You Only Read Once: Constituency-Oriented Relational Graph Convolutional Network for Multi-Aspect Multi-Sentiment Classification

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Abstract

Most of the existing aspect-based sentiment analysis (ABSA) models only predict the sentiment polarity of a single aspect at a time, focusing primarily on enhancing the representation of this single aspect based on the other contexts or aspects. This one-to-one paradigm ignores the fact that multi-aspect, multi-sentiment sentences contain not only distinct specific descriptions for distinct specific aspects, but also shared global context information for multiple aspects. To fully consider these issues, we propose a one-to-many ABSA framework, called You Only Read Once (YORO), that can simultaneously model representations of all aspects based on their specific descriptions and better fuse their relationships using globally shared contextual information in the sentence. Predicting the sentiment polarity of multiple aspects simultaneously is beneficial to improving the efficacy of calculation and prediction. Extensive experiments are conducted on three public datasets (MAMS, Rest14, and Lap14). Experimental results demonstrate the effectiveness of YORO in handling multi-aspect, multi-sentiment scenarios and highlight the promise of one-to-many ABSA in balancing efficiency and accuracy.

Introduction

Aspect-based sentiment analysis (ABSA) is a task of fine-grained sentiment analysis that focuses on inferring the sentiment polarity (positive, negative, or neutral) of multiple aspects in a sentence. For example, consider the sentence "Food was served very promptly but our wait for drinks was surprisingly long." which contains three aspects: "served", "wait", and "drink". The goal of ABSA is to predict the sentiment of "served" as positive, "wait" as negative, and "drink" as neutral. ABSA can be widely used in product reviews, social media, and user feedback texts to mine emotional information in various aspects of data.

Considering the contexts related to aspects are crucial for understanding sentiment cues, how to accurately learn and represent this relevant context information is important for ABSA. Previous works have modeled aspect-related information in multiple ways: 1) Modeling position information using attention mechanisms, where the core idea is that contexts close to the aspect receive greater attention (Wang et al. 2016; Fan, Feng, and Zhao 2018; Huang, Ou, and Carley 2018; Gu et al. 2018; Li, Liu, and Zhou 2018; Phan and Ogunbona 2020). 2) Modeling the dependencies between the words and aspects using graph convolutional networks (GCN (Kipf and Welling 2017)), where the main idea is to aggregate the syntactic and semantic dependencies between words into aspects, so as to obtain semantically and syntactically related aspect representations (Liang et al. 2020; Li et al. 2021; Zhang, Zhou, and Wang 2022; Tian, Chen, and Song 2021; Bai, Liu, and Zhang 2021). For example, Tian, Chen, and Song (2021) proposed a type-aware GCN to encode different types of dependency relations; Bai, Liu, and Zhang (2021) incorporated dependency tags to graph attention networks to better learn the correlation between words; Liang et al. (2020) proposed two independent GCNs to model the aspect-focused and inter-aspect features. These models have proven that relational information is significant for determining the contribution of different words. 3) Aspect-oriented tree construction. In addition to using existing dependency trees to model relational information, some researchers transform dependency trees into aspect-oriented tree structures to enhance GCN structure and better capture aspect-related information (Wang et al. 2020; Zhou et al. 2021; Chen et al. 2022). For example, Wang et al. (2020) reshaped and pruned a dependency parsing tree to construct an aspect-oriented tree to capture aspect-related information; Chen et al. (2022) used reinforcement learning and regularization to induce discrete opinion trees to shorten the distance of corresponding opinion words.

Although the above works achieved remarkable results, there is still a limitation, which is that they primarily focus on enhancing the representation of a single specific target aspect based on other contexts or aspects and only predict the sentiment polarity of the target aspect at a time. A natural question arises: can we encode all aspects simultaneously with their local specific contexts, fuse their relationships with the global shared contexts, and predict the sentiments of all aspects simultaneously?

To answer this question, we propose a one-to-many ABSA framework named you only read once (YORO), which takes only one sentence as input and outputs the sentiment of all aspects, simultaneously. We treat the ABSA task as a token-level classification task and use the representations of all aspect words for the final classification.

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Jointly predicting the sentiment polarity of multiple aspects requires the model to accurately capture the corresponding important information for each aspect. Therefore, we propose a constituency-oriented relational graph convolutional network (CorrGCN) to model multi-source relationships. Unlike previous work that uses dependency trees, we employ constituency parsing trees to construct our graph. The constituency parsing tree recursively divides sentences into several phrases according to grammatical rules, and its hierarchical structure can reflect aspect-context and aspect-aspect relationships. Based on its hierarchy, we propose four task-related relationship types, namely aspect-specific, inter-aspect, globally-shared, and opinion word. Specifically, the aspect-specific relationship is used to locate the corresponding description for each aspect. This relationship aims to capture the local contexts that are highly relevant to the specific aspect. The globally-shared relation provides common contextual information for each aspect, avoiding the loss of global information. The sentiment of one aspect may depend on its neighbor aspects, thus, the purpose of the inter-aspect relationship is to use the interaction information of other aspects to assist prediction. In addition, opinion words are critical sentiment cues, explicitly expressing likes and dislikes about aspects. We introduce the opinion word relation to enhance the attention to opinion words. Furthermore, our YORO also introduces an opinion sentiment classification task to help the model learn the sentiment information of opinion words, and use supervised contrastive learning to better distinguish the relationship between sentiment polarity labels. The main contributions of this paper can be summarized as follows:

(1)We propose a one-to-many framework called you only read once (YORO), which provides a new solution for ABSA, especially fit in the case of multi-aspect multi-sentiment.

(2)We design a constituency-oriented relational graph convolutional network (CorrGCN) to learn local, global, interaction, and opinion information.

(3)We conduct comprehensive experiments on three public datasets (MAMS, Rest14, and Lap14), the results demonstrate the effectiveness of our model and the promise of one-to-many ABSA.

Related Work

The core of ABSA is to capture useful aspect-related contexts and obtain their sentiment cues. To this end, the existing methods mainly focus on modeling the specific aspect and inter-aspect relationship.

Aspect-specific Modeling. Aspect-specific modeling methods focus on the individual aspect, and researchers have proposed various techniques. Early studies have employed different attention mechanisms to capture aspect and sentence correlations (Wang et al. 2016; Tang, Qin, and Liu 2016; Ma et al. 2017; Chen et al. 2017; Fan, Feng, and Zhao 2018; Huang, Ou, and Carley 2018). Subsequently, position information was introduced into ABSA. Aspect-based relative distance modeling makes these models pay more attention to the context around the aspect (Gu et al. 2018; Li, Liu, and Zhou 2018; Huang et al. 2022). Zeng et al. (2019) proposed a local context focus (LCF) mechanism based on the relative distance. Phan and Ogunbona (2020) proposed a variant of LCF that uses syntactic relative distance over the dependency tree. With the rise of pre-trained language models (PLMs) and graph neural networks (GNNs), more and more studies adopt PLMs (such as BERT (Devlin et al. 2019), RoBERTa (Liu et al. 2019)) to encode semantic representations and employ GNNs (such as GCN (Kipf and Welling 2017), GAT (Veličković et al. 2018)) to fuse syntax features (Zhou et al. 2021; Li et al. 2021; Tang et al. 2022; Zhang, Zhou, and Wang 2022; Liu et al. 2022; Wang et al. 2023; Zheng, Li, and Nie 2023).

Inter-aspect Modeling. Inter-aspect modeling methods aim to explore the interactions and dependencies among multiple aspects within a sentence. Early studies have proposed a two-stage strategy to classify aspects simultaneously (Majumder et al. 2018; Hazarika et al. 2018; Ma et al. 2019; Zhou et al. 2020; Zhang et al. 2022; Li et al. 2022). Recent work utilized GCNs to model different relational information. For example, Zhao, Hou, and Wu (2020) regarded aspects as nodes in a graph and proposed two relational connection strategies. Wang et al. (2020), Tian, Chen, and Song (2021), and Bai, Liu, and Zhang (2021) focus on modeling the dependencies between words, considering the fusion of edge labels. Zeng et al. (2022) and Li, Li, and Xiao (2023) introduced auxiliary tasks to jointly learn relational information and help the model capture multi-aspect potential associations.

Although these models achieved outstanding performance, predicting one aspect at a time is less efficient in real-world scenarios. In addition, previous models that predict simultaneously require multiple inputs, and their performance is inferior to that of the former. Unlike previous work, we propose a one-to-many ABSA framework that requires only one input to predict the sentiment polarity of each aspect simultaneously. We propose a constituency-oriented relational graph convolutional network (CorrGCN) to model local, global, interaction, and opinion information in order to fully exploit relational information.

Approach

As shown in Figure 1, the overall architecture of our YORO framework consists of the encoder module, the constituency-oriented graph module, and the output module.

Task Definition

Given a n-word sentence $\boldsymbol{S} = \{w_1, w_2, ...w_n\}$ with m aspects $\boldsymbol{A} = \{a_1^1, a_1^2, a_2^2, ..., a_1^m, ..., a_k^m\}$, in which each aspect has k-word, a_k^m denotes the k-th word of the m-th aspect. The goal of our model is to predict the sentiment polarity of all aspects $\boldsymbol{Y} = \{y_1, y_2, ...y_m\}$ of a sentence at once.

Encoder Module

Similar to previous work, we use BERT (Devlin et al. 2019) as the basic encoder. Previous ABSA models mainly used the sequence "[CLS] + sentence + [SEP] + aspect + [SEP]" as input, where "aspect" is used to indicate the specific aspect and distinguish different aspects in the same sentence.

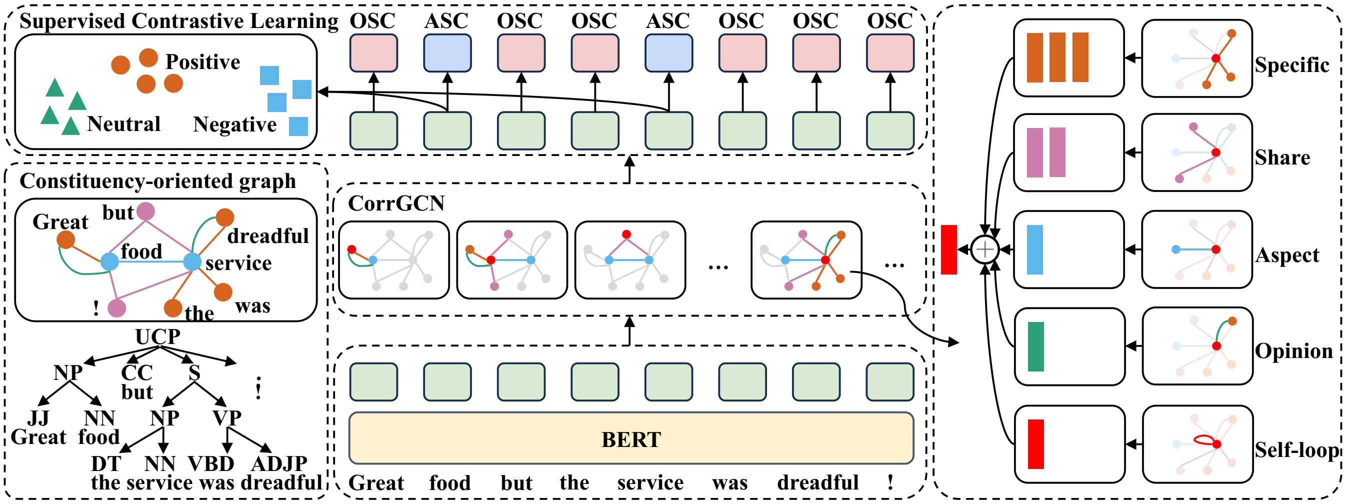

Figure 1: The overall architecture of our proposed YORO. ASC and OSC represent aspect sentiment classification and opinion sentiment classification.

However, our input sequence only needs the sentence since our model can predict all aspects at once. As shown in Equation 1, we obtain the hidden states of the last layer of BERT to encode the sentence.

$$\boldsymbol{H} = \text{BERT}([\text{CLS}] + \text{sentence} + [\text{SEP}]) \tag{1}$$

Constituency-oriented Graph Module

Graph neural networks can aggregate information of various neighbors, which is suitable for aspects to learn more contextual features. Previous work mainly constructed graphs based on dependency parsing trees containing the dependencies between words. In fact, the words directly connected to the aspect in the dependency tree are limited, and much important information needs to be captured through multi-hop aggregation. In addition, dependency tags reflect the relationship of words in syntactic rules, and cannot capture task-related relationships, such as aspect-specific context and inter-aspect relationships.

Considering the above issue, we propose a constituency-oriented graph that uses constituency parsing trees to achieve the aim of modeling fine-grained task-related relationships. Constituency parsing trees split sentences into phrases and words, with the root node representing the entire sentence, internal nodes representing phrases, and leaf nodes representing individual words. This “sentence-phrase-word” hierarchy facilitates understanding the corresponding descriptions of aspects and the connections between aspects. As shown in Figure 2, we take the sentence “Food was served very promptly but our wait for drinks was surprisingly long” as an example to illustrate the details of the construction of our graph. The aspects in this example are “served”, “wait”, and “drink”, and their corresponding sentiment polarities are positive, negative, and neutral. The construction of our graph contains four steps, representing four useful task-related relationships.

Aspect-specific Some aspects have detailed descriptions that indicate their sentiment polarity. For example, the phrase “Food was served very promptly” is the description of the aspect “served”, expressing positive sentiment explicitly. Thus, we first extract the aspect-specific phrase in order to obtain as much local information as possible. We consider that an aspect-specific phrase must contain the corresponding aspect, and no other aspects will appear. To this end, we adopt a top-down strategy to traverse the constituency parsing tree and stop until we obtain aspect-specific phrases for all aspects. Specifically, we regard the first word of the aspect as the root node (an aspect may have multiple words) and the rest words in the aspect-specific phrase are the children nodes of the aspect. In this way, we obtain three subtrees of aspects, aiming to learn their respective local information.

Inter-aspect In addition to relying on aspect-specific context, inferring the sentiment of an aspect may require leveraging information from other aspects. For example, there is a latent comparison between the aspect “served” and “wait”. According to this comparative relationship, we can infer the sentiment of “wait” is negative. Therefore, the second step is to establish inter-aspect connections, thus mining potential associations between aspects. As shown in Figure 2, we interconnect the first word of the aspect, namely “served”, “wait”, and “drink”, to learn the interactions of aspects.

Globally-shared After the operation of aspect-specific and inter-aspect, there are still some words that are not linked. These contexts also contain useful information and may be related to multiple aspects. For example, the phrase “was surprisingly long” both related to the aspect “wait” and “drink”. And “but” reflects the reversal of the sentiments of “served” and “wait”. Practically, we connect the words that have not been linked in the first two steps with the first word of each aspect. We provide these words as shared information to aspects, avoiding the loss of global semantics.

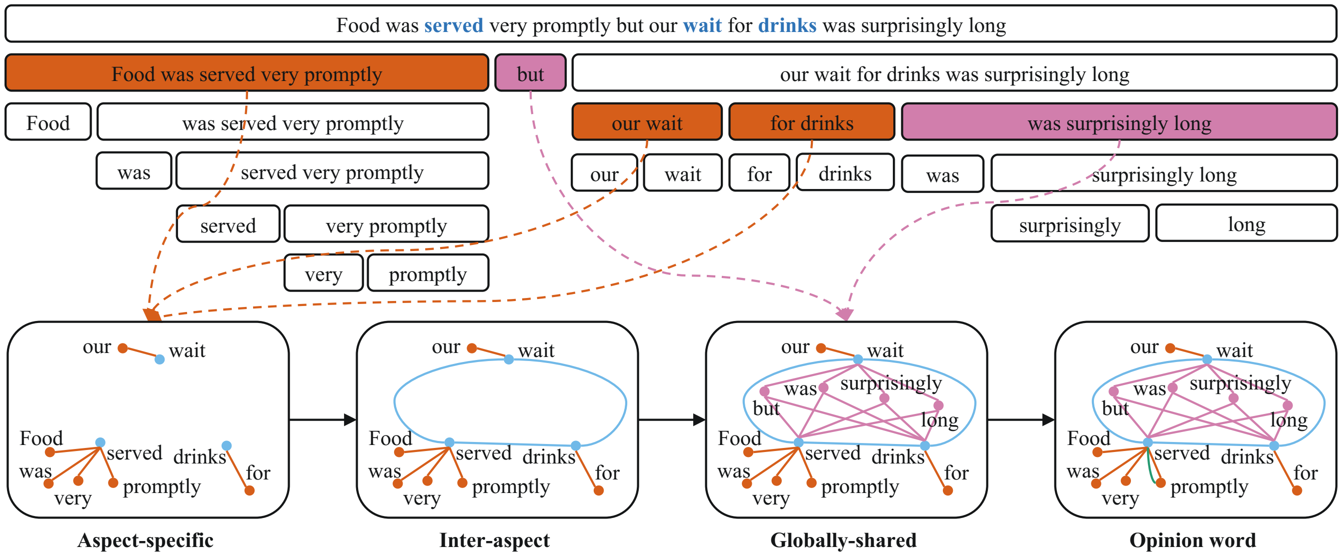

Figure 2: An example of constructing a constituency-oriented graph for CorrGCN. Our graph has four types of relations, including aspect-specific (orange), inter-aspect (blue), globally-shared (purple), and opinion word (green), to learn specific, interaction, shared, and opinion information.

Opinion word The opinion lexicon is an important external resource for sentiment analysis, as it annotates the sentiment polarity of various common opinion words. And opinion words are key cues for guiding the model to make correct predictions. We use Bing Liu's opinion lexicon (Hu and Liu 2004) to look up the sentiment polarity of non-aspect words and find that "promptly" is a positive opinion word. As shown in Figure 2, we add an opinion relationship between "served" and "promptly". It is worth noting that we do not consider whether aspects are opinion words because if aspects belong to the opinion word, they will establish opinion relations with all their neighbors, leading to the introduction of a useless connection. In addition, we do not construct different relationships for opinion words with different sentiment polarities, such as positive, negative, and neutral, because we hope that the model just pays more attention to these opinion words, rather than predicting directly based on the sentiment polarity of opinion words.

Since some sentences may have only one aspect, if we construct the graph structure as above, we will obtain a graph in which all words are connected to the aspect as the aspect-specific relation. This fully connected graph does not contain inter-aspect and globally-shared relations, which is not conducive to the model to better learn the context. To solve this problem, we propose the idea of "pseudo-aspects" to obtain multiple aspects. Specifically, we first select the constituent containing the aspect from the first level of the constituency tree as the aspect-specific phrase. Then, according to the constituent labels of the aspect-specific phrase, the rest constituents with the same label are treated as aspect-specific phrases for pseudo aspects. It should be noted that if a phrase is considered as an aspect-specific phrase, we will skip traverse its subtree to ensure that each aspect-specific phrase is independent. We take the first word of these phrases as pseudo aspects, which are used to construct aspect-specific relations within their aspect-specific phrases, as well as inter-aspect relations between the real aspect and pseudo-aspects. Besides, the rest words and opinion words are connected to real and pseudo aspects as mentioned above. In this way, we can generate a graph structure for a single aspect sentence.

Relational Graph Convolutional Network

According to our constituency-oriented graph, the adjacency matrix can be written as Equation 2:

$$D_{ij} = \begin{cases} 1, & \text{if } (w_i, w_j) \in \boldsymbol{Rel} \\ 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where w_i and w_j denotes i-th and j-th word in sentence. $\boldsymbol{Rel} \in \{\mathbf{AS}, \mathbf{IA}, \mathbf{GS}, \mathbf{OW}\}$ denotes four types of relations: Aspect-specific, Inter-aspect, Globally-shared, Opinion word. The diagonal elements D_{ii} of the adjacency matrix $\boldsymbol{D} \in R^{n \times n}$ are set to one for self-loop.

Previous studies demonstrate that position information is a useful feature for aspects to capture important context. To introduce hierarchical position information and better model the importance of words, we use syntactic distance as position information based on the depth of the constituency parsing tree. To fully understand how we calculate the syntactic distance SD, we take the word "served" as an example in Figure 2. Since each word in the tree is a leaf node, it does not belong to a constituent phrase. Therefore, we start from the parent node of the leaf node and end at the root node of the whole tree. Since the word "promptly" can directly arrive at the word "served" in the phrase "served very promptly", $SD(\text{served}, \text{promptly})$ is 0. And the word "was" in the phrase "was served very promptly" requires one hop to reach the word "served", SD(served, was)=1.

As shown in Equation 3 and 4, we incorporate syntactic distance into the original adjacency matrix $\boldsymbol{D}$ to obtain an updated adjacency matrix $\boldsymbol{A}$.

$$A_{ij} = \begin{cases} 1 + p_{ij}, & \text{if } (w_i, w_j) \in \boldsymbol{Rel} \\ 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$p_{ij} = 1 - \frac{SD(w_i, w_j)}{\max_{k=0}^{n} SD(w_i, w_k) + 1} \tag{4}$$

where p_{ij} denotes the position weight. $SD(w_i, w_j)$ denotes the syntactic distance between i-th word and j-th word. $\max_{k=0}^{n} SD(w_i, w_k)$ denotes the maximum hops in the path of the i-th word. Relational graph convolutional network (Schlichtkrull et al. 2018) is suitable for modeling relational data. To better model our proposed four relations, we propose a constituency-oriented relational graph convolutional network (CorrGCN) to help aspects aggregate neighbors with different relations. We stack multi-layer CorrGCN to enhance the model performance. The operation of each layer of CorrGCN is shown in Equation 5:

$$\boldsymbol{h_i^{(l+1)}} = \sigma\left(\sum_{r \in R} \sum_{j \in N_i^r} \boldsymbol{\hat{A} W_r^{(l)} h_j^{(l)}} + \boldsymbol{W_s^{(l)} h_i^{(l)}}\right) \tag{5}$$

where N_i^r denotes all neighbor nodes of node i under relation $r \in \boldsymbol{R}$. $\boldsymbol{\hat{A}} = \hat{D}^{-\frac{1}{2}} A \hat{D}^{-\frac{1}{2}}$ is the normalized adjacency matrix and $\hat{D} = \sum_j A_{ij}$ is the degree of i-th row of adjacency matrix A. $\boldsymbol{W_r^{(l)}}$ is a relation-specific trainable weight matrix and $\boldsymbol{W_s^{(l)}}$ is used to learn the self-loop relation. σ is rectified linear unit (ReLU) activation function.

Output Layer Module

To improve the sensitivity of the model to opinion words (Chen and Li 2020), we jointly use multi-task learning for aspect sentiment classification and opinion sentiment classification. We perform non-aspect zero-masking and aspect zero-masking on the output of CorrGCN to obtain aspect and context representations H_a and H_c in Equation 6 and 7. We then feed the masked hidden state into two independent fully connected layers for aspect and opinion sentiment classification in Equation 8 and 9. We argue that predicting the sentiment of aspects is based on context, and opinion is based on the word itself. Therefore, we use two classifiers to predict the sentiment of aspect and context respectively.

$$\boldsymbol{H_a} = [\boldsymbol{h_0^a}, \boldsymbol{h_1^a}, \boldsymbol{h_2^a}, ..., \boldsymbol{h_m^a}] \tag{6}$$
$$\boldsymbol{H_c} = [\boldsymbol{h_0^w}, \boldsymbol{h_1^w}, \boldsymbol{h_2^w}, ..., \boldsymbol{h_o^w}] \tag{7}$$
$$\boldsymbol{y_a} = \text{softmax}(\boldsymbol{W_a H_a} + \boldsymbol{b_a}) \tag{8}$$
$$\boldsymbol{y_c} = \text{softmax}(\boldsymbol{W_c H_c} + \boldsymbol{b_c}) \tag{9}$$

where $\boldsymbol{h_m^a}$ denotes the m-th aspect. For the convenience of training and testing, we use the first word of each aspect to represent the whole aspect for classification. $\boldsymbol{h_o^w}$ denotes the o-th context word in the sentence. It is worth mentioning that $\boldsymbol{y_a} \in \boldsymbol{R}^{m \times d}$ and $\boldsymbol{y_c} \in \boldsymbol{R}^{n \times d}$ denote the prediction of aspects and context words, d is the number of labels to be classified.

Loss Function

For the aspect sentiment classification task and opinion sentiment classification task, we use two cross entropy as loss functions in Equation 10 and 11.

$$L_{asp} = -\frac{1}{N} \sum_{i=1}^{N} \frac{1}{M} \sum_{j=1}^{M} \sum_{k=1}^{C} \boldsymbol{y_{ij,k}^a} \log(\boldsymbol{\hat{y}_{ij,k}^a}) \tag{10}$$

$$L_{opi} = -\frac{1}{N} \sum_{i=1}^{N} \frac{1}{M'} \sum_{j=1}^{M'} \sum_{k=1}^{C} \boldsymbol{y_{ij,k}^c} \log(\boldsymbol{\hat{y}_{ij,k}^c}) \tag{11}$$

where N and C denote the number of training samples and sentiment classes. i and k is the index of the sentence and sentiment class, respectively. M and M' denote the number of aspect and non-aspect words in one sentence. j is the index of hidden state of $\boldsymbol{y_a}$ or $\boldsymbol{y_c}$. $\boldsymbol{y_{ij,k}^a}$ and $\boldsymbol{y_{ij,k}^c}$ are predicted labels and $\boldsymbol{\hat{y}_{ij,k}^a}$ and $\boldsymbol{\hat{y}_{ij,k}^c}$ are gold labels.

Besides, to further enhance the inter-aspect modeling and distinguish inter-class relationships, we use supervised contrastive learning to assist model training. As shown in Equation 12, we regard aspect representations with the same sentiment polarity in the mini-batch as positive examples and the different ones as negative examples.

$$L_{sup} = -\sum_{i \in B} \frac{1}{C(i)} \sum_{y_i = y_c, c \neq i} \frac{\exp(\boldsymbol{z_i} \cdot \boldsymbol{z_c}/\tau)}{\sum_{b \in B, b \neq i} \exp(\boldsymbol{z_i} \cdot \boldsymbol{z_b}/\tau)} \tag{12}$$

where $i \in B$ denotes the index of an aspect sample in the entire mini-batch B. $C(i) = |\{c|y_c = y_i, c \neq i\}|$ is the number of positive samples of the i aspect. z is aspect representations from Equation 6. τ is the temperature hyper-parameter.

The total loss of our model is defined as:

$$L = L_{asp} + L_{opi} + \alpha L_{sup} + \lambda ||\boldsymbol{\Theta}||^2 \tag{13}$$

where α is a hyper-parameter. λ is the coefficient of L2 regularization and θ are all trainable parameters.

Experiments and Discussion

Datasets

We use three benchmark datasets to evaluate our proposed model, including Multi-Aspect Multi-Sentiment (Jiang et al. 2019), SemEval 2014 Restaurants (Pontiki et al. 2014), and SemEval 2014 Laptops (Pontiki et al. 2014)). All datasets have only three sentiment polarities, which are positive, neutral, and negative. For Multi-Aspect Multi-Sentiment (MAMS), all sentences contain multiple aspects with different sentiment polarities. For SemEval 2014 Restaurants (Rest14) and SemEval 2014 Laptops (Lap14), sentences have one or multiple aspects, and multiple aspects may have the same or different sentiment polarities. Therefore, MAMS is a more challenging dataset.

Model	MAMS		Rest14		Lap14	
	Acc(%)	F1(%)	Acc(%)	F1(%)	Acc(%)	F1(%)
IARM (Majumder et al. 2018)	74.48*	73.66*	80.00	-	73.80	-
MIAD (Hazarika et al. 2018)	-	-	79.00	-	72.50	-
StageI+StageII (Ma et al. 2019)	-	-	80.10	-	73.10	-
CDT (Sun et al. 2019)	80.70†	79.79†	82.30	74.02	77.19	72.99
Joint+PRET (Zhou et al. 2020)	-	-	81.96	71.80	73.04	69.16
RepWalk (Zheng et al. 2020)	-	-	83.80	76.90	78.20	74.30
BERT-SPC (Song et al. 2019)	82.82†	81.90†	84.46	76.98	78.99	75.03
CapsNet♯ (Jiang et al. 2019)	83.46	82.89	84.91	76.59	77.12	71.84
SDGCN (Zhao, Hou, and Wu 2020)	77.10‡	75.99‡	83.57	76.47	81.35	78.34
InterGCN* (Liang et al. 2020)	82.49	81.95	85.45	77.64	78.06	73.83
R-GAT(Wang et al. 2020)	83.16*	82.42*	86.60	81.35	78.21	74.07
T-GCN (Tian, Chen, and Song 2021)	83.38	82.77	86.16	79.95	80.88	77.03
RGAT (Bai, Liu, and Zhang 2021)	84.52	83.74	86.68	80.92	80.94	78.20
RMN (Zeng et al. 2022)	79.97	78.79	84.56	79.05	77.95	70.83
dotGCN (Chen et al. 2022)	84.95	84.44	86.16	80.49	81.03	78.10
CHGMAN (Niu et al. 2022)	85.05	84.29	86.88	81.62	81.52	77.68
APSCL (Li, Li, and Xiao 2023)	84.06	83.50	86.86	81.28	81.02	**78.47**
YORO	**86.08**	**85.51**	**87.14**	**81.83**	**81.82**	78.32

Table 1: The performance of different models on MAMS, Rest14, and Lap14. Acc and F1 indicate the accuracy and macro-average F1 score, respectively. The results with ∗, † ,and ‡ are retrieved from (Niu et al. 2022), (Bai, Liu, and Zhang 2021), and (Zeng et al. 2022). ♯ denotes our implementation according to the released code of the published paper. '-' means not reported and no implementation available. The best results are in bold.

Implementation Details

For the encoder module, we employ the "bert-base-uncased" version of BERT with 110 million parameters. For the graph module, we use Berkeley Neural Parser (Kitaev, Cao, and Klein 2019) to obtain the constituency parsing trees (https://parser.kitaev.io/). We adopt two-layer CorrGCN and the dimension of hidden states is 768. The supervised contrastive loss uses a temperature τ of 0.07 and the hyper-parameter of α is weighted to 0.5. The coefficient λ of L2 regularization is 0.0001. We fine-tune the entire model using the Adam optimizer (Kingma and Ba 2015) with a learning rate of 0.00002 and a batch size of 16. We train the model for 20 epochs, implementing the early stopping strategy with a patience of 5. Additionally, we applied a dropout strategy with a ratio of 0.3. Following previous work, we adopt accuracy and macro-average F1 as metrics to evaluate the model. Our code is available at https://github.com/gdufsnlp/YORO.

Baselines

In this paper, we compare with some baselines as follows. We use IARM (Majumder et al. 2018), MIAD (Hazarika et al. 2018), StageI+StageII (Ma et al. 2019), CDT (Sun et al. 2019) as baselines for their modeling aspect-related information using LSTMs. We also use Joint+PRET (Zhou et al. 2020), RepWalk (Zheng et al. 2020), BERT-SPC (Song et al. 2019), CapsNet (Jiang et al. 2019), SDGCN (Zhao, Hou, and Wu 2020), InterGCN (Liang et al. 2020), R-GAT (Wang et al. 2020), T-GCN (Tian, Chen, and Song 2021), RGAT (Bai, Liu, and Zhang 2021), RMN (Zeng et al. 2022), dotGCN (Chen et al. 2022), CHGMAN (Niu et al. 2022) and APSCL (Li, Li, and Xiao 2023) as baselines, as they focus on inter-aspect relations or aspect-oriented tree structure using GCNs and BERT.

Main Results

We compare our proposed model (YORO) with the baselines mentioned in Table 1. YORO achieves the best performance in MAMS, Rest14, and the accuracy of Lap14, the F1 score of Lap14 is also close to SDGCN and APSCL. In particular, our model performs well on MAMS, with 1.03% and 2.62% higher accuracy and 1.22% and 2.62% higher F1 scores than CHGMAN and CapsNet. This outstanding improvement shows that YORO is suitable for multi-aspect multi-sentiment complex situations.

For Rest14, the accuracy of YORO is 0.26% and 0.28% higher than CHGMAN and APSCL, and the F1 score is 0.21% and 0.55% higher than that of CHGMAN and APSCL. These results also prove the effectiveness of our proposed method. For Lap14, despite achieving a good performance of 81.82 in accuracy, the F1 score is slightly lower than SDGCN and APSCL by 0.02% and 0.15%. We argue that "pseudo aspect" is an effective idea for a single aspect sentence, but it still has room for improvement. We intend to leave it for future work because our paper focuses more on how to improve multi-aspect relationship modeling.

Ablation Study

The ablation results in Table 2 provide valuable insights into the contribution of different components in YORO. We observe the following trends: 1) Removing the CorrGCN module (w/o CorrGCN) leads to an explicit drop in performance on all datasets. This shows that the constituency-oriented relational graph convolutional network is crucial in capturing

Model	MAMS		Rest14		Lap14	
	Acc(%)	F1(%)	Acc(%)	F1(%)	Acc(%)	F1(%)
YORO	**86.08**	**85.51**	**87.14**	**81.83**	**81.82**	**78.32**
w/o CorrGCN	84.06	83.57	85.54	79.05	79.00	74.74
w/o Relational	82.49	82.09	84.82	77.40	77.59	73.28
w/o L_{opi}&L_{sup}	85.18	84.67	86.70	81.51	79.94	76.10
w/o L_{opi}	85.10	84.63	85.71	79.14	79.47	75.34
w/o L_{sup}	84.43	83.74	85.62	79.99	79.78	75.08
w/o OW	85.63	85.05	86.88	81.39	81.19	77.97
w/o pseudo	-	-	86.34	79.07	80.72	77.85
single	-	-	84.56	77.89	80.69	74.58
multi	-	-	88.02	83.19	82.59	79.30
benepar2	85.63	85.12	86.52	80.89	79.78	76.70

Table 2: The performance of ablation models on MAMS, Rest14, and Lap14. w/o CorrGCN: remove CorrGCN; w/o Relational: do not distinguish edge relationships; w/o L_{opi}&L_{sup}: remove both opinion sentiment classification and supervised contrastive learning; w/o L_{opi} and w/oL_{sup} are removed them separately; w/o OW: removes the relationship of the opinion word in CorrGCN; w/o pseudo: do not use the "pseudo aspects" strategy; single: only conduct experiment on single-aspect instances; multi: only conduct experiment on multi-aspect instances; benepar2: use another parser.

No.	Sentence	YORO w/o Relational	YORO
1	It's sad that everything about this place was great (even the **service** and **decor**) except for the **steak**.	(Pos$_{\checkmark}$, Pos$_{\checkmark}$, Pos$_{\times}$)	(Pos$_{\checkmark}$, Pos$_{\checkmark}$, Neg$_{\checkmark}$)
2	nice place, good **service** but the price is a little bit more expensive when compare with the area, **location** and small **dishes**.	(Neu$_{\times}$, Neu$_{\checkmark}$, Neu$_{\times}$)	(Pos$_{\checkmark}$, Neu$_{\checkmark}$, Neg$_{\checkmark}$)

Table 3: Case studies of our YORO model and YORO w/o Relational.

aspect-specific context and inter-aspect relations, which significantly enhances the overall performance of YORO. 2) When replacing CorrGCN with a vanilla GCN (w/o Relational), the performance degrades rapidly. This demonstrates that relational information is a vital feature for CorrGCN to distinguish different neighbors and learn correlations between neighbors. 3) The importance of both the opinion sentiment classification task and supervised contrastive learning is evident from the results of w/o L_{opi}&L_{sup}. Although removing both auxiliary tasks results in a notable decrease, its performance is still higher than w/o CorrGCN. This proves that the effectiveness of our model does not completely depend on the auxiliary tasks. 4) Individually removing the opinion sentiment classification task (w/o L_{opi}), opinion word relations (w/o OW), or supervised contrastive learning (w/o L_{sup}) also leads to reduced performance, although the impact is not as significant as when both tasks are removed. This indicates that ABSA models can take into account the role of the opinion lexicon and the internal connections of sentiment labels. 5) YORO performs stably in different scenarios (single and multi) and the "pseudo aspects" strategy is suitable for dealing with single aspect instances (w/o pseudo). 6) We use another parser (benepar2) for comparative experiments, where the performance of the parser is Berkeley (YORO used) $>$ benepar2. As the performance of the parser improves, our model obtains better results.

Case Study

To better understand the behavior of the model, we use two examples to compare YORO and YORO w/o Relational models in Table 3. For the first example, YORO makes a correct prediction of all aspects. YORO w/o Relational correctly predicts "service" and "decor" as positive, but incorrectly predicts "steak" as positive. We believe that the misprediction of "steak" is due to ignoring the important global information of "sad". In addition, "except for" indicates that the sentiment of "service" and "decor" are different from "steak", while YORO w/o Relational does not capture the inter-aspect relationship. For the second example, YORO successfully predicts three aspects with different sentiment polarities. However, YORO w/o Relational predicts them all to be neutral. We argue that it is difficult for the model to identify the most relevant context for each aspect after removing relational information.

Conclusions

In this paper, we propose a one-to-many ABSA framework named you only read once (YORO) to predict the sentiment polarities of all aspects in a sentence at once. In the framework, a constituency-oriented relational graph convolutional network (CorrGCN) is proposed to capture multiple relations about all aspects in a sentence. We also introduce two auxiliary tasks to help the model learn sentiment knowledge and the internal relationship of sentiment labels. We conduct extensive experiments on three public datasets and achieve excellent results in the MAMS dataset, demonstrating the effectiveness of YORO in dealing with multi-aspect multi-sentiment complex situations. In future work, we intend to focus on aspect interactions between those sentences with only one aspect to further improve the efficiency of YORO.

Acknowledgments

This work is supported by the National Natural Science Foundation of China [grant number: 61976062].

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