Aspect Information Enhanced Contrastive Learning for Aspect-based Sentiment Analysis

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Abstract

Aspect-based sentiment analysis (ABSA) is a fine-grained sentiment classification task. Despite significant improvements in this field, progress is hindered by challenges such as the scarcity of context for specific aspects, interference from irrelevant words in sentences, and a lack of research focus on leveraging correlations between samples. To address these issues, we introduce a novel method named ***A**spect **I**nformation **E**nhanced **C**ontrastive **L**earning **(AIECL)*** for ABSA. Firstly, we employ advanced prompting techniques with Large Language Models (LLMs) to generate nuanced aspect-specific descriptions, thereby enhancing contexts related to the aspect. Subsequently, we design a novel fusion module to seamlessly integrate aspectual insights with the original sentence structure. Finally, we develop three pioneering contrastive learning strategies to explore and learn complex correlations between samples, which are crucial for fine-grained sentiment analysis. Experiments on six benchmark datasets demonstrate that our AIECL method substantially outperforms state-of-the-art techniques and provides valuable insights for applying LLMs to downstream tasks.

1 Introduction

Aspect-based sentiment analysis (ABSA) is a branch of sentiment analysis which aims to recognize the sentiment polarity of a specific aspect in a sentence. For example, given the sentence "*The restaurant has delicious food, but the atmosphere there is really noisy*", ABSA task aims to predict the sentiment polarity of the two aspects "*food*" and "*atmosphere*", which should be positive and negative, respectively.

Recent research (Tang et al., 2016a; Chen et al., 2017; Gu et al., 2018; Huang et al., 2018; Xing et al., 2019) exploits attention mechanisms to model the relationships between the specific aspect and contexts. In addition, various methods (Zhang et al., 2019; Tang et al., 2020; Wang et al., 2020; Li et al., 2021; Tian et al., 2021) leverage graph neural networks to process dependency trees and develop outstanding models. With the emergence of the fine-tuning paradigm, many approaches armed with Pre-trained Language Models (Zhang et al., 2022a, 2023; Ma et al., 2023; Sun et al., 2024) exhibit substantial performance in ABSA task.

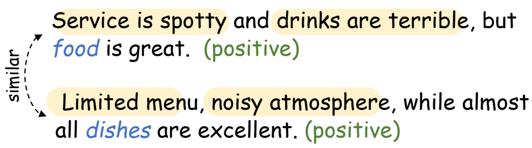


Figure 1: Two example sentences with the same label. Aspect words are italicized in blue, and irrelevant contexts for the specific aspect are marked in yellow. We can see the two samples are similar in semantics.

Despite the advancements made by previous methods, they still struggle to address sentences that have multiple aspects and opinions. As shown in Figure 1, aspect-related words are often sparse, while other opinion words could interfere with sentiment analysis. Most existing methods involve studying how to reduce the influence of irrelevant contexts, such as exploiting attention mechanisms to assign attention scores or introducing syntactic information to enhance constraints. However, they ignore to attenuate influence of irrelevant words from the reverse perspective, such as straightforwardly enriching aspect-related information for the origin sentence. On the other hand, although aspect-related words are sparse in a single sample, correlations between samples could assist in sentiment classification. Fortunately, contrastive learning can capture similarities and differences between samples (Gao et al., 2021; He et al., 2020).

Recently, Large Language Models (LLMs) have achieved great success in a wide range of NLP fields (Wang et al., 2023a; Dai et al., 2023a; Wadhwa et al., 2023), including contextual understanding, relation extraction and data generation. In addition, LLMs are knowledgeable and could be exploited to conduct data augmentation (Dai et al., 2023b; Liu et al., 2022). Therefore, leveraging LLMs to generate aspect-specific information from original sentences holds significant potential.

Inspired by this, to address the above issues, we propose a novel framework named Aspect Information Enhanced Contrastive Learning (AIECL). Specifically, we leverage cutting-edge prompt techniques with LLMs to generate aspect-related descriptions as aspect information, which enriches aspect-related words and contains external knowledge and semantic understanding from LLMs. Then, we propose a method that efficiently integrates aspect information with the origin sentence, which yields aspect-enhanced semantic features. The features contain both the overall semantics of the sentence and aspect-oriented semantic information, thus making it suitable for contrastive learning at sample level. Finally, we introduce three pioneering contrastive learning methods to model correlations between samples. More concretely, we define positive and negative samples from distinct perspectives to establish varying distances between samples in the same semantic space.

To summarize, our contributions are highlighted as follows:

- To the best of our knowledge, we are the first to induce LLMs to generate aspect-related descriptions as aspect information for origin sentences. Then, we design a novel module to incorporate sentences with aspect information and obtain aspect-enhanced semantic features.

- We address ABSA from a novel perspective by proposing an innovative aspect-enhanced semantic contrastive learning method. This method leverages correlations between data samples, effectively alleviating the issue of data sparsity to specific aspects.

- Extensive experiments on six public benchmark datasets show that our AIECL outperforms state-of-the-art baselines, demonstrating its effectiveness.

2 Related Works

2.1 Aspect-based Sentiment Analysis

ABSA is a fine-grained sentiment analysis task for any aspect in a sentence, rather than simply allocating a general sentiment polarity at the document- or sentence-level. Earlier works (Titov and McDonald, 2008; Jiang et al., 2011; Kiritchenko et al., 2014) model the connections between aspects and contexts based on handcrafted features. With the development of deep learning, various works apply attention mechanisms to model the semantic relationship of an aspect to its context (Tang et al., 2016b; Ma et al., 2017; Fan et al., 2018; Wang et al., 2018; Xing et al., 2019; Tan et al., 2019; Zhang et al., 2021). For instance, Huang et al. (2018) employed cross attention to capture interactions between contexts; Fan et al. (2018) established a multi-grained network to connect aspect and sentence; Tan et al. (2019) presented a dual attention approach to discriminate conflicting opinions.

Another research trend is to leverage syntactic knowledge to model the syntactic relationships between aspect and its corresponding opinion words (Huang and Carley, 2019; Zhang et al., 2019; Wang et al., 2020; Tang et al., 2020; Chen et al., 2020a; Li et al., 2021). For example, Tang et al. (2020) proposed a dependency graph enhanced dual-transformer network to fuse flat representations; Li et al. (2021) utilized both dependency parsing and attention mechanisms to build a SynGCN module and a SemGCN module; Tian et al. (2021) designed a type-aware GCN to explicitly incorporate dependency type information.

More recently, many approaches have modeled the ABSA task using Pre-trained Language Models. Zhang et al. (2022a) designed a dynamic reweighting adapter to select important words at each step; Zhang et al. (2023) considered the consistency of multi-word expressions at the span-level; Ma et al. (2023) replaced the syntactic dependency tree with the semantic structure called Abstract Meaning Representation. However, these methods ignore to learn correlations between samples.

2.2 Contrastive Learning

Contrastive Learning (CL) has achieved remarkable performance in the field of NLP. The main goal of contrastive learning (He et al., 2020; Chen et al., 2020b) is to learn representations between samples by contrasting positive pairs and negative pairs. CL could be divided into two types. Unsupervised CL attempts to contrast grouped or perturbed instances to produce more robust representation of unlabeled data (Gao et al., 2021; Kim et al., 2021; Wang et al., 2021), and supervised CL is label-aware and aims to learn distinct representations for

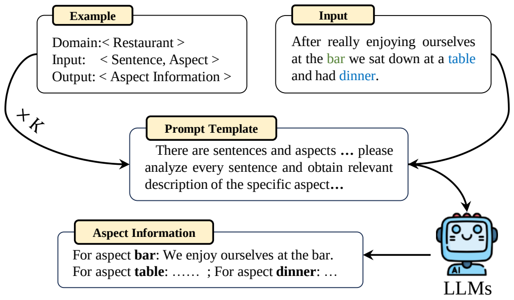


Figure 2: The process of Aspect Information Generation through Large Language Models.

differently labeled data (Khosla et al., 2020; Suresh and Ong, 2021; Huang et al., 2022).

In ABSA, Chai et al. (2023) designed multi-view graph CL on nodes to integrate syntax and semantics at token-level. Although it is inappropriate for this fine-grained task to model connections directly at sample-level, our method amalgamate aspect insights from LLMs and enhance aspect-oriented semantics, thus offering new possibilities for capturing the rich knowledge between samples.

2.3 Large Language Models

Large Language Models (LLMs) have exhibited excellent performance on various natural language understanding and generation tasks (Wang et al., 2023a; Dai et al., 2023a; Laskar et al., 2023). Many studies prove that the performance of LLMs is significantly influenced by the In-context Learning (ICL) demonstrations (Brown et al., 2020; Liu et al., 2022; Zhang et al., 2022b). The method is widely applied in various tasks, such as machine translation (Agrawal et al., 2023), relation extraction (Wadhwa et al., 2023) and data generation (Dai et al., 2023b). In our approach, we thoroughly harness the semantic understanding and generative capabilities of LLMs, and then enrich aspect-related information within each sentence as data augmentation for adaptation to ABSA task.

3 Methodology

In this section, we introduce the technical details of our method. Specifically, we start with problem definition, followed by an overall architecture of AIECL, which is illustrated in Figure 3.

Problem Definition. In ABSA, a sentence-aspect pair (S, A) is given, where $S = \{w_1, w_2, ..., w_n\}$, and $A = \{a_1, a_2, ..., a_m\}$. The goal of ABSA task is to precisely predict the sentiment polarity C_a of the given aspect A in the sentence S.

Overall Architecture. AIECL consists of three parts: 1) Aspect Information Generation; 2) Fusion and Re-weighting Module; 3) Semantics-based Contrastive Learning. The technical details of each part will be elaborated as follows.

3.1 Aspect Information Generation

In ABSA task, aspect-related contexts are usually sparse in each sentence. Data augmentation technique is widely used to solve data scarcity in many tasks. However, conventional data augmentation (i.e., Crop, Mask) may be unsuitable for ABSA because they probably delete aspect-related contexts or increase irrelevant words, which instead hurt prediction in sentiment polarity. Recent works have shown that LLMs like ChatGPT exhibit incredible capabilities in text understanding and generation, which inspires us to leverage LLMs to generate aspect-related information.

In this work, to obtain high-quality aspect information, we explore prompt templates to leverage the understanding and inference abilities of LLMs. The prompt templates mainly consist of three parts: task description, output requirements, and input examples. Specifically, we first briefly introduce the core of the ABSA task to LLMs and concretely give the definition of "*aspect*", "*sentiment polarity*" and "*aspect information*". Then, we list output requirements and suggest some representative examples to induce LLMs' understanding in this generation task. Finally, we input the original sentence-pair (S, A) into LLMs and obtain aspect information, which is denoted as $T = \{t_1, t_2, ..., t_l\}$, where l is the length of the aspect information. The overall process is shown in figure 2. Considering the distinct domain knowledge and data distribution characteristics inherent in different datasets, we have crafted unique prompts and examples specifically tailored for each one. Moreover, the aspect information generated by LLMs is diverse, depending on the depending on the complexity of the sentences and the LLMs' comprehension ability. Due to the page limitation, prompt templates, few-shot examples and detailed analysis of the aspect information are presented in Appendix A and B.

After getting aspect information T derived from LLMs, we integrate it with original sentence S and input them into the subsequent modules.

3.2 Fusion and Re-weighting Module

Encoder. We adopt BERT as an encoder to get contextual embeddings like previous work. Given sen-

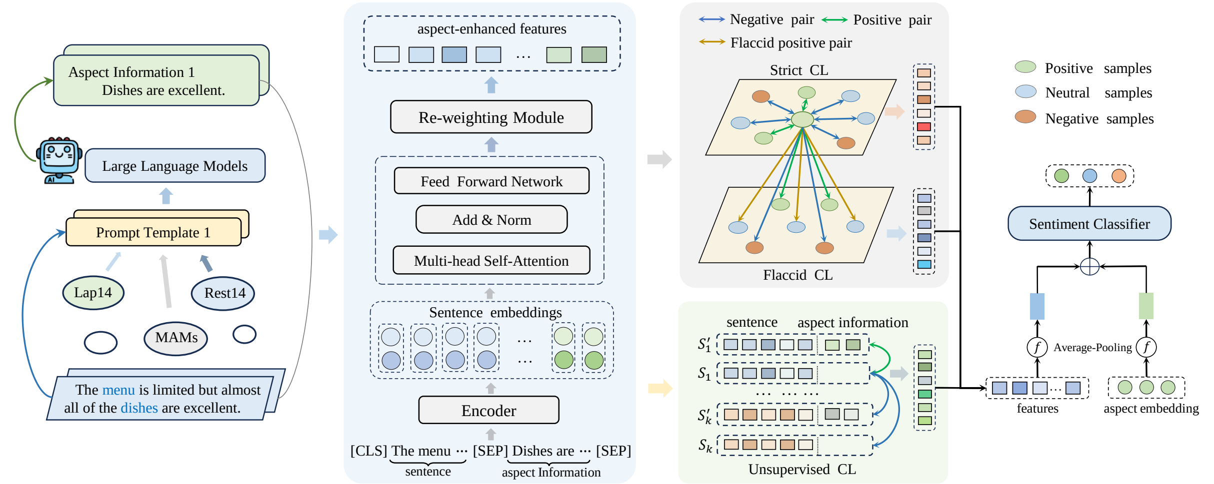


Figure 3: The overall architecture of AIECL. From left to right, the modules are Aspect Information Generation, Fusion and Re-weighting Module, Semantics-based Contrastive Learning and Sentiment Classifier.

tence S and aspect information T, we construct input as "$[CLS]\ S\ [SEP]\ T\ [SEP]$" to transform it into hidden state H, and H contains sub-sequence $H_a = \{h_{a_1}, h_{a_2}, ..., h_{a_m}\}$, which is the representation of aspect term.

Multi-head Self-attention Mechanism. We first use multi-head self-attention (MultiHead) to obtain the overall semantics of the sentence. Through MultiHead, the hidden state H is transformed to:

$$H_m = \text{MultiHead}(HW_h^q, HW_h^k, HW_h^v), \quad (1)$$

where W_h^q, W_h^k, W_h^v are learnable parameters in the attention mechanism.

Position-wise Feed-Forward Network. The output of MultiHead is followed by a Feed-Forward Network (FFN) to facilitate learning unlinear features, which is defined as:

$$H_f = \max(0, H_m W_1 + b_1) W_2 + b_2, \quad (2)$$

where W_1, b_1, W_2, b_2 are weight parameters.

Aspect-enhanced Semantic Features. Considering that aspect information just assists in enriching aspect-related semantics, it may change overall semantics of origin sentence while its content is excessive. Thus, we re-weight aspect information based on its length, treating aspect length as a penalty. Moreover, we emphasize the importance of contexts that are near the aspect. Through this approach, we aim at reducing the noise that may naturally arisen from attention weights. More formally, we design a function P applied to H_f for extracting aspect-enhanced semantic features z:

$$q_i = \begin{cases} 1 - \frac{r+1-i}{n} & 1 \le i < r+m, \\ 1 - \frac{i-r-m}{n} & r+m < i \le n, \\ \frac{m}{l} & n < i \le n+l, \end{cases} \quad (3)$$

$$z = P(H_f) = qH_f, \quad (4)$$

where q_i is the weight value for i-th token, r is the start position of the aspect, m is the length of aspect term and l is the length of aspect information. The feature z contains both overall semantics and aspect-oriented semantics, which could be feasible for contrastive learning at sample-level.

3.3 Semantics-based Contrastive Learning

In this section, we devise three contrastive learning methods to capture correlations between samples. Suppose a batch which contains n samples $D = \{(S_1, C_1), (S_2, C_2), ..., (S_n, C_n)\}$, S_i is the i-th sample with label C_i, and $I = \{1, ..., n\}$ is the sample index set. Moreover, the aspect-enhanced semantic features of i-th sample S_i are denoted as z_i, while origin sentence features are denoted as z_i'.

Unsupervised Contrastive Learning. Unsupervised Contrastive Learning (UCL) often obtains positive pairs by data augmentation. In our approach, considering that z_i and z_i' contain similar semantic features for the specific aspect, we use features z_i and z_i' to construct positive pairs . Through this construction, UCL helps distill a LLM's understanding and knowledge about the sentence. On the other hand, it can effectively prevents aspect information from excessively altering origin semantics. In addition, z_i and z_k (features of other sentences) constitute negative pairs, which highlight the uniqueness of each sample, so unsupervised contrastive learning can be formulated as :

$$L_U = \sum_{i \in I} \frac{-1}{|I|} \log \frac{e^{(z_i \cdot z_i'/r)}}{\sum_{k \in I} e^{(z_i \cdot z_k/r)} + e^{(z_i \cdot z_k'/r)}}. \tag{5}$$

Strict Label Contrast. Strict Label Contrast (SLC) is a supervised method which treats all samples of the same sentiment polarity as positive pairs and different ones as negative pairs. As a result, SLC makes features of samples with the same label closer than others. Given sample S_i in a batch, all other samples which have the same sentiment polarity as S_i make up the set $P(i) \equiv \{p \in I \backslash \{i\} : \boldsymbol{C}_p = \boldsymbol{C}_i\}$, and we define the set $O(i) \equiv I \setminus \{i\}$. The SLC function is defined as:

$$L_S = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P_{(i)}} \log \frac{e^{(z_i \cdot z_p/r)}}{\sum_{j \in O(i)} e^{(z_i \cdot z_j/r)}}. \tag{6}$$

Flaccid Label Contrast. Different from traditional categorization problems, sentiment analysis should consider sentiment intensity, and we design Flaccid Label Contrast (FLC) to achieve this. Specifically, the distance of sentiment features between positive and neutral (or negative and neutral) samples tends to be smaller compared to those positive and negative samples.

In order to model this distance relationship, we construct matrix $M \in R^{N \times N}$ to implement FLC. The elements of M are initialized to zero, where m_{ij} represents the weight between sample i and sample j. The FLC function is denoted as:

$$m_{ij} = \begin{cases} \alpha & \text{if } C_i = C_j, \\ \beta & \text{if } C_i \neq C_j, C_i \text{ or } C_j \text{ is Neu}, \end{cases} \tag{7}$$

$$L_F = \sum_{i \in I} \frac{-1}{|I|} \sum_{j \in O_{(i)}} \log \frac{m_{ij} \cdot e^{(z_i \cdot z_j/r)}}{\sum_{k \in O(i)} e^{(z_i \cdot z_k/r)}}. \tag{8}$$

3.4 Model Training

We obtain the final classification features by concatenating origin aspect representation H_a and the aspect-enhanced semantic features z, then we feed it into a fully-connected layer with softmax and map it to the probability distribution over the three sentiment polarities:

$$H_a^{final} = [\text{Avg}(H_a), \text{Avg}(z)], \tag{9}$$

$$\hat{y} = \text{softmax}(W_s H_a^{final} + b_s), \tag{10}$$

where Avg is an average pooling function, W_s, b_s are learned parameters. Finally, we train the model to minimize the loss function:

$$\mathcal{L} = -\sum_{i=1}^{|D|} \sum_{j=1}^{|C|} y_i^j \log \hat{y}_i^j + \lambda_1 L_U + \lambda_2 L_S + \lambda_3 L_F, \tag{11}$$

where y_i^j is the ground truth sentiment polarity, D contains all training samples and C contains all sentiment polarities. λ_1, λ_2, λ_3 are contrastive learning coefficients.

Datasets	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
Lap14	994	341	464	169	870	128
Rest14	2164	728	637	196	807	196
Rest15	912	326	36	34	256	182
Rest16	1240	469	69	30	439	117
MAMs	3380	400	5042	607	2764	329
Twitter	1561	173	3127	346	1560	173

Table 1: The statistics of six benchmark datasets.

4 Experiments

4.1 Datasets

We conduct our experiments on six benchmark datasets, including Lap14 and Rest14 (Dong et al., 2014), Rest15 (Pontiki et al., 2015), Rest16 (Pontiki et al., 2016), Twitter (Dong et al., 2014) and MAMs (Jiang et al., 2019). All datasets consist of three sentiment labels, including positive, neutral and negative. Each data item includes a sentence, an aspect and its corresponding sentiment polarity. We adopt the official data splits as original papers. The statistics are shown in Table 1.

4.2 Implementation Details

In the implementation, we use *chatgpt* to generate aspect information and build our framework based on *bert-base-uncased*. The hidden size of Multi-Head Attention is set to 300. The learning rate is tested among [1e-5, 2e-5, 4e-5] and the batch size is adjusted in [16, 32]. The dropout rate is set to 0.5. The hyper-parameter α and β set to 0.8 and 0.4. The coefficients λ_1, λ_2 and λ_3 have been carefully adjusted, and finally are set to 1, 1 and 4 respectively. We run our model on a single NVIDIA V100 GPU and evaluate it with accuracy and macro-F1 value.

Models	Lap14		Rest14		Rest15		Rest16		Twitter		MAMs	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
BERT-SPC (Song et al., 2019)	78.99	75.03	84.46	76.98	83.03	63.92	90.75	74.00	73.41	72.38	82.82	81.90
R-GAT (Wang et al., 2020)	78.21	74.07	86.60	81.35	83.22	69.73	89.71	76.62	76.15	74.88	82.71	82.21
DGEDT (Tang et al., 2020)	79.80	75.60	86.30	80.00	84.00	71.00	91.90	79.00	77.90	75.40	-	-
kumaGCN (Chen et al., 2020a)	81.98	78.81	86.43	80.30	86.35	70.76	92.53	79.24	77.89	77.03	-	-
T-GCN (Tian et al., 2021)	80.88	77.03	86.16	79.95	85.26	71.69	92.32	77.29	76.45	75.25	83.38	82.77
DualGCN (Li et al., 2021)	81.80	78.10	87.13	81.16	82.33	68.12	90.91	77.86	77.40	76.02	83.83	83.47
DR-BERT (Zhang et al., 2022a)	81.45	78.16	87.72	82.31	-	-	-	-	77.24	76.10	-	-
TF-BERT (Zhang et al., 2023)	81.80	78.46	87.09	81.15	-	-	-	-	78.43	77.25	-	-
APARN (Ma et al., 2023)	81.96	79.10	87.76	82.44	-	-	-	-	79.76	78.79	85.59	85.06
RSC-LLM (Wang et al., 2023b)	81.56	75.92	87.45	82.41	83.98	70.86	92.75	75.48	-	-	84.68	84.23
TextGT (Yin and Zhong, 2024)	81.33	78.71	87.31	82.27	-	-	-	-	77.70	76.45	-	-
CEIB (Chang et al., 2024)	82.92	79.50	87.77	82.08	86.16	72.97	92.86	81.08	-	-	84.95	84.41
Our AIECL	**84.17**	**81.16**	**89.73**	**84.27**	**88.15**	**74.17**	**94.31**	**82.56**	**81.21**	**80.61**	**85.64**	**85.11**

Table 2: Experiment results (%) on six benchmark datasets. The best scores are bolded, and the second-best ones are underlined. The results with "-" denote that no results were reported or code was not released in the original paper. All baselines are based on BERT.

4.3 Baseline methods

We compare our AIECL with a series of advanced ABSA models based on *bert-base-uncased*, this section provides a brief summary of baselines.

BERT-SPC (Song et al., 2019) puts the contexts and aspects into the BERT model directly.

R-GAT (Wang et al., 2020) utilizes a relational graph attention network to encode the new tree reshaped by an ordinary dependency parse tree.

DGEDT (Tang et al., 2020) proposes a dependency graph enhanced dual-transformer network, fusing representations of sequences and graphs.

kumaGCN (Chen et al., 2020a) proposes gating mechanisms to dynamically combine information from word dependency graphs and latent graphs.

T-GCN (Tian et al., 2021) designs a type-aware GCN to explicitly incorporate dependency type information for ABSA.

DualGCN (Li et al., 2021) uses both dependency parsing and attention mechanism to build a SynGCN module and a SemGCN module.

DR-BERT (Zhang et al., 2022a) presents a Dynamic Re-weighting BERT model to change attention at each step.

TF-BERT (Zhang et al., 2023) considers the consistency of multi-word opinion expressions at the span-level for sentiment polarity classification.

APARN (Ma et al., 2023) integrates information from original sentences and AMRs via the path aggregator, then use relation-enhanced self-attention mechanism to relieve parser unreliability.

RSC-LLM (Wang et al., 2023b) uses LLMs to generate explanation for aspect's sentiment, using it to reduce spurious correlations.

TextGT (Yin and Zhong, 2024) proposes a double-view graph transformer for ABSA. In TextGT, alleviating the over-smoothing problem.

CEIB (Chang et al., 2024) utilizes the information bottleneck principle and LLMs to reduce spurious correlations for ABSA.

4.4 Main Results

The experiment results of the ABSA methods on six benchmark datasets are reported in Table 2. We can observe that our AIECL substantially and consistently outperforms all compared baselines on the overall datasets in terms of both accuracy and macro-F1 score. Specifically, our AIECL achieves an improvement of 1.25% ~ 1.96 % in accuracy and 1.20% ~ 1.83% in F1 value on five benchmark datasets (i.e., Lap14, Rest14, Rest15, Rest16, Twitter) compared with state-of-the-art baselines (i.e., APARN, CEIB), which verifies the effectiveness of our proposed approach. We attribute these advancements to the LLMs' high-quality aspect information, which significantly mitigates the issue of aspect-related data sparsity in the ABSA task. It could be observed that the performance improvement on the MAMs dataset was relatively modest, and we speculate it's because MAMs is a challenging dataset with more complex expressions and opinions, increasing challenges for LLMs to extract accuracy aspect information.

Compared to methods using attention mechanism and dependency graphs, our method achieves

Models	Lap14		Res14		Res15		Res16		Twitter		MAMs	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1	Acc	F1
AIECL	**84.17**	**81.16**	**89.73**	**84.27**	**88.15**	**74.17**	**94.31**	**82.56**	**81.21**	**80.61**	**85.64**	**85.11**
w/o Aspect-enhanced	82.13	79.32	87.32	81.63	86.16	70.39	92.68	78.82	78.03	77.09	84.66	84.30
w/o Fusion	82.92	79.84	88.78	82.70	86.85	70.76	93.33	80.89	79.48	78.69	84.81	84.16
w/o UCL	83.23	80.24	89.11	83.35	87.59	72.97	93.66	81.23	79.91	79.10	84.88	84.25
w/o SLC	83.54	80.66	89.20	83.94	87.22	71.69	93.50	81.08	80.49	79.74	85.18	84.66
w/o FLC	83.39	80.56	88.93	83.38	87.41	73.38	93.50	81.50	80.64	79.76	85.10	84.46

Table 3: Ablation study results (%) on six benchmark datasets.

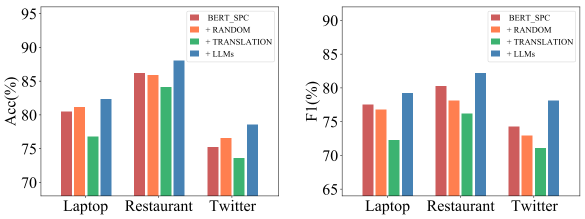
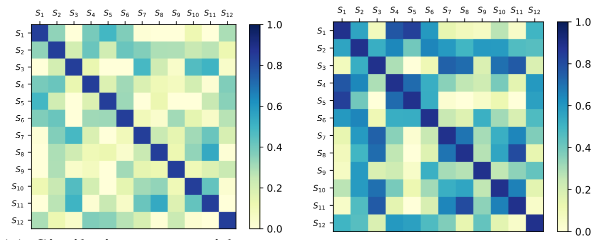


Figure 4: BERT-SPC with different augmentation methods on Lap14, Rest14 and Twitter datasets. The methods include: Add random words; Translate sentences into synonyms; Add aspect information derived from LLMs.



(a) Similarity scores without contrastive learning.

(b) Similarity scores with contrastive learning.

Figure 5: We randomly select 12 samples from a batch to visualize semantic similarity scores.

significant results, which verifies aspect information derived from LLMs could provide better aspect sentiment cues than syntactic information. On top of that, our model still performs better than many updated methods (e.g., TF-BERT, TextGT, CEIB), showing that the combination of LLMs and contrastive learning can effectively leverage semantic similarities between samples.

4.5 Ablation Study

In this subsection, ablation studies were conducted on six datasets to dissect the contribution of every component. The results, presented in Table 3, reveal that each element plays a significant role in model's performance. The model without aspect-enhanced means the absence of aspect information, and the decrease proves that aspect information generated by LLMs could help the model minimize

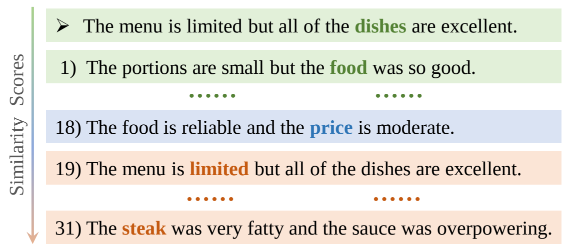


Figure 6: Semantic similarity scores within batches sorted from largest to smallest. Samples in green, blue and red are postive, neutral and negative respectively.

interference from irrelevant contexts. The model without fusion illustrates the importance of devising an effective strategy to incorporate the original sentence with aspect information. In addition, ablation of any contrastive method results in a reduction of accuracy. The phenomenon implies that unsupervised method facilitate the alignment of origin sentence with knowledge from LLMs, while supervised methods leverage implicit knowledge between samples. Moreover, the improvement by FLC further confirms our idea that it's necessary to construct comparison at various levels according to different sentiment polarities.

4.6 Analysis

Analysis on Aspect Information. Our work exploits aspect information derived from LLMs, which could be viewed as data augmentation for origin sentence. To evaluate whether the method is suitable for ABSA task, we compare it with conditional data augmentation methods on BERT-SPC. The results shown in Figure 4 show that our approach makes big steps forward. This indicates that aspect information gives both insider knowledge about the specific aspect and outsider knowledge from LLMs. Moreover, we can find other methods that may not be suitable in ABSA because they may strip away vital information or introduce irrelevant words. More discussions about aspect information are placed in Appendix B.

Case Examples	BERT-SPC	DualGCN	AIECL
Sentence: Two complaints - their appetizer selection stinks , it would be nice to get some mozzarella sticks on the menu. **Aspects**: appetizer selection (Neg); mozzarella sticks (Neu); menu (Neg)	Neg/Pos/Pos ✓ ✗ ✗	Neg/Pos/Pos ✓ ✗ ✗	Neg/Neu/Neg ✓ ✓ ✓
Sentence: A mix of students and area residents crowd into this narrow, barely there space for its quick, tasty treats at dirt-cheap prices. **Aspect:** space (Neg); prices (Pos)	Neu/Pos ✗ ✓	Neg/Pos ✓ ✓	Neg/Pos ✓ ✓
Sentence: After really enjoying ourselves at the bar we sat down at a table and had dinner. **Aspect**: bar (Pos); table (Neu); dinner (Neu)	Pos/Pos/Pos ✓ ✗ ✗	Pos/Pos/Neu ✓ ✗ ✓	Pos/Neu/Neu ✓ ✓ ✓

Table 4: Case study of our AIECL compared with BERT-SPC and DualGCN. The colored words in brackets represent the ground truth sentiment polarity of the corresponding aspects. We denote positive, neutral and negative sentiment as Pos, Neu and Neg, respectively.

Analysis on Contrastive Learning. We visualize similarity scores of samples from a batch with and without CL. As illustrated in Figure 5, our approach models correlations between samples, making the similarity scores explicitly stratified by sentiment polarity. In addition, we selected a positive sample as an anchor to investigate semantic similarity scores within a batch, and the results are organized in Figure 6. It is observed that samples with higher similarity scores tend to be positive, those with lower scores tend to be neutral, and those with the lowest scores tend to be negative. Specifically, although the selected sample and the 19-th sample has the same sentence, they have low similarity scores due to the opposing polarities of their aspects *"dishes"* and *"menu"*, which verifies the semantic features are aspect-oriented.

4.7 Case Study

To evaluate whether AIECL is able to address sentences with multiple aspects, we conducted case study with a few samples. As illustrated in Table 4, we compare our AIECL with BERT-SPC and DualGCN. Specifically, BERT-SPC fails to filter out irrelevant words. For instance, BERT-SPC incorrectly attaches the words "*narrow*", "*quick*", and "*tasty*" to aspect "*space*" in the second sentence, leading to an inaccurate prediction. While DualGCN attempts to mitigate this issue by leveraging syntactic information, it struggles with sentences that contain limited useful dependency connections. For instance, "*menu*" in the first sentence and "*table*" in the third sentence lack substantial dependency links to opinion words, resulting in erroneous predictions. However, our method effectively mitigates the interference from the irrelevant opinion words. For example, for the aspect "*space*" in the second sentence, LLMs generate "*the space is crowded and narrow*" as aspect information, which could enrich relevant words of aspect. Moreover, our contrastive learning methods enable AIECL to learn from similar negative samples, ultimately achieving the correct sentiment Negative.

4.8 Sentence Length Study

Table 5 compares the accuracy of our model and other models for sentences of different lengths in Rest14 dataset. Long sentences are often more challenging because their scarcity of contexts for certain aspects could be more serious. The results indicate that our model consistently outperforms others across all sentence lengths, with a marked superiority in addressing long sentences.

Sentence Length	< 15	15-24	25-34	>35
BERT-SPC (Song et al., 2019)	88.12	85.32	85.69	85.72
APARN (Ma et al., 2023)	89.40	87.15	86.64	86.71
Our AIECL	**91.70**	**88.42**	**89.95**	**90.35**

Table 5: Accuracy of BERT-SPC, APARN, AIECL for sentences of different lengths in Rest14.

5 Conclusion

In this paper, we propose a novel framework, AIECL for aspect-based sentiment analysis. Specifically, we leverage cutting-edge prompting techniques to stimulate LLMs to generate aspect information. Subsequently, we integrate the original sentence with the aspect information by employing a fusion and re-weighting module. Finally, we devise an unsupervised contrastive learning method to distill knowledge from LLMs and supervised methods to model semantic correlations between samples. Extensive experiments on six benchmarks demonstrate that our AIECL surpasses baselines.

Limitations

One limitation is that for simple sentences that are easy to analyze sentiment polarity, our method generates redundant aspect information that increases training time and computational cost. Another limitation is that the performance of our model is affected by the quality of outcomes produced by LLMs. The good news is that research on LLMs is continuing to make progress. In the future, our AIECL with higher-quality LLMs is expected to achieve more impressive results in ABSA.

Ethics Statement

The datasets utilized in our research are derived from publicly accessible data sources, which guarantee there are no privacy concern or violations. Furthermore, no personally identifiable information is collected, ensuring that the data conforms to legal and ethical protocols. In addition, our approach uses LLMs to generate aspect information, which is based on datasets; therefore, there will not be any negative social impacts.

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A Prompt Templates

In this section, we present prompt templates of our AIECL and give some few-shot examples for different datasets. Specifically, we provide concepts of aspect, sentiment polarity and aspect information and give our requirements to LLMs. The prompts on Lap14 dataset are shown in Table 6, and some few-shot examples are listed in Table 7.

B Details on Aspect Information

Examples In summary, the aspect information derived from Large Language Models (LLMs) demonstrates a rich diversity. For certain sentences, LLMs produce outputs that closely mirror components of the original text; for others, they creatively articulate aspect-related descriptions in innovative ways. For sentences that are easily comprehensible, LLMs are typically capable of generating high-quality and precise aspect information. When faced with sentences that pose comprehension challenges, LLMs might either directly replicate the original sentence or offer aspect information that is somewhat less precise. Here are some examples of generated aspect information, and more examples of Aspect Information are presented in Table 8. :

- Sentence: Once you get past learning how to use the poorly designed Windows 8 Set-Up you may feel frustrated.
  Aspect: Windows 8 Set-Up
  Aspect Information: the windows 8 set-up is poorly designed. (Windows 8 Set-Up)

- Sentence: After really enjoying ourselves at the bar we sat down at a table and had dinner.
  Aspect: bar, table
  Aspect Information: We really enjoyed ourselves at the bar. (bar)
  We had dinner at a table. (table)

More Discussions Sentences generated by LLMs can either be portions of the original sentence or new descriptions that pertain to a specific aspect, and both types constitute aspect information. Moreover, with the prompts we have meticulously crafted, there is few hallucinations, and the generated aspect information is usually pertinent to the original texts. Our experimental results demonstrate that LLMs exhibit an advanced level of comprehension for this task, generating useful aspect information that exhibits strong correlations with the original sentences.

As ABSA is a fine-grained classification task, it is unreasonable to directly model the similarities or differences between sentences based on labels. For instance, considering the sentence "The service is good but the price is expensive", there may be two samples with identical sentences but focusing on different aspects "service" and "price", which are positive and negative, respectively. Distinguishing these two samples solely by their labels could lead to a contradiction. Our proposed aspect information addresses this issue by adding aspect insights to the original sentence, which makes semantics more fine-grained. Therefore, the correlations and knowledge between samples could be effectively explored and utilized.

Prompt Templates
You are an expert in English and sentiment analysis. According to the following sentiment elements definition: ‘‘‘ - The “aspect” refers to a specific feature, attribute, a product or other objects that the sentence may express an opinion about. - The “sentiment polarity” refers to the sentiment of positivity, negativity or neutrality expressed in the opinion towards the specific aspect. - The “aspect information” refers to the description of the specific aspect in the sentence. ’’’ In the following text, there are sentence and aspect. The sentence may have one aspect or many aspects, you should analyze the sentence and get “aspect information” of the specific aspect that I give you. You can express the aspect information in your way, but remember you can not change the “aspect” word, it is very important. Remember, the aspect may has sentiment or just be neutral in many situations, you should be careful to analyze the sentence and give “aspect information” by your comprehension. Please give me your answer in the format as the following strictly: - sentence: - aspect: - aspect information:

Table 6: Complete prompts for Lap14.

	Some few-shot examples	
Sentence	**Aspect**	**Aspect Information**
- My father uses it mostly for creation, photo editing, audio, video, and so on.	photo editing	the photo editing is used for creation.
- I need a bigger screen and a CD drive.	CD drive	the CD drive is needed.
- I am watching the tutorial to learn how to use some features of this laptop.	tutorial	the tutorial is mentioned to be watched.
- I had purchased it from a major electronics store and took it to their service department to find out what the problem was.	service department	the service department just mentioned.
- The design and atmosphere is just as good.	design	the design is excellent.
- The menu is limited but almost all of the dishes are excellent.	menu	the menu is so limited.
- their sake list was extensive , but we were looking for purple haze , which was n’t listed but made for us upon request.	sake list	the sake list is extensive.
- i tend to judge a sushi restaurant by its sea urchin , which was heavenly at sushi rose .	sea urchin	sea urchin was heavenly.
- the service varys from day to day- sometimes they ’re very nice , and sometimes not.	service	the service is very inconsistent.
- I would kill for a 1 hour sit down interview with SaBeiNing.	SaBeiNing	SaBeiNing is worth to interview.
- received my google account today!	google account	the google account is received.
- I like that movie where lindsay lohan does the twins .what’s the name of that movie?	lindsay lohan	I like lindsay lohan.
- ESPN Soccer Net News Ardiles backs Maradona for World Cup glory.	Maradona	Maradona is backed for world cup glory.
- thank you ! Bill do you have the new laptop ? what do you think about it ?	laptop	a new laptop is mentioned.

Table 7: Some few-shot examples for LLMs.

	Aspect Information	
Sentence	**Aspect**	**Aspect Information**
- The food was lousy - too sweet or too salty and the portions tiny.	portions	the portions are tiny.
- The food was excellent as well as service, however, i left the four seasons very disappointed.	service	the service was excellent.
- The food was excellent as well as service, however, i left the four seasons very disappointed.	the four seasons	the four seasons left a negative impression.
- Despite the confusing mirrors this will likely be my go - to for modern Japanese food for the foreseeable future.	mirrors	the mirrors are confusing.
- Despite the confusing mirrors this will likely be my go - to for modern Japanese food for the foreseeable future.	modern japanese food	this is likely to be the go-to for modern Japanese food.
- The wine list was extensive - though the staff did not seem knowledgeable about wine pairings.	wine list	the wine list was extensive.
- The wine list was extensive - though the staff did not seem knowledgeable about wine pairings.	staff	the staff may be not knowledgeable about wine pairing.
- Fabulous service , fantastic food , and a chilled out atmosphere and environment	atmosphere	the atmosphere is chilled out.
- Go here for a romantic dinner but not for an all out wow dining experience	dining	the dining experience is amazing.
- Half a chicken with a mountain of rice and beans for $6.25.	rice	a mountain of rice is served with half a chicken.
- I would highly recommand requesting a table by the window.	table by the window	requesting a table by the window is highly recommended.
- While we enjoyed the food , we were highly disappointed by the poor service waiter was not quite competent and slow service and lack of remorse.	waiter	the waiter is not competent and the service is slow.
- Even with virus protection , it always turned off when updates were needed and installed .	updates	the updates are not good.
- first it took us a long time to find the place.	place	to find the place took a long time.
- the pizza is delicious - they use fresh mozzarella instead of the cheap , frozen , shredded cheese common to most pizzaria's.	fresh mozzarella	they use fresh mozzarella instead of the cheap, frozen, shredded cheese common to most pizzeria's.
- the service was the only thing good about this restaurant.	service	the service was good.
- the hanger steak was like rubber and the tuna was flavorless not to mention it tasted like it had just been thawed.	tuna	the tuna was flavorless and tasted like it had just been thawed.
- love the enchiladas and chicken soup - and be sure to check out their specials.	specials	the specials are recommended.
- there was a really nice vibe about the place ... good music , atmosphere and happy looking people.	music	the music has a nice vibe.
- The battery life is probably an hour at best.	battery life	the battery life is very short.
- love selena gomez !!!! she rock !!!!!!!!!!!!!!!! and she 's cool she 's my idol.	selena gomez	I love selena gomez.
- back in love with my psp! thanks rockstar !!!	psp	I love my psp again.
- My dining companion and I have nothing but raves about the environment and the food.	food	the food is highly praised.
- We hunted the waitress to at least pay for the drinks.	drinks	the drinks were consumed.
- It just works out of the box and you have a lot of cool software included with the OS .	software	the software included with the OS is cool.
- It is so simple to use , I use it more than my desktop.	use	the use is easy and frequent.

Table 8: Some examples of generated Aspect Information.