspect terms in a sentence. Most previous approaches mainly use an attention mechanism or graph neural networks based on dependency trees to explicitly model the connections between aspect terms and opinion words. However, these methods may not effectively address cases where the sentiment of an aspect term is implicitly described, as the corresponding opinion words may not directly appear in the sentence. To alleviate this issue, in this paper, we propose a GCNet that explicitly leverages global semantic information to guide context encoding. Particularly, we design a semantics encoding module that incorporates global semantic features into sequential modeling process to enable the consideration of the overall sentiment tendency of a sentence, while the global semantic features are also refined by adaptively focusing on different parts of the sentence. Moreover, for a comprehensive sentence analysis, we also include a syntactic feature encoding module along with a pre-fusion module to integrate the refined global features with the syntactic representations. Extensive experiments on three public datasets demonstrate that our model outperforms state-of-the-art methods, indicating the robustness and effectiveness of our approach.

Keywords: Sentiment Analysis, Aspect-Based Sentiment Analysis, Graph Attention Network, Collaborative Learning

1. Introduction

Aspect-Based Sentiment Analysis (ABSA) (Hu and Liu, 2004) is a fine-grained task within sentiment analysis, aiming at determining the sentiment polarities of specified aspect terms in a sentence. For example, in the sentence "The hotel is great, but the price is too expensive," the aspect "hotel" carries a positive sentiment polarity, while the aspect "price" conveys a negative sentiment polarity.

The key problem of ABSA is to model the relationships between the context and aspect terms. Existing modeling methods can be broadly classified into two categories: The first one is attention-based methods(Ma et al., 2017, Gu et al., 2018, Jiang et al., 2019), which selectively focus on various parts of the sentence and capture semantic relationships between words. These methods primarily center on extracting the semantic information inherent within the sentence. The second one is graph encoding methods based on the dependency parsing results, including Graph Convolutional Networks (GCN) (Kipf and Welling, 2016), Graph Attention Networks (GAT) (Veličković et al., 2018), and their various variants (Zhang et al., 2019b,Tang et al., 2020,Wang et al., 2020). These methods primarily center on extracting the syntactic information implicit in the sentence's syntactic structure. There are also methods that utilize both attention-based methods and graph methods

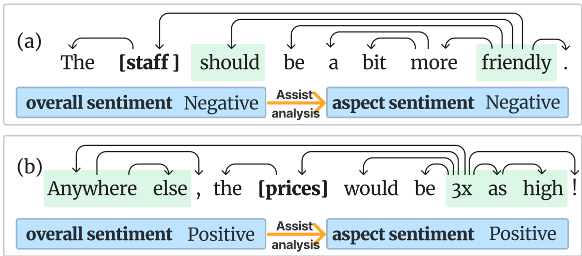

Figure 1: Two examples for ABSA where the sentiments of aspects are implicitly described. The words in [·] indicates the aspects for sentiment prediction and the words in boxes are the key to understand the overall sentiment tendency.

based on syntactic structure, harnessing the advantages of both approaches. (Tang et al., 2020, Li et al., 2021)

However, the aforementioned methods focus on encoding the relationships between tokens within the sentence but do not explicitly consider the global features of a sentence. The global features encompasses the overall semantic information as well as the overall sentiment tendency of the sentence, both of which can assist in determining the sentiment polarities of specified aspect terms, especially when the sentiment towards an aspect is implicitly described. Take the sentence in Figure 1 (a) as an example, where the sentiment of the aspect term "staff" is implicitly described, with its ground truth label being "negative". In this

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scenario, using either self-attention (Wang et al., 2016) or graph methods based on syntactic structure (He et al., 2018) will be difficult to find the opinion context of the aspect term, because there is no explicit description of the aspect "staff" in the sentence. Instead, "friendly" might confuse both of them, resulting in a misclassification as positive. However, by considering the overall sentiment tendency of the sentence, the negative sentiment of the overall comment can be perceived, which can guide the correct prediction of "negative" sentiment for aspect "staff". Therefore, it is crucial to consider the global features of a sentence during context modeling.

An intuitive way to obtain global features is by applying average pooling to all tokens' embeddings. However, this approach is too coarse and lacks the ability to discern tokens that significantly contribute to the understanding of overall semantics from those that do not. This could potentially result in an inaccurate portrayal of the sentiment tendency present within the global features, thus might interfere with predictions. Taking the sentence in Figure 1 (b) as an example, the key words to correctly understand the overall semantics of the sentence are "anywhere else" and "3x as high", which should have greater weight in the process of generating global features. Therefore, it is necessary to dynamically focus on the context when learning global features.

To this end, we propose a novel NETwork based on Global-and-Context collaborative learning (GCNet) to fully explore the association between context modeling and global features learning. Noted that to comprehensively analysis the sentences, the context modeling contains both attention-based semantic representation learning and graph-based syntactic representation learning. Specifically, for semantic representation learning, we design a method based on Transformer encoder (Vaswani et al., 2017). In this method, global features are involved in the process of encoding semantic information, enabling the consideration of the sentence's overall sentiment. The encoder with the same structure is also used to refine the global features, which are initialized through the average pooling of sentence's hidden representation and refined through multi-head attention to allocate attention across words within the sentence. Moreover, to further strengthen the correlation between the semantic representation and global features, we align their semantic space by sharing parameters during their encoding processes. For syntactic representation learning, we employ the Hybrid GAT (Zhang et al., 2022b) to analyze the sentence from a syntactic perspective. In order to enable the syntactic representation to also perceive global features, we introduce a pre-fusion module that integrates the refined global features into the syntactic representation.

Our contributions can be summarized as follows:

- We propose a GCNet for ABSA task by incorporating global semantic features into context modeling to enable the consideration of the overall sentiment tendency of a sentence.
- We design a semantic encoding method that jointly refines both global features and sequential representations through multi-head attention and parameters sharing to strengthen the interaction between them.
- We conduct experiments on the Semval2014 and twitter datasets, and the experimental results demonstrate the effectiveness of our method.

2. Related Work

Aspect-based sentiment analysis has been widely studied in recent years. Based on how they model the relationship between aspect terms and context, we can classify these research methods into the following three categories:

Attention-based methods Much of the previous research has employed attention to model the semantic relationship between aspect terms and context (Wang et al., 2016, Ma et al., 2017, Gu et al., 2018), and yielding satisfactory experimental results. For instance, ATAE-LSTM (Wang et al., 2016) utilizes an attention mechanism on the hidden layer representations encoded by LSTM to capture crucial context for a given aspect. RAM (Chen et al., 2017) employs a multi-layer attention mechanism to capture the relationships between distant words in a sentence. MGAN (Fan et al., 2018) combines coarse-grained and fine-grained attention to capture the word-level interaction between aspect and context. AOA-LSTM (Huang et al., 2018) generates mutual attention from both aspect to text and text to aspect.

Syntax-based methods Recently, more studies have focused on using graph neural network methods based on dependency trees to learn sentence syntactic representations, and some works have shown that dependency relationships can better model the aspect-term and opinion-context relationship compared to attention-based methods.(Tang et al., 2020, Huang et al., 2020) In these syntax-based methods, CDT (Sun et al., 2019) uses a GCN that operates directly on the dependency tree of the sentence to enhance the sentence representation learned by Bi-LSTM. TD-GAT (Huang and Carley, 2019) explicitly captures aspect-related information using a graph attention network and LSTM. T-GCN(Tian et al., 2021) uses

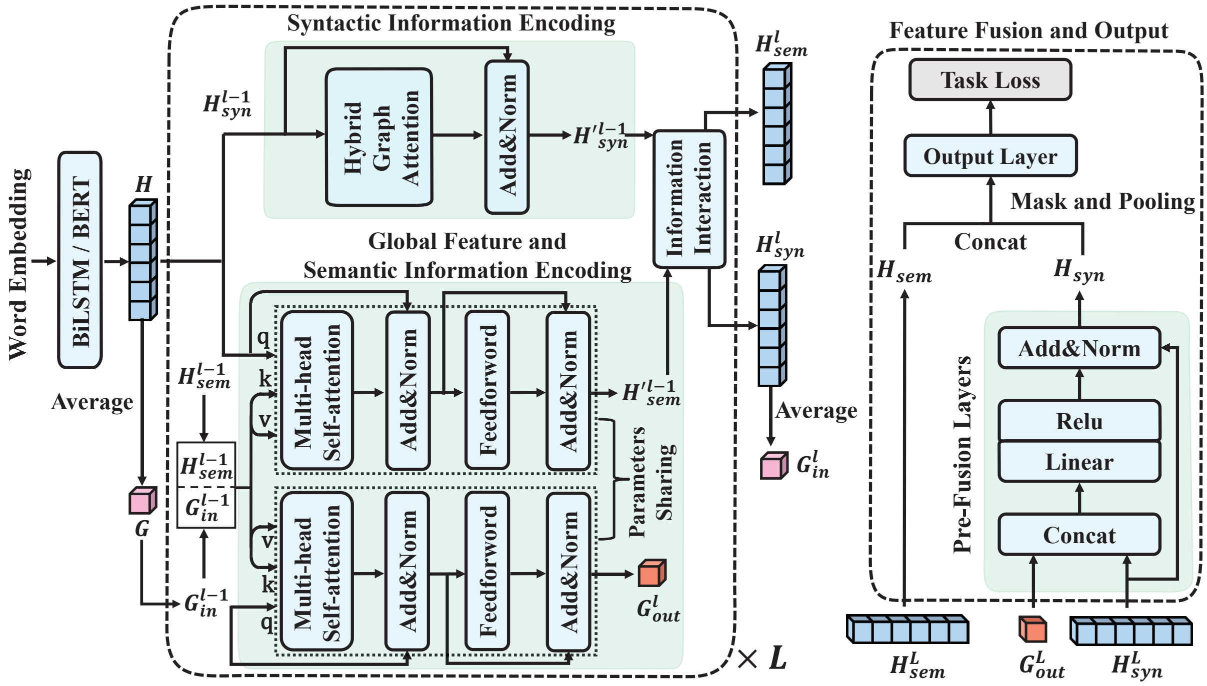


Figure 2: The overview of our proposed model.

attention to distinguish different type of edges. There are some works based on modifying syntactic dependency trees. R-GAT (Wang et al., 2020) constructs an aspect-oriented dependency tree by reorganizing and pruning the traditional dependency tree. APARN (Ma et al., 2023) replaces the syntactic dependency tree with the Abstract Meaning Representation. Some methods also incorporate external knowledge while utilizing syntactic graphs. For instance, BiGCN (Zhang and Qian, 2020) designs a global lexical graph to encode corpus-level word co-occurrence information. SenticGCN (Liang et al., 2022) leverages SenticNet as external knowledge.

Methods combining the two above While dependency tree-based graph encoding methods have yielded satisfactory results, errors in dependency parsing can impact the analysis. To mitigate this issue and better adapt to informal datasets, recent research has explored the complementarity of attention-based and graph encoding methods. For example, DGEDT (Tang et al., 2020) learns both the flat representation and the graph-based representation through a dual-transformer network enhanced by a dependency graph. DualGCN (Li et al., 2021) uses dual GCNs that utilize the dependency tree adjacency matrix and attention matrix respectively. HD-GCN (Zhou et al., 2023) employs a multi-layer stacked framework to learn different levels of syntactic and semantic information.

The aforementioned methods generally focus on modeling internal word relationships. However, the impact of the overall semantics is still underexploited. In this paper, we will explore the connection between overall semantic features and context modeling.

3. Methodology

Task Definition Given a sentence $s = \{x_1, ..., x_n\}$ with aspect term $a = \{x_i, ..., x_{i+m}\}$ annotated, our goal is to predict the sentiment polarity $y \in \{positive, negative, neutral\}$ of the target aspect.

Framework Overview The architecture of our model is depicted in Figure 2. Given an input sentence, we first employ BiLSTM or BERT to encode its word embeddings, yielding the hidden layer representation denoted as H_o. The global features are initialized by average pooling of H_o. Subsequently, we employ a hybrid Graph Attention Network to capture syntactic information, alongside a Transformer-based semantic features extractor to concurrently refines both global features and the semantic representation. These syntactic and semantic representations will then mutually exchange information through an interaction gate. Finally, the syntactic representation is enriched with the refined global features through a pre-fusion module, after which the aspect tokens from both syntactic and semantic representations are aggregated via average pooling and then input to the output layer for prediction.

3.1. Syntactic Information Encoding

To explore the syntactic information in dependency parsing trees and obtain sentence syntactic representations, graph attention (GAT) is commonly used. GAT encodes the graph by iteratively updating the hidden state of each node i in layer l through a weighted summation of neighboring nodes from layer $l-1$ for node i.

However, traditional GAT is unable to differentiate between various dependencies and simply categorizes them into binary states of being connected or not, which resulting in the omission of valuable syntactic information inherent in these dependencies. Therefore, we employ a Hybrid GAT (Zhang et al., 2022b) to amplify the impact of dependencies in the information exchange among nodes, aiming to fully leverage the syntactic information of sentences. Specifically, the Hybrid GAT consists of two distinct types of GATs employing different encoding strategies, i.e. relation-aggregation and relation-activation. In the case of relation-aggregation, it learns relation weights by concatenating dependencies with their corresponding node states at both ends. This process can be formulated as follows:

$$s_{ij}^{lk} = \sigma\left(g^{lk}\left[W^{lk}H_{syn,i}^{l} \parallel W^{lk}H_{syn,j}^{l} \parallel W^{lk}r_{ij}\right]\right), \tag{1}$$

$$a_{ij}^{lk} = \frac{exp\left(s_{ij}^{lk}\right)}{\sum_{j=1}^{\mathcal{N}_i} exp\left(s_{ij}^{lk}\right)}, \tag{2}$$

$$h_{aggr_i}^{l+1} = \parallel_{k=1}^{\mathcal{K}} \sigma\left(\sum_{j\in\mathcal{N}_i} a_{ij}^{lk} W^{lk} H_{syn,j}^{l}\right), \tag{3}$$

where W^{lk} and g^{lk} are learnable parameters, $\parallel$ indicates the concatenation operation, σ denotes the LeakyReLU function, $\mathcal{K}$ is the attention head number, and r_{ij} is the dependency embedding between node i and j. Besides, H_{syn}^{l} is the syntactic output of layer $l(l>0)$, and $H_{syn}^{0} = H_o$.

Since relation-aggregation is intuitive and direct, it might not comprehensively capture the intricate interactions between nodes. Thus, to comprehensively explore these relationships, Hybrid GAT also incorporates relation-activation for graph encoding. Particularly, it utilizes scaled dot-product attention to dynamically distribute the influence of diverse dependencies and their associated neighboring nodes as follows:

$$t_{ij}^{lk} = \frac{\left(W_Q^{lk}H_{syn,i}^{l}\right)\left(W_K^{lk}H_{syn,j}^{l} + W_{Kr}^{lk}r_{ij}\right)^{\mathsf{T}}}{\sqrt{d/k}}, \tag{4}$$

$$b_{ij}^{lk} = \frac{exp\left(t_{ij}^{lk}\right)}{\sum_{j=1}^{\mathcal{N}_i} exp\left(t_{ij}^{lk}\right)}, \tag{5}$$

$$h_{actv_i}^{l+1} = \parallel_{k=1}^{\mathcal{K}} \sigma\left(\sum_{j\in\mathcal{N}_i} b_{ij}^{lk}\left(W_V^{lk}H_{syn,j}^{l} + W_{Vr}^{lk}r_{ij}\right)\right), \tag{6}$$

where W_Q^{lk}, W_K^{lk}, W_{Kr}^{lk}, W_V^{lk}, W_{Vr}^{lk} are learnable transformation matrices, and $\mathcal{N}_i$ denotes the neighbors of node i.

The outputs of relation-aggregation and relation-activation will be spliced together as the output of the hybrid module as follows:

$$h_{hybrid_i}^{l+1} = h_{aggr_i}^{l+1} \parallel h_{actv_i}^{l+1}. \tag{7}$$

In addition, we add a residual connection and a layernorm layer to obtain the syntactic representation of this layer:

$$\tilde{H}_{syn}^{l+1} = LayerNorm\left(H_{hybrid}^{l+1} + H_{syn}^{l}\right). \tag{8}$$

3.2. Global Feature and Semantic Information Encoding

Considering the robust text semantic encoding capability of the Transformer, we leverage it to design a global feature-enhanced semantic encoder. This encoder enhances semantic features by exploring the relationships between words and the associations between words and global features. Specifically, we initiate the global feature G^0 by conducting average pooling of the hidden layer representation H_o of the sentence. The global features will be incorporated as an extra token within the attention calculation of the word sequence, added to both the key and value, which can be formulated as follows:

$$\begin{aligned}\hat{H}_{sem}^{l+1} = LayerNorm(H_{sem}^{l} + MSA(W_Q^{l}H_{sem}^{l},\\ W_K^{l}\left[H_{sem}^{l} \parallel G^{l}\right], W_V^{l}\left[H_{sem}^{l} \parallel G^{l}\right])),\end{aligned} \tag{9}$$

$$\tilde{H}_{sem}^{l+1} = LayerNorm(\hat{H}_{sem}^{l+1} + FFN(\hat{H}_{sem}^{l+1})), \tag{10}$$

where W_Q^{l}, W_K^{l} and W_K^{l} are leanable transformation matrices, $MSA(\cdot)$ is the multi-head self attention, and $FFN(\cdot)$ denotes the FeedForward Layer. In addition, G^{l} is the global feature from the output of layer l except G^0, H_{sem}^{l} is the semantic output of layer $l(l>0)$, and $H_{sem}^{0} = H_o$.

Simultaneously, the global feature also functions as an additional query for conducting Multi-Head Self-Attention calculations across all tokens within the sentence, which enables the refinement of the global feature itself:

$$\begin{aligned}\hat{G}^{l+1} = LayerNorm(G^{l} + MSA(W_Q^{l}G^{l},\\ W_K^{l}\left[H_{sem}^{l} \parallel G^{l}\right], W_V^{l}\left[H_{sem}^{l} \parallel G^{l}\right])),\end{aligned} \tag{11}$$

$$G^{l+1} = LayerNorm(\hat{G}^{l+1} + FFN(\hat{G}^{l+1})). \quad (12)$$

Noted that G^l denotes the global feature derived through averaging the output syntactic or semantic representation from layer l. In experiments we explore two scenarios: one using syntactic global features in all layers and the other utilizing semantic global features, selected through a hyperparameter. Moreover, to strengthen the correlation between global features and semantic representations, we share parameters in the word sequence encoding and global feature encoding processes.

3.3. Attention-based Information Interaction

To facilitate the information exchange between syntactic and semantic representations and thereby elevate the model's performance, we adopt an attention-like strategy for interaction. Specifically, to leverage semantic information in updating the syntactic representation at layer l, we first calculate the correlation coefficient matrix R through the following procedure:

$$e^l_{ij} = (\tilde{H}^l_{syn,i})^{\mathsf{T}} \times \tilde{H}^l_{sem,j}, \quad (13)$$

$$R^l_{sem2syn,ij} = \frac{exp\,(e_{ij})}{\sum_{k=1}^{n} exp\,(e_{ik})}. \quad (14)$$

Subsequently, we regard matrix R as a gate that determines which components of the semantic representation are added to the syntactic representation:

$$H^l_{syn} = \tilde{H}^l_{syn} + R^l_{sem2syn} \cdot \tilde{H}^l_{sem}. \quad (15)$$

The semantic representation can be updated in a similar way using syntactic representation as follows:

$$H^l_{sem} = \tilde{H}^l_{sem} + R^l_{syn2sem} \cdot \tilde{H}^l_{syn}. \quad (16)$$

3.4. Feature Fusion and Output

Pre-Fusion Layers Most models overlook the global features of sentence while generating final features. However, the global features hold the emotional tone of the entire sentence, thereby partially affecting model performance. Given that the global features are refined alongside the semantic representation, the semantic representation generated by the last semantic information encoding layer already encompasses the global feature, our focus shifts to the fusion of the global feature and the syntactic representation. Therefore, we introduce a pre-fusion layer that integrates the refined global features into the syntactic representation. This process can be formulated as follows:

$$H_{syn} = LayerNorm(H^L_{syn} + \sigma(W_f[H^L_{syn} \parallel G^L_{out}])), \quad (17)$$

where W_f is a learnable transformation matrix and $\sigma(\cdot)$ is $ReLU$ function

Output Layers The ultimate syntactic representation H_{syn} is acquired via the pre-fusion layer, while the final semantic representation H_{sem} is directly taken as H^L_{sem}. Subsequently, the aspect tokens within H_{syn} and H_{sem} are aggregated using average pooling and then combined to generate the ultimate feature for sentiment classification. Finally, a probability distribution p is computed by employing a linear layer followed by a softmax layer. The process can be expressed as follows:

$$H^{asp}_{syn} = avg([H_{syn,a}, ..., H_{syn,a+m}]), \quad (18)$$

$$H^{asp}_{sem} = avg([H_{sem,a}, ..., H_{sem,a+m}]), \quad (19)$$

$$p(s,a) = softmax(W_p[H^{asp}_{syn} \parallel H^{asp}_{sem}] + b_p), \quad (20)$$

where $avg(\cdot)$ denotes average pooling, W_p and b_p are learnable parameters.

3.5. Training Objective

Our training goal is to minimize the following cross-entropy loss:

$$L = -\sum_{\mathcal{D}} \sum_{\mathcal{C}} log\ p(s,a), \quad (21)$$

where $\mathcal{D}$ is the collection of all sentence-aspect pairs and $\mathcal{C}$ contains all sentiments among $\{positive, negtive, neural\}$.

4. Experiment

4.1. Datasets

Our experiments are conducted on three public standard ABSA datasets, including Laptop and Restaurant from SemEval 2014 task 4 (Pontiki et al., 2014), and Twitter built by Dong et al. (2014). Among them, Laptop consists of reviews on laptop computers, Restaurant contains online reviews on restaurants, and Twitter is a collection of tweets from Twitter. Particularly, following previous work (Li et al., 2021, Zhou et al., 2023), we remove the aspect terms with “conflict” labels and the sentences without any aspect terms.

4.2. Experiment setup

We use LAL-Parser(Mrini et al., 2020) in all our experiments to obtain the syntactic structure of sentences, and following previous work (Marcheggiani and Titov, 2017, Li et al., 2021),we add a self-loop for each node. We initialize the word embeddings using pretrained 300-dimensional Glove3 vectors (Pennington et al., 2014). Additionally, we set the dimensionality of position embeddings

Table 1: Experimental results compared with different models. The results with † are reported based on open-source codes, and the remaining results are reported by previous works. The best scores are in bold, and “-” denotes that the model is not tested on the dataset in the original paper. Our results are averaged across five different random seeds.

Models	Laptop		Restaurant		Twitter	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
MGAN (Fan et al., 2018)	75.39	72.47	81.25	71.94	72.54	70.81
ASGCN (Zhang et al., 2019a)	75.55	71.05	80.77	72.02	72.15	70.40
BiGCN (Zhang and Qian, 2020)	74.59	71.84	81.97	73.48	74.16	73.35
InterGCN (Liang et al., 2020)	77.86	74.32	82.23	74.01	-	-
RGAT (Wang et al., 2020)	77.42	73.76	83.30	76.08	75.57	73.82
CPA-SA (Huang et al., 2022)	75.18	71.50	82.64	73.38	-	-
RMN (Zeng et al., 2022)	74.50	69.79	81.16	73.17	-	-
SILTN (Zhang et al., 2022a)	76.96	73.03	83.12	75.86	73.02	73.07
AGCN (Zhao et al., 2022)	75.07	70.96	80.02	71.02	73.98	72.48
CRF-GCN(Huang et al., 2023)	75.83	**74.78**	82.71	73.87	-	-
SEGCN (Zheng et al., 2023)	77.43†	73.21†	83.26†	75.82†	76.16	74.82
GCNet (ours)	**78.10**	74.39	**83.57**	**76.79**	**76.34**	**75.20**
SILTN + BERT (Zhang et al., 2022a)	-	76.34	-	77.04	-	75.52
C3DA + BERT (Wang et al., 2022)	80.61	77.11	86.93	81.23	76.66†	75.79†
AGCN + BERT (Zhao et al., 2022)	79.94	76.52	82.77	73.29	75.43	74.11
RMN + BERT (Zeng et al., 2022)	77.95	70.83	84.56	79.05	-	-
MTL + BERT (Zhao et al., 2023)	80.56	77.00	86.88	81.16	76.59	74.67
SEGCN + BERT (Zheng et al., 2023)	80.56†	77.07†	86.96	81.34	77.17	75.26
GCNet + BERT (ours)	**80.79**	**77.61**	**87.08**	**81.35**	**77.55**	**76.59**

and part-of-speech (POS) embeddings to 30. The word, position, and POS embeddings will then be concatenated to form the input for our model. For BiLSTM, we set the hidden size to 100 and set the dropout rate to 0.1 to prevent overfitting. The dropout rate of the syntactic information encoding and global feature and semantic information encoding modules are set to 0.1, and the layers for Laptop, Restaurant and Twitter datasets are set to 3, 3, 2. The weights of all models are initialized using a uniform distribution. We use Adam (Kingma and Ba, 2014) as the optimizer and our model with the learning rate initialized around 0.001. For BERT, we use the bert-base-uncased4 English version, and the learning rate is set around 0.00002. Moreover, the global features for Laptop, Restaurant and Twitter are updated through semantics, syntax, syntax representations of previous layer, respectively. The experiments are conducted using an NVIDIA GeForce RTX 2080Ti GPU.

4.3. Baseline Models

We evaluate our GCNet against state-of-the-art baselines models, which are briefly described as follows.

1) **MGAN** (Fan et al., 2018) utilizes a multi-attention architecture to acquire aspect and contextual features at both coarse and fine levels.

2) **ASGCN** (Zhang et al., 2019a) constructs a directed graph of sentences using dependency trees and employs GCN to extract information.

3) **BiGCN** (Zhang and Qian, 2020) employs a bidirectional interactive GCN to utilize corpus-wide word co-occurrence data and various dependency relations.

4) **InterGCN** (Liang et al., 2020) builds a diverse graph per instance using aspect-specific and inter-aspect-contextual dependencies.

5) **RGAT** (Wang et al., 2020) transforms the dependency tree into an aspect-rooted tree and uses a relational graph attention network for encoding.

6) **CPA-SA** (Huang et al., 2022) employs asymmetric functions for dynamic word position weighting and context encoding via GRUs.

7) **RMN** (Zeng et al., 2022) proposes a multitask learning network that effectively utilizes similar or contrasting aspects.

8) **SILTN** (Zhang et al., 2022a) facilitates learning and reasoning with a differentiable first-order logic language for aspect-term sentiment analysis.

9) **C3DA** (Wang et al., 2022) uses generative large-scale pre-trained language models to generate domain-specific multi-aspect samples for data augmentation.

10) **AGCN** (Zhao et al., 2022) proposes an Aggregated GCN that efficiently captures long-distance context using two aggregation functions.

11) **SEGCN** (Zheng et al., 2023) designed a sentiment knowledge fusion mechanism that helps the model grasp sentiment information from various opinion words in the dataset.

12) **CRF-GCN**(Huang et al., 2023) combines conditional random fields and graph convolutional networks.

13) **MTL**(Zhao et al., 2023) proposes a multi-task

Table 2: Results of an ablation study (%).

Models	Laptop		Restaurant		Twitter	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
GCNet	**80.79**	**77.61**	**87.08**	**81.35**	**77.55**	**76.59**
w/o Global Feature	79.97	76.19	86.38	80.49	76.28	74.99
w/o Prefusion Module	80.41	76.66	86.34	80.29	76.45	75.18
w/o Hybrid GAT	80.19	76.66	86.17	80.24	76.75	75.76
replace Hybrid GAT with common GAT	79.54	75.90	86.59	80.75	76.40	75.41

framework that predicts sentiment polarity and extracts aspect terms and uses multi-head attention to connect the tasks.

We use accuracy and macro-F1 score as performance metrics. Accuracy measures the proportion of correctly predicted samples in the test set, while the macro-F1 score is calculated as the unweighted mean of the metrics for each label.

4.4. Experimental Results and Analysis

The experimental results are shown in Table 1, from which we can observe that our model performs almost the best on three datasets containing both formal and informal sentences. This may be because our model can comprehensively analyze sentences by integrating global semantic information into modeling context compared to methods that focus on modeling relationships between internal words. Compared to syntax-free models such as MGAN and CPA-SA, our GCNet can fully exploit the rich implicit associations between words embedded in the sentence's syntactic structure through Hybrid GAT, thereby mitigating the noise introduced by modeling solely through semantic relationships. Moreover, our model outperforms networks that utilize syntactic structures, such as RGAT, RMN, and AGCN, indicating our superiority: On the one hand, using multi-head attention to extract sentence semantic representations can mitigate the negative impact of syntactic parsing errors in cases of incomplete or informal sentences; on the other hand, explicitly utilizing global semantic information helps better determine the sentiment polarity of aspect terms that are implicitly described by considering the overall sentiment tendency of the sentence.

4.5. Ablation Study

To further explore the roles of different components in GCNet, we conduct ablation experiments. The experimental results are shown in Table 2. Overall, utilizing global semantic features in text modeling and using Hybrid GAT to extract syntactic information contributes to the model's capability, resulting in an enhancement in sentiment classification performance. GCNet outperforms the model that does not explicitly learn and use global semantic features, indicating that the collaborative learning of global semantic features and context modeling can provide a more comprehensive analysis of sentences, thus enhancing the model's robustness. In addition, the model without the prefusion module cannot perform as well as GCNet, which indicates that enabling syntactic features to perceive global features is necessary. It is within our expectation that either removing the syntactic encoding process (i.e., Hybrid GAT) or replacing Hybrid GAT with a common GAT leads to performance degradation. It can be concluded that using both dependency tree-based syntactic information and attention-based semantic information complements can result in a better understanding of sentences. Moreover, unlike the common GAT, which does not distinguish between different dependency relations during computation, Hybrid GAT emphasizes the role of different dependency relations when modeling syntactically adjacent words adjacent, thus avoiding the loss of syntactic information implicit in the edges of the dependency tree.

4.6. Case Study

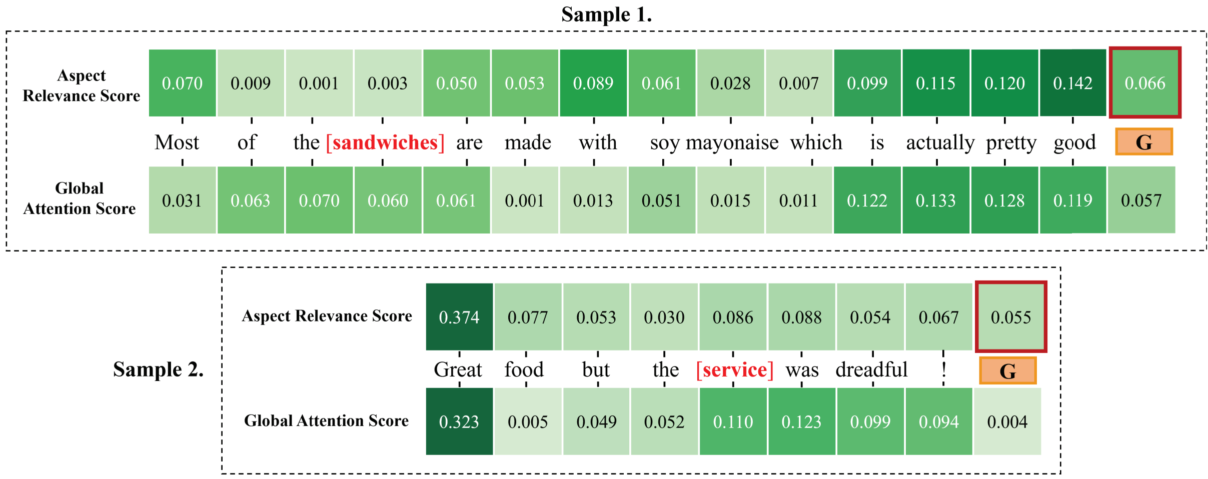
Table 3 presents a few sample cases analyzed using different state-of-the-art models. We select DualGCN (Li et al., 2021) that extracts both syntactic information and semantic information (i.e., features obtained using attention) and SEGCN (Zheng et al., 2023) that enhances GCN with global sentiment knowledge from the dataset.

In S1, there are no adjectives describing the aspect term "usb ports" or explicit sentiment-conveying verbs like "love" or "hate". In such case, the sentiment knowledge from the dataset can not assist in the analysis since there are no sentiment words. Additionally, trying to find the opinion context for the aspect term through either semantic relevance or syntactic structure is challenging. In S2, although there are words like "pretty good" with clear sentiment tendency, these adjectives do not directly describe the aspect term "sandwiches" but rather the intermediary term "soy mayonnaise". In such case, GCNs fail to correctly model the relationship between "sandwiches" and the opinion words. Therefore, in these two samples, both DualGCN and SEGCN incorrectly classify the senti-

Table 3: Case studies comparing our GCNet model with the state-of-the-art baselines.

	Example	DualGCN	SEGCN	GCNet (ours)
Laptop	S1. this laptop has only 2 **[usb ports]**$_{neg}$, and they are both on the same side.	neu✗	neu✗	neg✓
Restaurant	S2. most of the **[sandwiches]**$_{pos}$ are made with soy mayonaise which is actually pretty good.	neu✗	neu✗	pos✓
	S3. this place has the strangest **[menu]**$_{neg}$ and the restaurants tries too hard to make fancy **[food]**$_{neg}$.	pos✗, neg✓	pos✗, pos✗	neg✓, neg✓
	S4. great **[food]**$_{pos}$ but the **[service]**$_{neg}$ was dreadful !	pos✓,neg✓	pos✓,neg✓	pos✓,neg✓
Twitter	S5. tryna get a wawa not a **[lady gaga]**$_{neg}$.	neu✗	neu✗	neg✓

Figure 3: Two examples visualizing the relevance scores for aspect terms and the attention distribution of global features in the Global Feature and Semantic Information Encoding module. "G" in colored box represents global feature.



ment polarity of the aspect term as neutral. Yet, GCNet, by extracting global semantic information from sentences, can utilize the overall sentiment tendency contained within it to assist in determining the sentiment polarity of aspect terms. For example, in the first sample, with word "only", the sentence expresses a negative sentiment, and the second sample conveys a positive sentiment.

S3 reflects that GCNet can capture the negative sentiment towards the restaurant and recognize that "too hard" implies dissatisfaction with the "food" rather than satisfaction. S4 indicates that the model can also correctly classify samples with aspect terms that have relative sentiment polarities like other models, demonstrating our model's robustness. S5 shows that it can also handle informal sentences without strict grammatical structure for sentiment classification.

4.7. Visualization

Figure 3 illustrates the aspect relevance score and the global feature attention score in the Global Feature and Semantic Information Encoding module. In Sample 1, the aspect term "sandwiches" is indirectly described. In such case, semantic analysis is more effective compared to syntactic analysis. For aspect "sandwiches", "actually pretty good" indeed receives more attention. In addition, the global features for this sentence assign a higher weight to "actually pretty good", indicating that global features can capture the overall positive sentiment in this sentence. By involving global features in the process of MSA, the global features can enhance the positive sentiment for the aspect term "sandwiches", contributing to the correct classification.

Sample 2 exists a sentiment reversal, and it can be observed that the semantic analysis wrongly focuses on "Great" for the aspect term "service". Meanwhile, even though the global features have a large weight on "Great", it also pay attention to "service was dreadful," neutralizing the strong positive sentiment of "Great". Including these global features in the attention calculation for the aspect term can mitigate errors, and with the help of syntactic analysis by using Hybrid GAT, GCNet can correctly classify the sentiment polarity of "service" as negative.

5. Conclusion

In this paper, we propose a GCNet that incorporates global semantic features into the modeling process between aspect terms and opinion context, leveraging the overall sentiment tendency of sentences to assist in the analysis for ABSA tasks. GCNet contains a semantics encoding module that collaboratively learns sequential representation and refines global features. Moreover, we employ a hybrid GAT to leverage syntactic knowledge for a more comprehensive sentence analysis, a pre-fusion module that integrates the refined global feature with the syntactic representation is also introduced. Extensive experiments on three detasets have demonstrated the effectiveness of our model. In the future, we will explore ways to enhance global features to make them more aspect-oriented for ABSA tasks and to provide more precise guidance for the sentiment analysis process.

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