C^{3}LPGCN:Integrating Contrastive Learning and Cooperative Learning with Prompt into Graph Convolutional Network for Aspect-based Sentiment Analysis

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Abstract

Aspect-based Sentiment Analysis (ABSA) is a fine-grained task. Recently, using graph convolutional networks (GCNs) to model syntactic information has become a popular topic. In addition, a growing consensus exists to enhance sentence representation using contrastive learning. However, incorrect modelling of syntactic information may introduce additional noise. Meanwhile, as a method that implicitly incorporates label information as prior knowledge, contrastive learning does not make sufficient use of this prior. To alleviate these problems, we propose C^{3}LPGCN, which integrates Contrastive Learning and Cooperative Learning with Prompt into GCN. To tackle the first issue, we propose mask-aware aspect information filter, which combines prompt-tuned information with aspect information to filter the syntactic information. We propose prompt-based contrastive learning and cooperative learning to utilise the label information further. We construct comparison samples containing labels so that the model pays more attention to aspect- and sentiment-related information during feature learning. Cooperative learning further extracts label information by aligning input samples' representation and output distribution with true label samples. Extensive experiments on three datasets demonstrate that our method significantly improves the model's performance compared to traditional contrastive learning methods. Moreover, our C^{3}LPGCN outperforms state-of-the-art methods. Our source code and final models are publicly available at github[1].

1 Introduction

Aspect-based Sentiment Analysis (ABSA) (Zhang et al., 2021, 2022a) aims to predict the sentiment polarity of a specific aspect in a sentence. Figure 1 shows a restaurant review in which the sentiment expression of "Indian" is "authentic" and the sentiment expression of "prices" is "amazing". Therefore, we discriminate the sentiment polarity of these two aspects as positive.

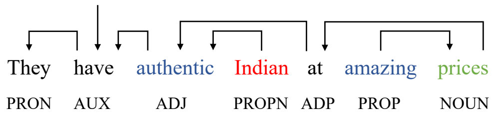


Figure 1: Example of the ABSA task.

Prior studies employed long short-term memory(LSTM) (Tang et al., 2015; Wang et al., 2016) and attention mechanism (Song et al., 2019; Ma et al., 2017) to encode long-distance dependencies, and these studies achieved remarkable results. Recently, with the rise of graph neural networks (Tang et al., 2020; Wang et al., 2020; Li et al., 2021), studies have been conducted to achieve syntactic-based aggregation of word information via graph convolutional network(GCN) (Tian et al., 2021; Sun et al., 2019) to enhance the performance of ABSA further. Although GCN has achieved good results, some situations may lead to errors in modelling syntactic information: there is no obvious syntactic relationship between aspect and sentiment in a sentence, the sentence does not have a complete syntactic structure, the syntactic dependency parser is wrong, and so on.

In addition, to enable better modelling of aspect and sentiment, many studies employ contrastive learning (Liang et al., 2021; Wang et al., 2022; Liu et al., 2022) to enhance sentence features. Supervised methods use sentiment polarity for sample construction, while unsupervised methods construct samples through data augmentation. These methods implicitly introduce label information as a priori. However, such methods do not make sufficient use of this label information.

To address the above problems, we propose a novel C^{3}LPGCN, integrating Contrastive Learning and Cooperative Learning with Prompt into Graph Convolutional Network. On the one hand, to

[1] https://anonymous.4open.science/r/C3LPGCN-2E3B/readme

mitigate the errors of GCN in modelling syntactic information, we propose mask-aware aspect information filter(MAF) based on prompt tuning, which combines the mask representation and aspect information to filter syntactic features further. Prompt tuning (Lester et al., 2021; Wang et al., 2023) is a method to convert downstream tasks into mask prediction tasks by constructing an auxiliary template. Due to the properties of the pre-trained language model(PLM) (Devlin et al., 2018; Liu et al., 2019), the representation obtained through prompt tuning contains PLM's understanding of ABSA and the reasons for making predictions, i.e., the sentiment expression. By filtering syntactic information by combining this representation with aspect information, the model can alleviate the noise generated by modelling syntactic information.

On the other hand, in response to the underutilization of label information as a priori, we propose prompt-based contrastive learning and cooperative learning. Specifically, we construct samples containing sentiment labels and perform contrastive learning, thus allowing the model to focus more on aspect- and sentiment-related information during feature learning. While in cooperative learning, we make the representations of input samples and true label samples feature consistent by calculating their KL divergence; at the same time, we pass them through the same network for sentiment analysis and use the output distribution of the true label samples as the label of the input samples. In this way, the prior knowledge contained in the label samples is further learned.

Our contributions can be summarized as follows:

- We propose C^{3}LPGCN mitigate the noise generated when modelling syntactic information by utilizing PLM's prediction. Meanwhile, we propose using label information as an explicit priori to learn aspect- and sentiment-related information adequately.
- We propose MAF, which realizes the filtering of syntactic information by combining aspect information with prompt tuning information. Meanwhile, we propose prompt-based contrastive and cooperative learning to learn further the prior knowledge contained in label samples.
- Extensive experiments on three datasets show that our method can be combined with existing contrastive learning methods to perform better, and our C^{3}LPGCN method outperforms state-of-the-art methods.

2 Related Work

2.1 Aspect-based Sentiment Analysis

With the development of deep learning, ABSA has achieved good performance. Several studies utilized attention mechanisms and LSTM to extract deep semantic information from sentences. Ma et al. (2017) proposed IAN to model the relation between aspect and context. Song et al. (2019) proposed an attention encoder to map the semantic interactions between aspect and context.

Subsequently, modelling syntactic information became a research hotspot. Li et al. (2021) alleviated the noise generated while modelling syntactic information by interactively incorporating syntactic and contextual information. Zhang et al. (2022b) proposed a self-attention-based aspect-aware attention mechanism to learn aspect-related semantic associations and global semantics. Ma et al. (2023) proposed using Abstract Meaning Representation to replace syntactic dependency trees and strengthen sentence features through an attention mechanism.

Recently, some studies have used contrastive learning for ABSA. Liang et al. (2021) leveraged contrastive learning to distinguish sentiment features from the perspectives of sentiment polarity and patterns. Liu et al. (2022) proposed eliminating the interference of aspect-irrelevant features through feature distillation and utilising supervised contrastive learning to capture internal information between sentences. Li et al. (2023) conducts supervised contrastive learning on different aspects, reducing the representation differences of aspects within the same relationship category.

2.2 Prompt Tuning

Prompt tuning is an approach that transforms downstream tasks into mask prediction tasks. Recently, Schick and Schütze (2020) proposed PET, which uses prompt tuning to make PLM understand the given task and then implements semi-supervised learning on a large scale of unlabeled data by assigning soft labels. Jiang et al. (2020) proposed a method based on encoding transformation to improve the PLM's ability to extract knowledge. Chen et al. (2022b) introduced KnowPrompt, which injects potential knowledge contained in relation labels into learnable prompt construction and uses this for relation extraction.

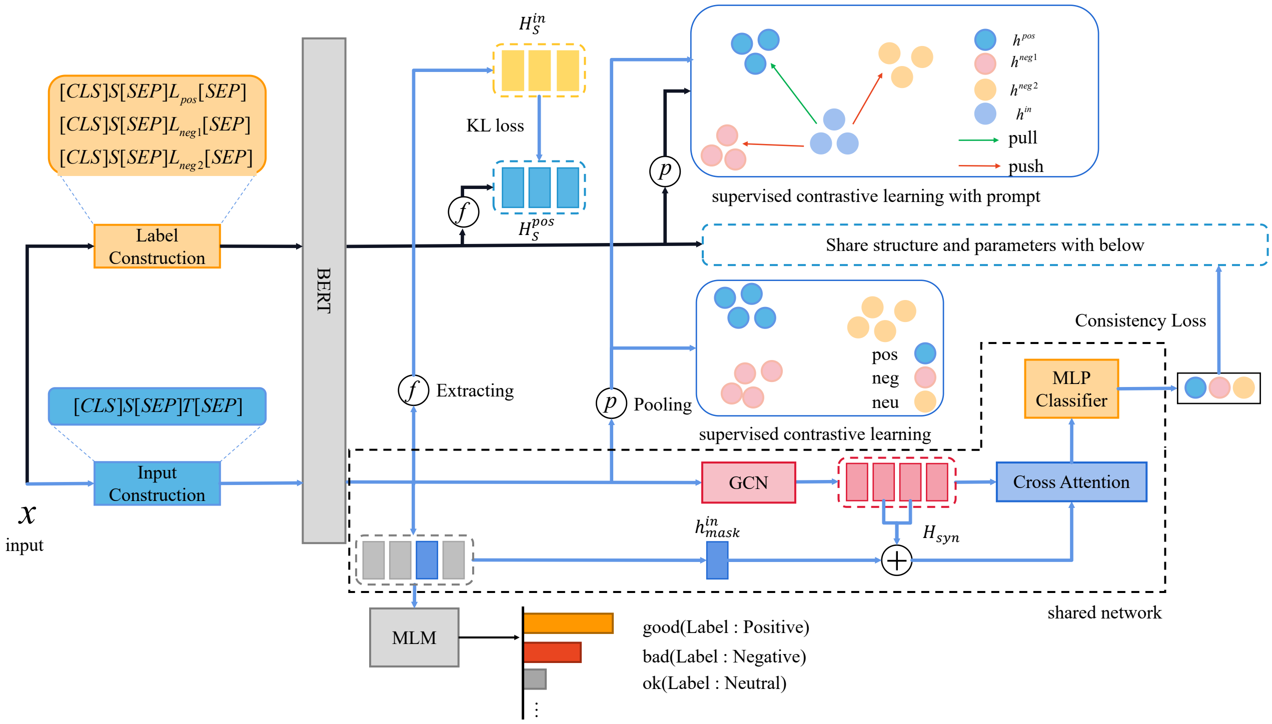


Figure 2: Overall architecture of the proposed C³LPGCN.

3 Proposed Model

Figure 2 shows an overview of C³LPGCN. In this section, we first introduce the definition of the ABSA task. After that, we will present our proposed C³LPGCN, composed of five components: input construction and embedding layer, contrastive learning, prompt-based cooperative learning, GCN layer and mask-aware aspect information filter layer.

3.1 Problem Formulation

For a given sentence S and its corresponding aspect a, where $S = \{w_1, w_2, ..., w_n\}$, $a = \{a_1, a_2, ..., a_k\}$, a is a subsequence of S, ABSA is to predict the sentiment polarity $y \in \{positive, negative, neutral\}$ of the given aspect. For the sake of simplicity, we perform prediction on one aspect at a time for sentences containing multiple aspects.

3.2 Input Construction and Embedding Layer

In contrast to other studies that use sentence-aspect pair as input, we construct prompt templates specific to the ABSA task and concatenate them with the sentence, using them as input of the BERT encoder. For a given sentence S and the aspect a, we construct its prompt template:

$$T_{prompt} = [p_1, p_2, ..., a, ..., [\text{MASK}]], \quad (1)$$

where p_i is the constructed template, while [MASK] is the token of PLM's masking process. Taking "No disk is included" as an example, where the aspect is "disk", we can construct a template like "the disk is [MASK]." Then, we can get a sample input for BERT:

$$S_{in} = [[\text{CLS}], S, [\text{SEP}], T_{prompt}, [\text{SEP}]] \quad (2)$$

Feeding S_{in} into BERT, we can obtain its representation H_{in} To perform prompt-based contrastive learning and cooperative learning, we construct label samples for the input, i.e., replacing [MASK] with the labels we set in the prompt template. We set up three kinds of label templates based on the real sentiment labels of the training data:

$$\begin{aligned} T_{pos} &= [p_1, p_2, ..., a, ..., L_{pos}], \\ T_{neg1} &= [p_1, p_2, ..., a, ..., L_{neg1}], \\ T_{neg2} &= [p_1, p_2, ..., a, ..., L_{neg2}], \end{aligned} \quad (3)$$

where L_{pos} is the true sentiment label of S and L_{neg1}, L_{neg2} are the false sentiment labels we constructed. Similarly concatenating them with S and feeding them into BERT, we can obtain their representations H_{pos}, H_{neg1}, H_{neg2}. It can be seen that the input sample and contrastive samples are identical in form , both can be represented as:

$$H_i = \{h^i_{cls}, h^i_1, ..., h^i_{n+m+2}\} \quad (4)$$

where $i \in \{in, pos, neg1, neg2\}$, $H_i \in \mathbb{R}^{t \times d_{bert}}$, n and m denote the length of S and the template, respectively, $t = m+n+2$. We conducted template experiment in Appendix A.

3.3 Contrastive Learning

In this section, we use supervised and prompt-based contrastive learning to improve further the model's ability to model aspects and sentiment expression.

3.3.1 Supervised Contrastive learning

Same as other supervised contrastive learning methods, for any input sample H_{in}^i, we take the samples with the same polarity within a batch B as positive samples. Otherwise, it is negative. Then, the contrastive loss is formulated as follows:

$$\begin{aligned} \mathcal{L}_{scl} &= \frac{1}{N} \sum \mathcal{L}_{sup}(h_i^{in}), \\ \mathcal{L}_{sup}(h_i) &= -\log \frac{\sum\limits_{y(a_i)=y(a_j)} sim(h_i, h_j)}{\sum\limits_{j \in B} sim(h_i, h_j)}, \end{aligned} \tag{5}$$

where N is the batch size and h_i^{in} is the pooled output of H_{in}^i, $sim(\cdot)$ is the cosine similarity, $y(a_i) = y(a_j)$ denotes h_i has the same sentiment polarity as h_j. With supervised contrastive learning, sentences with the same sentiment polarity are brought closer in feature space, while the distance between sentences with different sentiment polarities is pushed farther apart.

3.3.2 Prompt-based Contrastive Learning

In supervised contrastive learning, we use sentiment polarity to construct contrastive samples, equivalent to introducing label information as a priori into feature learning. However, since in supervised contrastive learning, we only know that the labels of the input and contrastive samples are different, this priori is implicit. To further utilize label information, we propose prompt-based contrastive learning to introduce label information explicitly. For a input sample H_{in}^i, we have constructed its corresponding label samples H_{pos}^i, H_{neg1}^i, H_{neg2}^i. Thus, our training objective can be formulated as follows:

$$\begin{aligned} \mathcal{L}_{pcl} &= \frac{1}{N} \sum \mathcal{L}_p(h_i^{in}), \\ \mathcal{L}_p(h_i^{in}) &= -\log \frac{sim(h_i^{in}, h_i^{pos})}{\sum\limits_{j \in B} sim(h_i^{in}, h_j^{all})}, \end{aligned} \tag{6}$$

where h_j^{all} denotes all the false label samples we constructed in batch B. Compared to supervised contrastive learning, our method explicitly introduces the true sentiment labels, thus allowing the model to learn information related to ABSA more directly during representation learning.

3.4 Cooperative Learning

To further utilize the prior knowledge contained in the true label samples, we propose cooperative learning, which consists of two components; on the one hand, for the input representation H_{in} and its true label sample H_{pos}, we take the representations of the corresponding parts H_{in}^S, H_{pos}^S of the original sentence S. After that, we compute the KL divergence between them to learn the prior distribution of true label samples:

$$\mathcal{L}_{KL} = \sum KL(H_{in}^S || H_{pos}^S) \tag{7}$$

On the other hand, we feed the true label sample and the input sample into the same ABSA network and obtain their predicted distribution $p(a)$, $p_{pos}(a)$, and use the $p_{pos}(a)$ as the label of $p(a)$ to calculate the consistency loss:

$$\begin{aligned} y_{pos}(a) &= argmax(p_{pos}(a)), \\ \mathcal{L}_{CL} &= -\sum_{S} \sum_{a \in A_S} y_{pos}(a) \cdot \log p(a) \end{aligned} \tag{8}$$

where A_S is the aspect collection of the sentence S.

3.5 GCN Layer

We leverage syntactic dependency trees to aid the model in learning syntactic features and establish the relationship between aspect and sentiment. We use the LAL-Parser (Mrini et al., 2019) to obtain the adjacency matrix of the dependency tree for the sentence. The syntactic dependency adjacency matrix A for each sentence is constructed by the following rule:

$$A_{ij} = \begin{cases} 1 & \text{if } i = j, \text{(self loop)}, \\ 1 & \text{if } i \text{ and } j \text{ are dependent}, \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Afterwards, we use GCN to aggregate the syntactic information. Given the sentence representation H_{syn}^{l-1} of layer $(l-1)$ and A, the $l-$th representation is defined as follows:

$$H_{syn}^l = \mathrm{RELU}(A H_{syn}^{l-1} W_{syn}^l + b_{syn}^l) \tag{10}$$

where W^l_{syn}, b^l_{syn} are trainable parameters of the $l-\mathrm{th}$ layer. And H^0_{syn} is the part of input representation H_{in} corresponding to the original sentence S, that is H^S_{in}.

3.6 Mask-aware Aspect Information filter

We introduce prompt tuning into ABSA to mitigate the noise generated when modelling syntactic information. The training process of PLM shows that the model's prediction of the mask position depends on the contextual information. PLM's prediction of the mask position certainly incorporates the understanding of the prompt we constructed and the sentence. Therefore, we propose mask-aware aspect information filter, which filters syntactic information by combining the prompt-tuned information with aspect information.

Given a masked language model L, we feed the representation of input samples H_{in} into it, resulting in predictions for the [MASK] position in the prompt template (e.g., great(positive), terrible(negative)). The process is depicted as follows:

$$\begin{aligned} H_{MLM} &= \mathrm{GELU}(H_{in}W_{MLM} + b_{MLM}), \\ H_{out} &= H_{MLM}W_{out} + b_{out}, \end{aligned} \tag{11}$$

where $H_{MLM} \in \mathbb{R}^{t\times d_{bert}}$, $H_{out} \in \mathbb{R}^{t\times d_{vocab}}$, W_{MLM}, b_{MLM}, W_{out}, b_{out} are trainable parameters. Subsequently, we define a mapping function $\mathcal{M} : \mathcal{Y} \rightarrow \mathcal{V}$ to map the true sentiment labels to the output words of the masked language model. By doing so, we can obtain the predicted probabilities $p_{pt}(a)$ for the true sentiment polarity $y(a)$ of the aspect in the sentence:

$$p_{pt}(a) = p([\mathrm{MASK}] = \mathcal{M}(y(a))|H_{out}) \tag{12}$$

Subsequently, we utilize cross-entropy as the loss function to fine-tune the PLM and the masked language model:

$$\mathcal{L}_{pt} = -\sum_{S}\sum_{a\in A_S} y(a)\cdot\log\left(p^{pt}(a)\right) \tag{13}$$

In the process of prompt tuning, we utilize MAF to combine the representation of mask position h^{in}_{mask} with aspect information h^{in}_a to achieve the filtering of syntactic information. The formulas are as follows:

$$\begin{aligned} H'_{syn} &= H^l_{syn}W'_{syn} + b'_{syn}, \\ h_{MAF} &= \Big(\frac{1}{k}\sum_{i=1}^{k} h^{syn}_{a_i} + h^{in}_{mask}\Big)W_a + b_a, \\ \alpha &= \mathrm{softmax}(h_{MAF} \times (H'_{syn})^T), \\ h^{MAF} &= \alpha H^l_{syn}, \end{aligned} \tag{14}$$

where k is the length of aspect in the PLM, $h^{syn}_{a_i}$, h^{in}_{mask} denote the representation of aspect words and [MASK] position in H^l_{syn} and H_{in}, respectively. W'_{syn}, b'_{syn}, W_a, b_a are trainable parameters. With this approach, the model can take into account both aspect information and prompt tuning information, thus mitigating the noise generated by modeling errors in syntactic information.

3.7 Target Aspect Sentiment Analysis

The final feature representation used for ABSA is obtained by utilizing the representations generated from the aforementioned components. The representation can be described as follows:

$$X_a = h^{in} \oplus h^{MAF} \oplus h^{in}_{mask} \tag{15}$$

where $\oplus$ is concatenation, h^{in} is the pooled output of H_{in} to represent the entire sentence, h^{MAF} is the output of MAF, while h^{in}_{mask} is the representation corresponding to the MASK position during prompt tuning. Then, we feed the obtained representations into a linear classifier with softmax to obtain the probability distribution $p(a)$ of sentiment polarity. The process can be represented as follows:

$$p(a) = \mathrm{softmax}(X_aW_p + b_p) \tag{16}$$

where W_p, b_p are trainable parameters.

3.8 Loss Function

We use the loss as follows in the training process for gradient descent:

$$\begin{aligned} \mathcal{L}_{total} = \mathcal{L}_{pre} + \lambda_1\mathcal{L}_{pt} + \lambda_2\mathcal{L}_{KL} \\ +\lambda_3\mathcal{L}_{CL} + \lambda_4\mathcal{L}_{scl} + \lambda_5\mathcal{L}_{pcl} \end{aligned} \tag{17}$$

where λs are hyperparameter, L_{pre} is the loss of final classifier:

$$L_{pre} = -\sum_{S}\sum_{a\in A_S} y(a)\cdot\log\left(p(a)\right) \tag{18}$$

Table 1: Statistics of datasets.

Dataset	Division	Positive	Negative	Neutral
Laptop	Train	976	851	455
	Test	337	128	167
Restaurant	Train	2164	807	637
	Test	727	196	196
Twitter	Train	1507	1528	3016
	Test	172	169	336

4 Experiments

4.1 Datasets

We conducted experiments on three publicly available benchmark datasets. Laptop is a collection of user reviews and opinions about laptops and related products. The Restaurant consists of reviews and opinions about restaurants. Both the Laptop and Restaurant are from SemEval14 (Pontiki et al., 2014). Twitter (Dong et al., 2014) is a collection of tweets. The three datasets consist of sentiment polarities: 'positive', 'negative', and 'neutral'. Laptop and Restaurant include sentences with single and multiple aspects, while the Twitter dataset contains sentences with only one aspect. The statistical information for these three datasets is summarized in Table 1.

4.2 Baseline Models

1) **AEN** (Song et al., 2019) proposes an attention-based encoder to model the relationship between aspect and context. 2) **IAN** (Ma et al., 2017) interactively learns the relationship between aspect and their context. 3) **BERT-SPC** (Song et al., 2019) uses the representation of the [CLS] token of BERT for ABSA. 4) **DualGCN** (Li et al., 2021) simultaneously considers syntactic and semantic information for ABSA. 5) **SSEGCN** (Zhang et al., 2022b) proposes aspect-aware attention to learn semantic associations and global semantics. 6) **dotGCN** (Chen et al., 2022a) utilizes reinforcement learning to construct a language-independent discrete latent opinion tree for ABSA. 7) **DLGM** (Mei et al., 2023) proposes leveraging neurons to extract specific language attributes. 8) **APARN** (Ma et al., 2023) utilizes a new semantic structure to replace syntactic dependency tree. 9) **BERT-SCon** (Liang et al., 2021) proposes using supervised contrastive learning to distinguish sentiment features in terms of sentiment polarity and patterns. 10) **AFDEN** (Liu et al., 2022) proposes a distillation module to better learn the aspect-unrelated features and eliminate the interference of aspect-unrelated features 11) **APSCL** (Li et al., 2023) proposes a framework that capturing relationships between aspects and enhances their features through contrastive learning.

4.3 Implementation Details

In this experiment, all models we implemented utilize BERT-base-uncased as the pre-trained language model. When calculating the training loss, λs is set to (0.01, 0.1, 0.1, 1.0, 0.3). We use the Adam optimizer for gradient descent. The learning rate for the PLM is set to 3e-5, while the learning rate for the other layers is set to 1e-4. In the GCN layer, we set the number of layers for the GCN in the range of [1, 3]. We use **Accuracy** and **Macro-F1** to evaluate the performance of our proposed C^{3}LPGCN as well as the baseline methods. For more implementation details, please refer to our code.

4.4 Main Result

We compared our model with other models, and the results are shown in Table 2. The results show that (1)Our C^{3}LPGCN obtained the best result in the three datasets. (2)Modeling syntactic information performs better than methods that model contextual information, such as attention. (3)Using PLM can make the model perform better, and it's become a consensus to use PLM. (4)Compared to methods that use syntactic information, methods that use contrastive learning methods tend to be simpler in structure and therefore perform slightly less well. (5)In our model, we combine prompt-tuned information and aspect information to filter syntactic information, thus alleviating the noise when modelling syntactic information. Also, we explicitly introduce sentiment label information using our proposed prompt-based contrastive learning and cooperative learning to obtain the best performance. (6)Compared to supervised contrastive learning, prompt-based contrastive learning can also improve the model's performance, and these two methods can be used together for better results.

4.5 Ablation Study

To verify the effectiveness of different modules, we performed ablation studies as shown in Table 2. First, the model's performance decreased after removing supervised contrastive learning, suggesting that supervised contrastive learning can learn the similarities and differences between samples. When prompt-based contrastive learning or cooperative learning is removed, the model's effectiveness likewise deteriorates because, with prompt-based contrastive learning and cooperative learning, the model learns information relevant to ABSA from true label samples. When we use only aspect information for sentiment classification, the model becomes less effective due to the noise generated when modelling syntactic information. Similarly, the model does not perform well when using only

Table 2: Performance of different methods on the three datasets. "∗" denotes our implementation. The best results are in **bold**, and the second-best are underlined.

Category	Models	Laptop		Restaurant		Twitter	
		ACC	Macro-F1	ACC	Macro-F1	ACC	Macro-F1
w. Contextual information	AEN	73.51	69.04	80.98	72.14	72.83	69.81
	AEN+BERT	79.93	76.31	83.12	73.76	74.71	73.13
	IAN	72.10	-	78.60	-	-	-
	BERT-SPC	79.91	76.30	85.61	79.05	76.21	74.78
w. Syntactic information	DualGCN-BERT	81.80	78.10	87.13	81.16	77.40	76.02
	dotGCN-BERT	81.03	78.10	86.16	80.49	78.11	77.00
	SSEGCN-BERT	81.01	77.96	87,31	81.09	77.40	76.02
	DLGM-BERT	$\underline{82.61}$	$\underline{79.24}$	87.35	81.88	74.96	73.37
	APARN-BERT	81.96	79.10	$\underline{87.76}$	**82.44**	**79.76**	**78.79**
w. Contrastive learning	BERT-SCon	80.23	76.48	86.51	80.55	-	-
	APSCL-BERT	81.02	78.47	86.86	81.28	-	-
	AFDEN	82.13	78.81	87.41	82.21	78.47	77.27
	BERT+SCL*	80.54	77.32	86.24	79.74	76.07	74.99
	BERT+PCL*	81.01	76.98	86.60	79.67	76.66	75.22
	BERT+C^{3}LP*	81.80	78.46	86.68	80.73	77.55	76.28
ours	Our C^{3}LPGCN	**82.75**	**79.61**	**87.85**	**82.44**	$\underline{79.32}$	$\underline{78.44}$
	w/o $\mathcal{L}_{CL}$	81.49	78.69	87.13	82.25	78.43	77.47
	w/o $\mathcal{L}_{KL}$	81.65	78.04	87.22	81.71	77.25	76.18
	w/o $\mathcal{L}_{pcl}$	81.17	77.68	86.86	80.60	76.66	75.55
	w/o MAF	81.08	77.42	85.43	77.40	75.63	74.93
	+aspect	81.33	77.70	86.33	80.38	77.10	75.73
	+mask	81.17	77.84	86.15	80.20	75.92	74.82

Table 3: Case studies of our C^{3}LPGCN model compared with other baselines

Sentences	AEN+BERT	DualGCN-BERT	Our C^{3}LPGCN
From the speed to the gestures this operating system beats windows easily.	$(\mathrm{O}_\times, \mathrm{O}_\times, \mathrm{P}_\surd, \mathrm{N}_\surd)$	$(\mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{N}_\surd)$	$(\mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{N}_\surd)$
It has all the expected features and a wide screen and more than roomy keyboard.	$(\mathrm{P}_\surd, \mathrm{O}_\times, \mathrm{P}_\surd)$	$(\mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{N}_\times)$	$(\mathrm{P}_\surd, \mathrm{P}_\surd, \mathrm{P}_\surd)$
I use it mostly for creation (audio) and its reliable.	$(\mathrm{P}_\surd, \mathrm{O}_\mathrm{F})$	$(\mathrm{P}_\surd, \mathrm{O}_\mathrm{F})$	$(\mathrm{P}_\surd, \mathrm{P}_\surd)$

aspect information for filtering. Whereas, when using only mask information, the model may ignore aspect information, and thus, the model becomes less effective(experiments in Sec 4.7 proved this point).

4.6 Case Study

We conducted a case analysis as shown in Table 3. The notations P, N and O represent positive, negative and neutral sentiment, respectively.The results indicate that modelling syntactic information leads to better results when there is a long distance between the aspect and sentiment expression. This is because, compared to direct attention-based aggregation, GCN enables more accurate aggregation of aspect and corresponding sentiment expression. On the other hand, when there is no explicit syntactic relationship between aspect and sentiment expression, our proposed C^{3}LPGCN outperforms other models because our model not only considers syntactic information but also incorporates sentiment expression modelling information from PLM and uses contrastive learning and cooperative learning to enhance sentence features further.

4.7 Attention Visualization

To explore the impact of our proposed MAF, we investigated the differences in attention weights using different information for filtering. We visualized the attention weights using sentence "*the durability of the laptop will make it worth the money.*" from the laptop dataset, where the aspect is "*durability*". As shown in Figure 3. When using only the aspect information, the model assigns the highest weight to the aspect, which indicates that the model focused more on the aspect. On the other hand, when using the mask information, the model assigns the highest weight to the sentiment expression "*it worth the money.*" It is shown that by prompt tuning, it is possible to obtain the reason for the sentiment prediction, i.e., the sentiment expression. In contrast, our proposed MAF combines the MASK position and aspect information to consider both aspect and sentiment expression. Therefore,

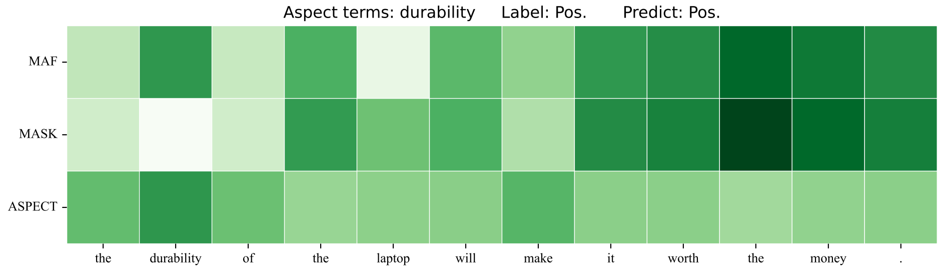
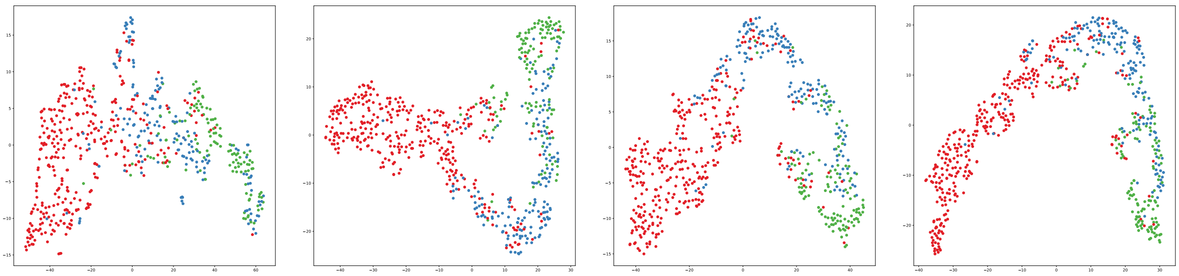


Figure 3: Visualization of attention weights calculated using different information.



(a) BERT (b) BERT+SCL (c) BERT+PCL (d) BERT+SCL+PCL

Figure 4: Feature visualization of using different methods

it somewhat alleviates the noise caused by wrong syntactic information.

4.8 Feature Visualization

To verify the effectiveness of prompt-based contrastive learning, we performed the visualization shown in Figure 4 using t-SNE (van der Maaten and Hinton, 2008). The results show that the feature distribution of different sentiments is tighter when using only BERT. After using supervised contrastive learning, the boundary distance between different sentiments increases significantly, indicating that the model learns the similarities and differences between different samples through supervised contrastive learning. Similarly, when using prompt-based contrastive learning, the feature distances of different sentiments become larger due to using false label samples of other sentences as negative samples. Still, the feature distribution of the same polarity is also slightly larger than supervised contrastive learning because there is only one positive sample for an input sample. After combining supervised contrastive learning with prompt-based contrastive learning, the boundaries of different sentiments become more obvious, and the distribution of the same sentiment becomes tighter.

5 Conclusion

In this paper, we propose C^{3}LPGCN. On the one hand, to mitigate the noise that may arise when modelling syntactic information, we propose mask-aware aspect information filter, which filters syntactic information by combining prompt-tuned representations with aspect information. On the other hand, we propose prompt-based contrastive learning and cooperative learning methods that explicitly introduce label information. Extensive experiments on three datasets demonstrate the effectiveness of our approach.

In this paper, we employed a manual construction approach for prompt templates. The uncertainty associated with manual construction leads to varying effects of different templates on the model performance. In future work, we plan to explore the use of continuous prompts. Additionally, we aim to extend our prompt-based contrastive learning and cooperative learning to a broader range of natural language processing tasks.

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A Template Analysis

We investigated the impact of different templates on model performance, and the results are shown in Table 5. The table presents the results obtained using the prompts constructed in Table 4. The following observations can be made: (1) Different

Table 4: The prompt templates and labels we constructed manually in our experiments, $< a >$ denotes the aspect. We concatenate them with the original sentence to form the input and labeling samples

Index	**Template**	**Label words**
t_0	The sentiment of $< a >$ is [MASK]	P:positive, N:negative, O:neutral
t_1	The sentiment of $< a >$ is [MASK]	P:nice, N:bad, O:none
t_2	The sentiment of $< a >$ is [MASK]	P:negative, N:neutral, O:positive
t_3	The $< a >$ is [MASK]	P:good, N:terrible, O:ok
t_4	The $< a >$ is [MASK]	P:positive, N:negative, O:neutral
t_5	How about $< a >$? it is [MASK]	P:good, N:terrible, O:ok
t_6	What do you think of the $< a >$? it is [MASK]	P:good, N:terrible, O:ok

Table 5: Experimental results on the three datasets with different templates. The best results are in **bold**.

Template	**Laptop**		**Restaurant**		**Twitter**	
	ACC	**Macro-F1**	**ACC**	**Macro-F1**	**ACC**	**Macro-F1**
t_0	**82.75**	**79.61**	**87.85**	**82.41**	**79.32**	**78.44**
t_1	81.80	78.97	87.04	81.16	76.96	75.74
t_2	81.48	77.86	86.15	79.29	76.96	75.83
t_3	81.33	78.41	86.24	80.15	74.89	73.33
t_4	81.65	78.72	86.15	80.57	75.63	74.46
t_5	82.28	78.86	85.43	79.23	75.18	74.09
t_6	81.80	78.60	86.51	80.38	76.96	75.86

prompts and label words have a significant influence on the model's performance. (2) When using the same prompt, different label words yield varying results. However, compared to the performance differences resulting from using different label words and the same prompt, the differences are relatively smaller. This indicates that the selection of the template plays a more crucial role. (3) When the semantic meaning of the label word is completely opposite to the sentiment label, there is a certain decrease in model performance. However, since our model also extracts other features of the sentence, the extent of performance degradation is limited.