# Refine, Align, and Aggregate: Multi-view Linguistic Features Enhancement for Aspect Sentiment Triplet Extraction

**Anonymous ACL submission**


## Abstract

*Aspect Sentiment Triplet Extraction* (ASTE) aims to extract the triplets of aspect terms, their associated sentiment and opinion terms. Previous works based on different modeling paradigms have achieved promising results. However, these methods struggle to comprehensively explore the various specific relations between sentiment elements in multi-view linguistic features, which is the prior indication effect for facilitating sentiment triplets extraction, requiring to align and aggregate them to capture the complementary higher-order interactions. In this paper, we propose ***M**ulti-**v**iew **L**inguistic **F**eatures **E**nhancement* (MvLFE) to explore the aforementioned prior indication effect in the "*Refine, Align, and Aggregate*" learning process. Specifically, we first introduce the *relational graph attention network* to encode the word-pair relations represented by each linguistic feature and refine them to pay more attention to the aspect-opinion pairs. Next, we employ the *multi-view contrastive learning* to align them at a fine-grained level in the contextual semantic space to maintain semantic consistency. Finally, we utilize the *multi-semantic cross attention* to capture and aggregate the complementary higher-order interactions between diverse linguistic features to enhance the aspect-opinion relations. Experimental results on several benchmark datasets show the effectiveness and robustness of our model, which achieves state-of-the-art performance.


## 1 Introduction

*Aspect Sentiment Triplet Extraction* (ASTE) is a new variant of *Aspect-Based Sentiment Analysis* (ABSA) (Pontiki et al., 2014), which is an information extraction style task to identify all sentiment triplets from a review to explain WHAT the targeted aspects are, HOW their sentiment polarities are and WHY they have such polarities (i.e., opinion terms). A sentence with triplets marking in Figure 1 illustrates the definition of the ASTE task.

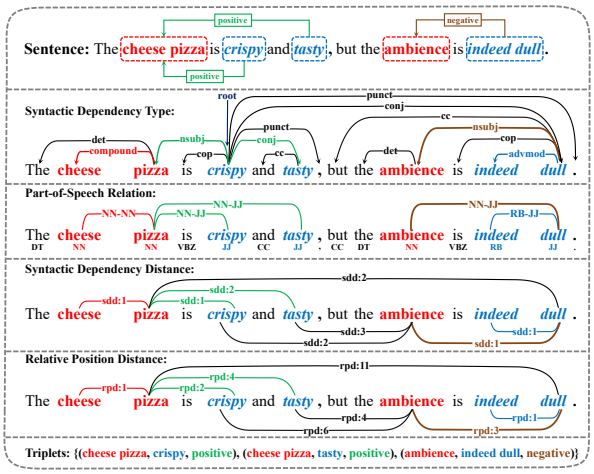


Figure 1: The prior indication effect of multi-view linguistic features for ASTE. It reveals various specific relations between matched aspect and opinion terms, also within the terms themselves in different views of linguistic features, which facilitate the extraction of sentiment triplets from input sentences. In the above triplet set, aspect and opinion terms are marked in red and blue, with *positive* sentiment in green and *negative* in brown. "*sdd/rpd:n*" denotes distance between two words is *n*.

Early work adopts the straightforward solution to decompose the ASTE task into several ABSA subtasks to separately extract sentiment elements of triplets with a two-stage pipeline approach (Peng et al., 2020). To exploit the association among multiple subtasks, Mao et al. (2021); Chen et al. (2021a); Liu et al. (2022) transform the ASTE task into the machine reading comprehension (MRC) paradigm with diverse task-specific queries, which jointly train multiple subtasks but pipeline inference. Obviously, these methods potentially lead to the well-known error propagation problem.

To alleviate this problem, most of recent studies focus on jointly extracting the sentiment triplets in an end-to-end fashion (Xu et al., 2020, 2021; Chen et al., 2022b; Yu et al., 2023). Some efforts formulate the ASTE task as a text generation problem to generate the sentiment triplets in one shot (Yan et al., 2021; Gao et al., 2022; Gou et al., 2023).

However, these approaches are constrained in capturing reciprocity among the sentiment elements.

Therefore, Jing et al. (2021); Zhang et al. (2022); Liang et al. (2023) construct the word-pair relations by designing a novel grid tagging scheme (Wu et al., 2020a) to capture such association. Chen et al. (2021b); Fei et al. (2022); Chen et al. (2022a) further leverage the syntax dependency or additional linguistic features to enrich the word-pair representations. Nevertheless, these methods only concatenate the linguistic features and the contextual features at a shallow level, which neglect to align and aggregate them to capture the complementary higher-order interactions. Consequently, they fail to exploit the prior indication effect of multi-view linguistic features for ASTE.

Naturally, two questions arise regarding the prior indication effect by our observations.

**Q1: What is the prior indication effect for ASTE?** We interpret it as there exist various specific relations between matched aspect-opinion pairs, also within aspect or opinion terms themselves in different views of linguistic features, which facilitate the sentiment triplets extraction. Take Figure 1 as an example. First, in the view of **syntactic dependency type**, we observe that the aspect term is the nominal subject of the opinion term due to the *"nsubj"* type. Besides, *"cheese"* and *"pizza"* comprise an aspect term by the *"compound"* type, while *"indeed"* is the adverbial modifier of *"dull"* so they combine as an opinion term. Thus, these dependency types facilitate not only the extraction of aspect and opinion terms but also their pairing. Second, in the view of **part-of-speech relation**, we find that aspect terms are nouns while opinion terms are adjectives. Hence, the word pair with the *"NN-JJ"* part-of-speech combination tends to form an aspect-opinion pair. In addition, we notice that the matched aspect and opinion terms are closer in terms of the **distance of syntactic dependency and relative position**.

**Q2: How to effectively exploit the prior indication effect to help ASTE?** We argue that exploring it requires the "*Refine, Align, and Aggregate*" learning process. First, there exist numerous irrelevant word-pair relations represented by multi-view linguistic features to ASTE (e.g., relations between commas and other words). Therefore, we need to refine the multi-view linguistic features to focus on the relations of the matched aspect-opinion pairs. Second, different views of linguistic features represent various relation types for the same aspect-opinion pairs, so they require to be aligned to maintain semantic consistency. Finally, since the prior indication effect of a single linguistic feature is one-sided for ASTE, it is crucial to capture and aggregate the complementary higher-order interactions between diverse linguistic features to enhance the aspect-opinion relations.

Motivated by the above observations, we propose ***M**ulti-**v**iew **L**inguistic **F**eatures **E**nhancement* (MvLFE) to explore the prior indication effect to enhance the word-pair relations. Firstly, we introduce the *relational graph attention network* to encode the word-pair relations represented by each linguistic feature as multi-channel edge features, which are normalized as doubly stochastic matrices to facilitate the aggregation and updating of word nodes, preventing over-smoothing across multi-layer learning. Moreover, edge features are updated by the edge refining strategy which considers the implicit results of aspect and opinion terms extraction to support their matching. Secondly, inspired by Image-Text Matching for cross-modal alignment (Lee et al., 2018; Diao et al., 2021; Pan et al., 2023), we employ the *multi-view contrastive learning* to align diverse aspect-opinion relations represented by different linguistic features in the semantic space which obtained by the biaffine transformation of contexts to maintain semantic consistency. Finally, we utilize the *multi-semantic cross attention* to aggregate the complementary higher-order interactions between diverse linguistic features to enhance aspect-opinion relations.

In summary, the key contributions are as follows:

- We propose a novel MvLFE model that effectively exploits the prior indication effect of multi-view linguistic features in the "*Refine, Align, and Aggregate*" learning process.
- We present the *relational graph attention network* to refine the relation-aware word-pair representations of multi-view linguistic features to attend the aspect-opinion pairs.
- We employ the *multi-view contrastive learning* and the *multi-semantic cross attention* to align and aggregate diverse linguistic features to enhance the aspect-opinion relations.

## 2 Related Works

*Aspect-Based Sentiment Analysis* (ABSA) (Pontiki et al., 2014) has received wide attention in recent years. Early works focus on identifying the

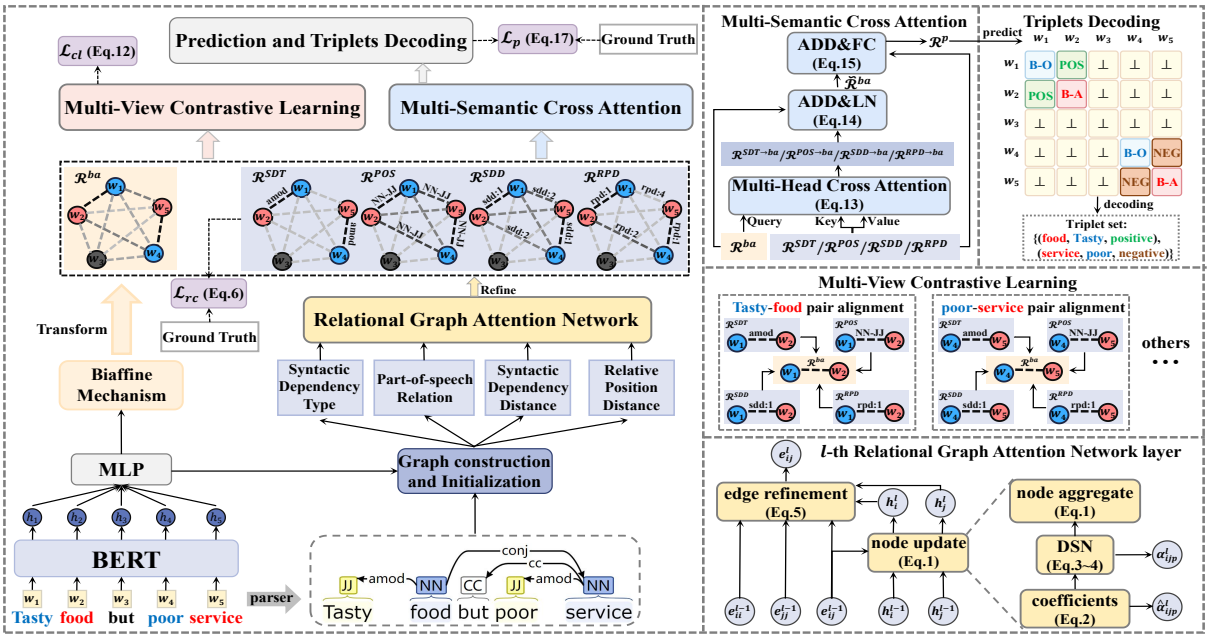


Figure 2: The overall architecture of our MvLFE model.

single sentiment element, i.e., *Aspect Term Extraction* (ATE) (Ma et al., 2019; Li et al., 2020; Wang et al., 2021), *Opinion Term Extraction* (OTE) (Dai and Song, 2019; Fan et al., 2019; Wu et al., 2020b) and *Aspect Sentiment Classification* (ASC) (Tang et al., 2022; Ma et al., 2023; Zhang et al., 2023). To further explore the interactions among sentiment elements, some efforts are devoted to coupling the individual subtasks, i.e., *Aspect-Opinion Pair Extraction* (AOPE) (Zhao et al., 2020; Chen et al., 2020b; Gao et al., 2021) and *Aspect Extraction and Sentiment Classification* (AESC) (He et al., 2019; Chen and Qian, 2020).

Based on their works, Peng et al. (2020) introduces the more challenging ASTE task to present a near-complete solution for ABSA. Subsequent works address ASTE task by different modeling paradigms: Sequence tagging (Xu et al., 2020; Zhang et al., 2020), Grid tagging (also known as table-filling) (Wu et al., 2020a; Chen et al., 2021b; Jing et al., 2021; Fei et al., 2022; Chen et al., 2022a; Zhao et al., 2022; Zhang et al., 2022; Liang et al., 2023), MRC-based methods with diverse task-specific queries (Mao et al., 2021; Chen et al., 2021a; Liu et al., 2022; Zhai et al., 2022) and Generative methods (Yan et al., 2021; Zhang et al., 2021; Gao et al., 2022; Mao et al., 2022; Lv et al., 2023; Mukherjee et al., 2023; Gou et al., 2023). However, these approaches generally ignore the prior indication effect of multi-view linguistic features for ASTE, which facilitates the triplet extraction.

## 3 Methodology

In this section, we first introduce the task definition and the adopted tagging scheme. Then we elaborate on the details of our MvLFE model and the training objective. The overall architecture is illustrated in Figure 2.

### 3.1 Task Definition and Tagging Scheme

Given an input sentence $X = \{w_1, w_2, \cdots, w_n\}$ with $n$ words, the objective of the ASTE task is to extract a sentiment triplets set $\mathcal{T} = \{(a, o, s)_k\}_{k=1}^{|\mathcal{T}|}$ from sentence $X$, where triplet $(a, o, s)$ refers to (*aspect term, opinion term, sentiment polarity*) and $s \in \{Positive, Neutral, Negative\}$.

Following by Grid Tagging Scheme (Wu et al., 2020a), we formulate the ASTE task as a unified tagging task by labeling the relations of all word pairs. Take Figure 3 as an example, the left side shows the tagging results for the sentence, while the right side explains the meaning of all tags of word-pair relations we used for ASTE. Specifically, we utilize tags {B-A, I-A, B-O, I-O} to determine the beginning and inside of aspect and opinion terms in the main diagonal of the grid. And we employ tags {A, O} to combine two words that belong to the same aspect term or opinion term in the non-diagonal region of the grid. Meanwhile, the sentiment tags {POS, NEU, NEG} are used not only to match the valid aspect-opinion pairs but also to judge their sentiment polarities.

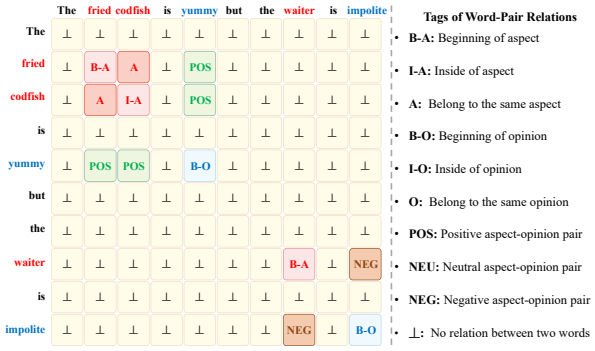


Figure 3: Grid tagging for triplet extraction in a sentence is illustrated, with each cell representing a word-pair relation. The meanings of all tags of word-pair relations are detailed on the right side.

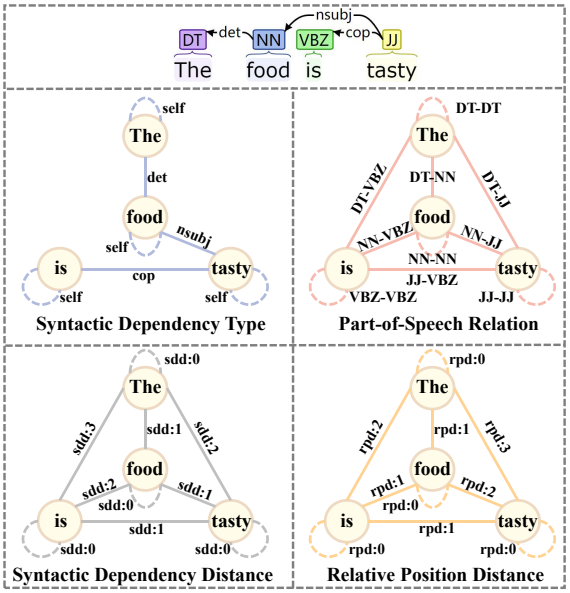


Figure 4: Word-pair relation graph construction of multi-view linguistic features. In each graph, the dashed edge is the self-loop for a word, and the solid edge is the relation between two words. "*sdd/rpd:n*" denotes the relational edge with distance *n* between two words.

### 3.2 Input and Encoding Layer

Pre-trained models have demonstrated their effectiveness in Natural Language Understanding (NLU) tasks (Qiu et al., 2020). In this work we utilize BERT (Devlin et al., 2019) as the context encoder. For a given sentence $X = \{w_1, w_2, \cdots, w_n\}$ with $n$ words, the encoding layer outputs the hidden contextual representations $\mathcal{H} = \{h_1, h_2, \cdots, h_n\}$ at the last Transformer block.

### 3.3 Relational Graph Attention Network

#### 3.3.1 Word-Pair Relation Graph Construction

Multi-view linguistic features of a sentence manifest various relations of each word pair. Therefore, it is intuitive to construct each view of linguistic feature as a word-pair relation graph.

Specifically, we utilize off-the-shelf CoreNLP toolkit (Manning et al., 2014) to parse sentences to obtain the different views of linguistic features for word-pair relations, including syntactic dependency type, part-of-speech relation, syntactic dependency distance and relative position distance. For each linguistic feature, we construct it as an undirected heterogeneous graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where $\mathcal{V}$ and $\mathcal{E}$ are sets of nodes and edges. Each word in the sentence is regarded as a node, while word-pair relations represented by the linguistic feature are considered edges. Figure 4 illustrates an example of the word-pair relation graph construction for multi-view linguistic features. For syntactic dependency type, we add a "*self*" dependency type to represent self-loop edge for each word node. For part-of-speech relation, we combine the part-of-speech tags as word-pair relation between two words. Besides, we further consider the distances between two words within the syntactic dependency tree and the sentence sequence as word-pair relations respectively. We initialize the node features with the hidden contextual representations of words and maintain different trainable embedding look-up tables to represent the edge features of various word-pair relation graphs.

#### 3.3.2 Linguistic Features Refinement

Next, we introduce *relational graph attention network* (RGAT) to refine the word-pair relations represented by each linguistic feature, denoise the irrelevant word-pair relations to the ASTE and pay more attention to the valid aspect-opinion pairs.

Specifically, for each word-pair relation graph constructed by diverse linguistic features, we denote the node features of $w_i$ and $w_j$ as $h_i \in \mathbb{R}^{d_h}$ and $h_j \in \mathbb{R}^{d_h}$ respectively, where $d_h$ is the dimension of hidden contextual representation. And $e_{ij} \in \mathbb{R}^P$ is defined as the relational edge feature represented by the word-pair ($w_i$,$w_j$), where $P$ signifies the channels of edge feature to quantify the association degree of the word-pair relation to each pre-defined tag. Features of each node will be updated by aggregating the features of neighboring nodes and simultaneously incorporating the corresponding edge features. The operation at the $l$-th RGAT layer is defined as follows:

$$h_i^l = \mathop{\Big\|}_{p=1}^{P} \sigma\Big(\sum\nolimits_{j=1}^{n} \alpha_{ijp}^l W^l h_j^{l-1}\Big) \qquad (1)$$

where $\|$ denotes the concatenation operator, $\sigma$ is the ELU activation function, and $W^l$ is the weight matrix for the linear transformation of the inputs at the $l$-th layer. Notably, $\alpha^l_{ijp}$ denotes the attention coefficients between word nodes $h^{l-1}_i$ and $h^{l-1}_j$ on the $p$-th channel of edge features. For a specific channel of edge features, the attention function is calculated by:

$$\hat{\alpha}^l_{ijp} = \exp\left\{L(a^T[W^l h^{l-1}_i || W^l h^{l-1}_j])\right\} e^{l-1}_{ijp} \quad (2)$$

$$\alpha^l_{ijp} = \mathrm{DSN}(\hat{\alpha}^l_{ijp}) \quad (3)$$

where $L$ is the LeakyReLU activation function, and $a^T \in \mathbb{R}^{2d_h}$ denotes the weight vector. DSN is the doubly stochastic normalization formulated as:

$$\tilde{\alpha}^l_{ijp} = \frac{\hat{\alpha}^l_{ijp}}{\Sigma^n_{t=1}\hat{\alpha}^l_{itp}}, \quad \alpha^l_{ijp} = \sum_{t=1}^{n} \frac{\tilde{\alpha}^l_{itp}\tilde{\alpha}^l_{jtp}}{\Sigma^n_{s=1}\tilde{\alpha}^l_{stp}} \quad (4)$$

Unlike the row normalization used in vanilla graph attention network (Velickovic et al., 2018), DSN normalizes the attention coefficients guided by edge features into the doubly stochastic matrices, which possess properties of symmetric, positive semi-definite and the largest eigenvalue 1. These properties contribute to preventing the edge matrix from exploding or shrinking to zero to stabilize the diffusion process, also mitigating the over-smoothing problem across multi-layer RGAT learning (Wang et al., 2018; Chen et al., 2020a).

Subsequently, we update edge features using an edge refining strategy, leveraging the implicit results of aspect and opinion term extraction to refine word-pair relation representations. For example, if $w_i$ is an aspect term and $w_j$ an opinion term, their pair ($w_i$,$w_j$) is more likely to denote a sentiment relation. The strategy is represented as:

$$e^l_{ij} = f(e^{l-1}_{ij} \oplus e^{l-1}_{ii} \oplus e^{l-1}_{jj} \oplus h^l_i \oplus h^l_j) \quad (5)$$

where $f$ is the multi-layer perceptron with softplus activation function, and $\oplus$ denotes concatenation.

#### 3.3.3 Relation Constraint

In order to more precisely steer RGAT to refine the word-pair relations, at the last layer, we conduct constraint on the refined word-pair relations $\mathcal{R}^v = \{r^v_{11}, r^v_{12}, \cdots, r^v_{nn}\}$ represented by each linguistic feature:

$$\mathcal{L}_{rc} = -\sum_{v\in V}\sum_{i}^{n}\sum_{j}^{n}\sum_{c\in\mathcal{C}} \mathbb{I}(y_{ij} = c)\log(r^v_{ij|c}) \quad (6)$$

where $V$ denotes multi-view linguistic features, $\mathbb{I}(\cdot)$ is the indicator function, $y_{ij}$ is the ground truth of word pair ($w_i$,$w_j$), and $\mathcal{C}$ signifies pre-defined tags.

### 3.4 Multi-View Contrastive Learning

Although different views of linguistic features represent various relation types for the same word pairs, they typically harbor analogous semantic implications, such as jointly reflecting the matching of aspect and opinion terms or the composition of sentiment terms. To ensure that multi-view linguistic features complement and reinforce each other at semantic level, it is vital to align them into the shared semantic space to maintain semantic consistency.

Specifically, we utilize the biaffine mechanism to transform the hidden contextual representations $\mathcal{H}$ to construct the semantic space $\mathcal{R}^{ba} = \{r^{ba}_{11}, r^{ba}_{12}, \cdots, r^{ba}_{nn}\}$ for word-pair relations, due to its proven expressive power in modeling the complex semantics between words (Dozat and Manning, 2017). The process is formulated as:

$$r^{ba}_{ij} = h^{\mathrm{T}}_i U_1 h_j + (h_i \oplus h_j)^{\mathrm{T}} U_2 + b \quad (7)$$

where $r^{ba}_{ij} \in \mathbb{R}^P$ denotes semantic features of the word pair ($w_i$,$w_j$) with $P$ dimensions. $U_1$, $U_2$ and $b$ are trainable weights and bias.

Inspired by Image-Text Matching for aligning text words and image regions at a fine-grained level (Lee et al., 2018; Diao et al., 2021; Pan et al., 2023), we project each linguistic feature into the semantic space and align them at the level of word-pair relations. First, we compute the cosine similarity matrix for all word pairs between each linguistic feature $\mathcal{R}^v$ and semantic feature $\mathcal{R}^{ba}$, i.e.,

$$s^v_{ijk} = \frac{(r^v_{ij})^T r^{ba}_{ik}}{||r^v_{ij}||||r^{ba}_{ik}||}, \quad i,j,k \in [1,n] \quad (8)$$

where $s^v_{ijk}$ denotes the similarity between word pair ($w_i$,$w_j$) in linguistic feature and word pair ($w_i$,$w_k$) in semantic feature. Then we integrate the attended semantic feature to obtain the projection of the linguistic feature in the semantic space:

$$a^v_{ij} = \sum_{k=1}^{n} \frac{exp(s^v_{ijk}/\tau)}{\sum^n_{m=1} exp(s^v_{ijm}/\tau)} r^{ba}_{ik} \quad (9)$$

where $\tau$ is the temperature hyperparameter.

Subsequently, we further calculate the cosine similarity between each word pair relation represented by the linguistic feature and its projection in the semantic space to measure the degree of alignment between them, i.e.,

$$\mathcal{Q}(r^v_{ij}, a^v_{ij}) = \frac{(r^v_{ij})^T a^v_{ij}}{||r^v_{ij}||||a^v_{ij}||} \quad (10)$$

Finally, we evaluate the overall degree of alignment of the linguistic feature in the semantic space

by LogSumExp pooling, i.e.,

$$\mathcal{S}(\mathcal{R}^v, \mathcal{R}^{ba}) = \frac{1}{\lambda} \log \sum_{i=1}^{n} \exp(\lambda \mathcal{Q}(r_{ij}^v, a_{ij}^v)) \quad (11)$$

where $\lambda$ is the scaling factor.

We align multi-view linguistic features into the shared semantic space as described above and minimize the hinge-based triplet loss with margin $\gamma$ as the alignment objective, i.e.,

$$\mathcal{L}_{cl} = \sum_{v \in V} [\gamma - \mathcal{S}(\mathcal{R}^v, \mathcal{R}^{ba}) + \mathcal{S}(\mathcal{R}^v, \hat{\mathcal{R}}^{ba})]_+ \quad (12)$$

where $[x]_+ \equiv max(x, 0)$. We select the linguistic feature $\mathcal{R}^v$ and semantic feature $\mathcal{R}^{ba}$ of the same sentence as the positive pair, and take the semantic feature $\hat{\mathcal{R}}^{ba}$ of other sentences within a mini-batch as negative pairs with linguistic feature $\mathcal{R}^v$. In this study, we focus on the hardest negative pair in a mini-batch following by Faghri et al. (2017), which is given by $\hat{\mathcal{R}}^{ba} = argmax_{d \neq \mathcal{R}^{ba}} \mathcal{S}(\mathcal{R}^v, d)$.

### 3.5 Multi-Semantic Cross Attention

Since the prior indication effect of a single linguistic feature is one-sided for ASTE, such as the noun-adjective part-of-speech combination commonly observed in matched or invalid aspect-opinion pairs, it is necessary to capture and aggregate the complementary higher-order interactions between diverse linguistic features to comprehensively enhance representations of word-pair relations.

Specifically, we employ multi-head cross attention (Vaswani et al., 2017) to capture the unique semantic representations of each linguistic feature. For the $h$-th attention head, we take $\mathcal{R}_h^Q = W_h^Q \mathcal{R}^{ba}$, $\mathcal{R}_h^K = W_h^K \mathcal{R}^v$ and $\mathcal{R}_h^{Va} = W_h^{Va} \mathcal{R}^v$ as query, key and value. The process is defined as:

$$\mathcal{R}^{v \to ba} = \mathop{\Big\|}_{h=1}^{H} softmax\left(\frac{\mathcal{R}_h^Q (\mathcal{R}_h^K)^T}{\sqrt{d_k}}\right) \mathcal{R}_h^{Va} \quad (13)$$

where $d_k$ is the dimension of key. Then we adopt residual connection and layer normalization to aggregate the semantic feature $\mathcal{R}^{ba}$ and each view's unique semantic representations $\mathcal{R}^{v \to ba}$, i.e.,

$$\tilde{\mathcal{R}}^{ba} = LayerNorm(\mathcal{R}^{ba} + \sum_{v \in V} \mathcal{R}^{v \to ba}) \quad (14)$$

Finally, we obtain the enhanced representations of word-pair relations $\mathcal{R}^p = \{r_{11}^p, r_{12}^p, \cdots, r_{nn}^p\}$ as logits for prediction by:

$$\mathcal{R}^p = f_p(\tilde{\mathcal{R}}^{ba} + \sum_{v \in V} \mathcal{R}^v) \quad (15)$$

where $f_p$ is the fully connected network.

### 3.6 Training Objective

Our objective is to minimize the training loss as:

$$\mathcal{L} = \mathcal{L}_p + \beta \mathcal{L}_{rc} + \mu \mathcal{L}_{cl} \quad (16)$$

where hyperparameters $\beta$ and $\mu$ are for adjusting the impact of corresponding relation constraint loss and contrastive learning loss. The standard cross-entropy loss $\mathcal{L}_p$ is used for the ASTE task, i.e.,

$$\mathcal{L}_p = -\sum_{i}^{n} \sum_{j}^{n} \sum_{c \in \mathcal{C}} \mathbb{I}(y_{ij} = c) \log(r_{ij|c}^p) \quad (17)$$

The triplets decoding is detailed in Appendix A.1.

## 4 Experiments

### 4.1 Datasets

We evaluate our proposed MvLFE model on four benchmark ASTE datasets (**ASTE-Data-V2**[1]) released by Xu et al. (2020), which is a refined version of the **ASTE-Data-V1** (Peng et al., 2020) to consider cases where one opinion is associated with multiple aspects. Those datasets are derived from Pontiki et al. (2014, 2015, 2016) with one in the laptop domain and three in the restaurant domain. Detailed statistics are shown in Appendix A.2.

### 4.2 Baselines

We compare our MvLFE model with the following four types of previous state-of-the-art methods: **1) Sequence tagging:** Peng-two-stage (Peng et al., 2020), OTE-MTL (Zhang et al., 2020) and JET (Xu et al., 2020). **2) Grid tagging:** GTS-BERT (Wu et al., 2020a), EMC-GCN (Chen et al., 2022a) and STAGE-3D (Liang et al., 2023). **3) MRC-based:** BMRC (Chen et al., 2021a), COM-MRC (Zhai et al., 2022) and RoBMRC (Liu et al., 2022). **4) Generative:** BARTABSA (Yan et al., 2021), LEGO-ABSA (Gao et al., 2022), EHG-Para (Lv et al., 2023) and CONTRASTE (Mukherjee et al., 2023). In addition, we investigate how well can ChatGPT (OpenAI, 2023) solve ASTE task with diverse experimental settings. More details are shown in Appendix B.

### 4.3 Implementation Details

We adopt the `bert-base-uncased`[2] as the sentence encoder. RGAT is stacked in 3 layers with 300 dimensions of nodes and 10 channels of edges. The hyperparameters $\tau$, $\lambda$ and $\gamma$ of multi-view contrastive learning module are set to 0.05, 6 and 0.2.

[1] https://github.com/xuuuluuu/SemEval-Triplet-data
[2] https://github.com/huggingface/transformers

| Category | Model | Res14 | | | Lap14 | | | Res15 | | | Res16 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | P | R | F1 | P | R | F1 | P | R | F1 | P | R | F1 |
| **Seq tagging** | Peng-tow-stage♯ | 43.24 | 63.66 | 51.46 | 37.38 | 50.38 | 42.87 | 48.07 | 57.51 | 52.32 | 46.96 | 64.24 | 54.21 |
| | OTE-MTL♮ | 62.00 | 55.97 | 58.71 | 49.53 | 39.22 | 43.42 | 56.37 | 40.94 | 47.13 | 62.88 | 52.10 | 56.96 |
| | JET-BERT | 70.56 | 55.94 | 62.40 | 55.39 | 47.33 | 51.04 | 64.45 | 51.96 | 57.53 | 70.42 | 58.37 | 63.83 |
| **Grid tagging** | GTS-BERT♮ | 68.09 | 69.54 | 68.81 | 59.40 | 51.94 | 55.42 | 59.28 | 57.93 | 58.60 | 68.32 | 66.86 | 67.58 |
| | EMC-GCN | 71.21 | 72.39 | 71.78 | 61.70 | 56.26 | 58.81 | 61.54 | 62.47 | 61.93 | 65.62 | 71.30 | 68.33 |
| | STAGE-3D | **78.58** | 69.58 | 73.76 | **71.98** | 53.86 | 61.58 | **73.63** | 57.90 | 64.79 | 76.67 | 70.12 | 73.24 |
| **MRC-based** | BMRC♮ | 75.61 | 61.77 | 67.99 | 70.55 | 48.98 | 57.82 | 68.51 | 53.40 | 60.02 | 71.20 | 61.08 | 65.75 |
| | COM-MRC | 75.46 | 68.91 | 72.01 | 62.35 | 58.16 | 60.17 | 68.35 | 61.24 | 64.53 | 71.55 | 71.59 | 71.57 |
| | RoBMRC | 72.51 | 72.73 | 72.62 | 68.13 | 57.09 | 62.12 | 65.90 | 65.36 | 65.63 | 69.98 | **76.65** | 73.16 |
| **Generative** | ChatGPT† | 47.18 | 53.62 | 50.19 | 34.22 | 47.91 | 39.92 | 42.83 | 57.94 | 49.25 | 43.75 | 57.09 | 49.54 |
| | BARTABSA | 65.52 | 64.99 | 65.25 | 61.41 | 56.19 | 58.69 | 61.54 | 62.47 | 61.93 | 65.62 | 71.30 | 68.33 |
| | LEGO-ABSA | - | - | 73.70 | - | - | 62.20 | - | - | 64.40 | - | - | 69.90 |
| | EHG-Para | - | - | 71.82 | - | - | 61.53 | - | - | 63.58 | - | - | 72.35 |
| | CONTRASTE | 73.60 | 74.40 | 74.00 | 64.20 | 61.70 | 62.90 | 65.30 | **66.70** | 66.10 | 72.20 | 76.30 | 74.20 |
| **Ours** | **MvLFE** | 76.37 | **74.46** | **75.40** | 66.12 | **62.33** | **64.17** | 69.97 | 64.14 | **66.93** | **77.02** | 73.41 | **75.17** |

Table 1: Experimental results on ASTE-Data-V2 dataset (Xu et al., 2020). The best results are in **bold** and the second best are underlined. The "♯" and "♮" mean that results are retrieved from Xu et al. (2020) and Chen et al. (2022a). The "†" denotes that ChatGPT results are obtained using 5-shot In Context Learning prompts with multi-view linguistic features by our setting. Other baseline results are derived from original papers.

For the joint training loss, the ratios $\beta$ and $\mu$ are set to 0.01 and 0.1. During training, AdamW optimizer (Loshchilov and Hutter, 2017) is used with a learning rate of 2e-5 for BERT fine-tuning and 1e-3 for the other trainable parameters. The model is trained for 100 epochs with dropout rate of 0.5 and batch size of 16. For each dataset, we select the model with the best F1 scores on the development set and report the average results of five runs with different random seeds. More details about the selection of hyperparameters and sensitivity analysis are shown in Appendix A.3. **Our code and data will be made publicly available**.

| Task | Model | Res14 | Lap14 | Res15 | Res16 |
|---|---|---|---|---|---|
| **ATE** | GTS-BERT | 82.76 | 80.44 | 78.27 | 81.13 |
| | EMC-GCN | 84.68 | 81.67 | 77.62 | 80.57 |
| | STAGE-3D | 84.99 | 82.62 | 81.21 | 83.86 |
| | **MvLFE** | **86.84** | **84.71** | **83.44** | **87.46** |
| **OTE** | GTS-BERT | 84.85 | 77.82 | 77.53 | 84.36 |
| | EMC-GCN | 85.62 | 78.85 | 78.97 | 85.33 |
| | STAGE-3D | 85.70 | 80.39 | 80.03 | 85.72 |
| | **MvLFE** | **87.56** | **82.63** | **81.97** | **88.03** |
| **AOPE** | GTS-BERT | 74.63 | 66.46 | 67.52 | 74.20 |
| | EMC-GCN | 76.33 | 67.94 | 67.26 | 74.15 |
| | STAGE-3D | 77.87 | 69.70 | 70.60 | 79.98 |
| | **MvLFE** | **79.86** | **71.57** | **73.61** | **82.17** |

Table 2: Test F1 scores on ATE, OTE and AOPE tasks. The baseline results are derived from Liang et al. (2023).

### 4.4 Main Results

The main results are reported in Table 1. Overall, our MvLFE model outperforms all baselines under the F1 metric and achieves superior precision and recall in most cases. The specific observations are that: (1) Methods based on other modeling paradigms outperform sequence tagging models, as the former considers the situation where one aspect or opinion term is associated with multiple opinion or aspect terms. (2) Compared with RoBMRC, MvLFE significantly improves F1 scores by 2.04% on average, overcoming the error propagation problem from pipeline inference in MRC-based models. (3) Our MvLFE model exceeds generative methods by an average of 1.18%~6.96% F1 scores, as the latter overlooks the reciprocity among the sentiment elements. Additionally, experiments on ChatGPT (see more details in Appendix B) reveal its limited ability to capture complex associations between multiple aspect and opinion terms. (4) Our MvLFE also modeled on grid tagging surpasses GTS-BERT and STAGE-3D by an average of 7.82% and 2.08% F1 scores, as it explores the prior indication effect of multi-view linguistic features for ASTE. Note that MvLFE outperforms EMC-GCN by large margins, while EMC-GCN also considers diverse linguistic features. We reckon MvLFE can capture the multi-hop interactions between matched aspect and opinion terms and focus on them with multi-layer RGAT but EMC-GCN only considers the one-hop association using a single layer GCN. Furthermore, different from EMC-GCN simply concatenates multi-view linguistic features, MvLFE employs multi-view contrastive learning and multi-semantic cross attention to align and aggregate them to maintain semantic consistency and capture the complementary higher-order interactions. More experiments and analyses are shown in Appendix A.3.

| Model | Res14 | Lap14 | Res15 | Res16 |
|---|---|---|---|---|
| MvLFE | **75.40** | **64.17** | **66.93** | **75.17** |
| w/o RGAT | 74.16 | 62.86 | 65.49 | 73.81 |
| w/o MVCL | 74.39 | 62.98 | 65.67 | 73.94 |
| w/o MSCA | 74.81 | 63.52 | 66.21 | 74.53 |
| w/o RC | 75.13 | 63.92 | 66.71 | 74.96 |

Table 3: Ablation study (average F1 reported).

### 4.5 Experiments on subtasks

To further demonstrate the effectiveness of our MvLFE model, we compare it with three state-of-the-art grid tagging baselines on ATE, OTE and AOPE subtasks. The results are shown in Table 2. Note that our method can directly address these subtasks without additional modifications. Specifically, we observe that our MvLFE model achieves significant improvements over baselines on ATE and OTE task, which suggests that MvLFE can effectively explore the prior indication effect of multi-view linguistic features to extract the aspect and opinion terms. In addition, our MvLFE model also exceeds the compared models by a large margin on AOPE task. It further proves that MvLFE can capture reciprocity among the sentiment elements not only for extraction of aspect and opinion terms but also for matching the valid aspect-opinion pairs.

### 4.6 Ablation Study

To verify the rationality of our MvLFE, we conduct an ablation study as shown in Table 3. Specifically, **w/o RGAT** denotes we directly use the initialized multi-view linguistic features for semantic alignment and feature fusion, which slightly decreases F1 scores by 1.34% on average, suggesting RGAT can refine multi-view linguistic features to attend matched aspect-opinion pairs. **w/o MVCL** means we remove *multi-view contrastive learning* for semantic alignment of multi-view linguistic features, resulting in an average decline of 1.17% on F1 scores, which shows MVCL can align the same word pairs represented by diverse linguistic features to maintain semantic consistency. **w/o MSCA** indicates we simply concatenate multi-view linguistic features without using *multi-semantic cross attention*. Thus, it fails to aggregate the complementary higher-order interactions between diverse linguistic features and achieves the dropping performance. **w/o RC** signifies that we remove the relation constraint loss, and the degraded performance shows that it can precisely steer RGAT to refine the word-pair relations. Overall, each MvLFE module contributes to the entire performance on ASTE.

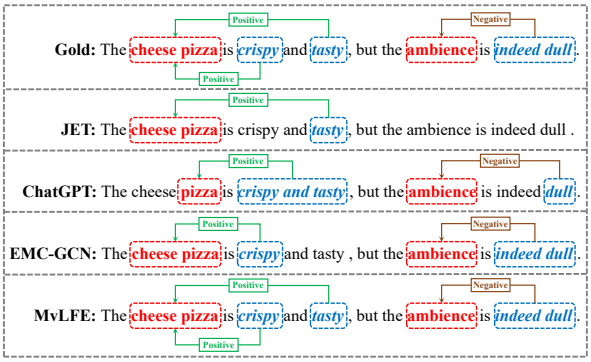


Figure 5: Case study. Aspect and opinion terms are highlighted in red and blue. The *positive* sentiment polarity is marked in green, while the *negative* in brown.

### 4.7 Case Study

A case study is given in Figure 5. Specifically, JET only extracts a triplet (*cheese pizza*, *tasty*, *positive*), as it cannot consider the one-to-many case. For ChatGPT, it struggles to extract aspect "*cheese pizza*" and opinion "*indeed dull*" that consist of multiple words. Moreover, it incorrectly combines two opinion terms "*crispy*" and "*tasty*" into a single opinion term. We reckon ChatGPT fails to understand the composition of sentiment elements and their association, even when given the appropriate prompts. For EMC-GCN, it ignores the triplet (*cheese pizza*, *tasty*, *positive*) as it only captures one-hop neighborhood information, while there are multi-hop connections between aspect "*cheese pizza*" and opinion "*tasty*" in syntactic dependency type. In contrast, our MvLFE model can explore the prior indication effect of multi-view linguistic features to precisely extract all sentiment triplets.

## 5 Conclusion

In this paper, we propose a MvLFE architecture to explore the prior indication effect of multi-view linguistic features for ASTE task in the "*Refine, Align, and Aggregate*" learning process. We first devise *relational graph attention network* to encode and refine diverse linguistic features to attend the aspect-opinion pairs. Then we employ *multi-view contrastive learning* for semantic alignment. Moreover, we utilize *multi-semantic cross attention* to aggregate them to capture the complementary higher-order interactions. Extensive experiments on benchmark datasets show the effectiveness and robustness of our MvLFE model, which consistently outperforms all baselines on ASTE task as well as several subtasks. In the future, we plan to extend our model for information extraction.

## Limitations

Despite obtaining state-of-the-art performance, our proposed approach still has some following limitations to consider for potential future directions.

- Our MvLFE model is constructed using the grid tagging paradigm. Although grid tagging methods can effectively capture the association among sentiment elements, they commonly suffer from a limitation, i.e., most of the relation labels between two words are irrelevant to sentiment elements (an example shown in Figure 3), which leads to the class imbalance problem of word-pair relations. Thus, when most irrelevant labels are predicted correctly but few for sentiment-related labels, it causes the phenomenon that the overall loss is low but limited F1 scores of sentiment triplet extraction, which potentially misguides the parameter optimization. Additionally, the requirement to construct a word-pair relations table takes up more memory compared to the models that only consider sequence representations.

- Experiments only verified the consistent improvement on ASTE task, while we intuitively reckon the idea of MvLFE that exploits the prior indication effect of multi-view linguistic features in the "*Refine, Align, and Aggregate*" learning process can be expanded to some triplet extraction tasks, such as *Relation Extraction* and *Event Extraction*.

- The performance of our MvLFE model is still somewhat affected by the parsing quality of the CoreNLP toolkit. The good news is that the CoreNLP toolkit has demonstrated its effectiveness in syntactic dependency analysis and part-of-speech tagging. Thus, despite this limitation, we can still utilize the CoreNLP toolkit to support our research.

## Ethics Statement

We conduct all the experiments on four publicly available datasets in the Laptop and Restaurant domain, which have been widely used in previous scientific publications. These datasets do not share personal information and do not contain sensitive content that can be harmful to any individual or community. We strive to maintain fairness and honesty in our analysis of experimental results, ensuring that our work does not cause harm to anyone. As for broader impact, this work may facilitate further research in aspect-based sentiment analysis, contributing to simplifying and automating the mining of user opinions in real-world applications.

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# A Additional Details

## A.1 Triplets Decoding

The details of sentiment triplets decoding are shown in Algorithm 1. Specifically, we first obtain the set of diagonal tags $\mathcal{D}$ from the prediction results. Each tag in $\mathcal{D}$ represents the relation between a word and itself. Then we extract each aspect term or opinion term based on consecutive occurrences of "B-A" and "I-A" labels or "B-O" and "I-O" labels in the diagonal tags set $\mathcal{D}$, thereby forming the aspects set $\mathcal{A}$ and the opinions set $\mathcal{O}$. Finally, we identify the sentiment polarities between the matched aspect and opinion terms based on their predicted relations, thus yielding the sentiment triplets set $\mathcal{T}$.

## A.2 Dataset Statistics

Table 4 shows details about the experiment dataset. We have counted the number of sentences, sentiment triplets for each sentiment polarity, aspect terms and opinion terms within each dataset.

## A.3 Additional Experiments and Analyses

### A.3.1 Impact of Different RGAT Layers

To explore the impact of the number of layers of RGAT, we conduct experiments on four benchmark datasets with single-layer to five-layer RGAT of our MvLFE model, where multiple layers indicate that our MvLFE can capture the multi-hop neighborhood information between words. As shown in Figure 7, our MvLFE model achieves the best performance when the RGAT is three layers. We reckon that the 3-hop interaction between words helps to match the valid aspect and opinion terms with vast distance. Note that the performance de-

| Dataset | | #S | #T | #POS | #NEU | #NEG | #A | #O |
|---|---|---|---|---|---|---|---|---|
| **Res14** | Train | 1266 | 2337 | 1691 | 166 | 480 | 2051 | 2061 |
| | Dev | 310 | 577 | 404 | 54 | 119 | 500 | 497 |
| | Test | 492 | 994 | 773 | 66 | 155 | 844 | 994 |
| **Lap14** | Train | 906 | 1460 | 817 | 126 | 517 | 1254 | 1460 |
| | Dev | 219 | 345 | 169 | 36 | 140 | 302 | 346 |
| | Test | 328 | 541 | 364 | 63 | 114 | 466 | 543 |
| **Res15** | Train | 605 | 1013 | 783 | 25 | 205 | 935 | 1013 |
| | Dev | 148 | 249 | 185 | 11 | 53 | 236 | 249 |
| | Test | 322 | 485 | 317 | 25 | 143 | 460 | 485 |
| **Res16** | Train | 857 | 1394 | 1015 | 50 | 329 | 1300 | 1394 |
| | Dev | 210 | 339 | 252 | 11 | 76 | 319 | 339 |
| | Test | 326 | 514 | 407 | 29 | 78 | 474 | 514 |

Table 4: Statistics for ASTE-Data-V2 dataset. #S and #T mean the total number of sentences and triplets. #POS, #NEU and #NEG denote the number of positive, neutral, and negative sentiment triplets respectively. #A and #O represent the number of aspect and opinion terms.

**Algorithm 1** Triplet Decoding for ASTE

**Input:** The predictions $\mathcal{P} = \{p_{11}, p_{12}, \cdots, p_{nn}\}$ of the sentence X with $n$ words. $p_{ij}$ denotes the tag label of the word pair ($w_i$,$w_j$).
**Output:** Triplets set $\mathcal{T}$ of the given sentence.

Initialize aspects set $\mathcal{A} = \{\}$, opinions set $\mathcal{O} = \{\}$, diagonal tags of predictions $\mathcal{D} = \{\}$ and triplets set $\mathcal{T} = \{\}$.
*# Get diagonal tags of predictions*
**while** $i \leq n$ **do**
    $\mathcal{D}$.append($p_{ii}$), $i \leftarrow i + 1$
**end while**
*# Get aspects*
**for** $p_{ii}$ in $\mathcal{D}$ **do**
    **if** $p_{ii}$ ==\"B-A\" **then**
        **while** $(i + 1) \leq n$ **do**
            **if** $p_{i+1,i+1}$! =\"I-A\" **then** $j \leftarrow i$
            **end if**
        **end while**
        $\mathcal{A}$.append($[w_i, w_{i+1}, \cdots, w_j]$)
    **end if**
**end for**
*# Get opinions*
**for** $p_{ii}$ in $\mathcal{D}$ **do**
    **if** $p_{ii}$ ==\"B-O\" **then**
        **while** $(i + 1) \leq n$ **do**
            **if** $p_{i+1,i+1}$! =\"I-O\" **then** $j \leftarrow i$
            **end if**
        **end while**
        $\mathcal{O}$.append($[w_i, w_{i+1}, \cdots, w_j]$)
    **end if**
**end for**
*# Get sentiment triplets*
**while** $a \in \mathcal{A}$ and $o \in \mathcal{O}$ **do**
    $\mathcal{S} = \{\}$
    **while** $w_i \in a$ and $w_j \in o$ **do**
        **if** $i < j$ **then** $tag = p_{ij}$
        **else** $tag = p_{ij}$
        **end if**
        **if** $tag \in \{POS, NEU, NEG\}$ **then**
            $\mathcal{S} \leftarrow \mathcal{S} \cup (tag)$
        **end if**
    **end while**
    **if** $\mathcal{S} \neq \{\}$ **then**
        $s = argmax(\mathcal{S}), \mathcal{T} \leftarrow \mathcal{T} \cup \{(a, o, s)\}$
    **end if**
**end while**

| Model | PLM | Res14 | Lap14 | Res15 | Res16 |
|---|---|---|---|---|---|
| MvLFE | BERT | 75.40 | 64.17 | 66.93 | 75.17 |
| | RoBERTa | 75.36 | 64.31 | 66.87 | 75.42 |
| | XLNet | 75.61 | 64.32 | 66.82 | 75.49 |
| | ALBERT | 75.19 | 64.21 | 66.79 | 75.24 |

Table 5: Comparison results with different pre-trained language models (F1 score).

clines as the RGAT goes deeper, which may be due to the model matching the invalid aspect and opinion terms.

In addition, we visualize the multi-view linguistic features of the sentence "*Tasty food but poor service*" after different layers of RGAT refinement to verify the effectiveness of each RGAT layer. The heat maps are shown in Figure 6. In short, we can conclude that as the RGAT layers deepen, multi-view linguistic features focus on representing the matched aspect-opinion pairs after the refinement of RGAT.

### A.3.2 Hyperparameters Analysis

We conduct additional experiments to demonstrate the sensitivity analysis of some hyperparameters. Based on the experimental results shown in Figure 8, Figure 9 and Figure 10, we finally set the margin $\gamma$ to 0.2 for the multi-view contrastive learning and the weights $\beta$ and $\mu$ to 0.01 and 0.1 for the joint training loss.

### A.3.3 Experiments on Different Backbones

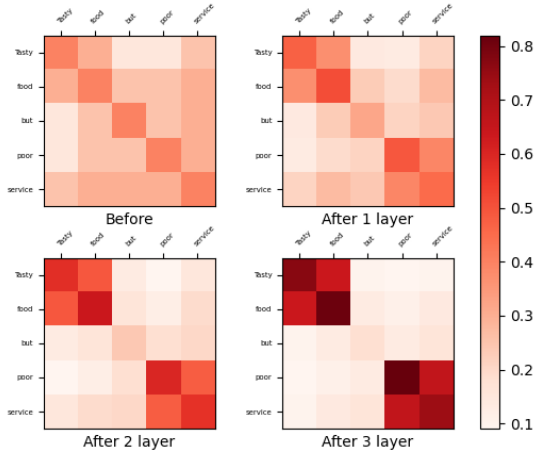
We conduct additional experiments to analyze the sensitivity of our MvLFE model using different pre-trained language models as sentence encoders. The experimental results in Table 5 demonstrate that the performance of our model does not exhibit significant variations when employing different pre-trained language models, which suggests the robustness of our model. To ensure fairness, we adopt BERT as the sentence encoder the same as most of the related studies.

## B Experiments with ChatGPT

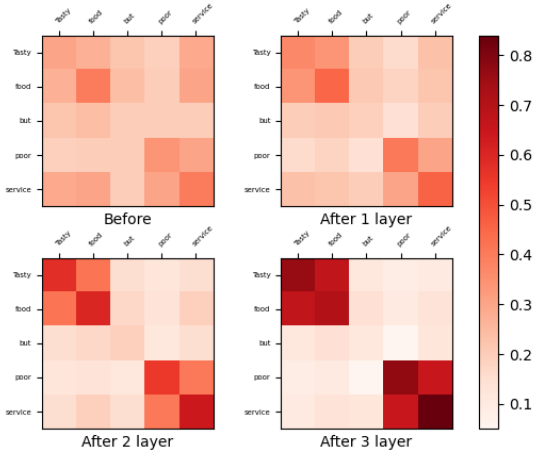
Recently, Large Language Models (LLMs) such as ChatGPT have sparked a revolutionary change in natural language processing technology. They are capable of achieving impressive in-context learning (ICL) (Brown et al., 2020) results with zero-shot and few-shot prompts for unseen tasks, without the need for any parameter updates.

In this paper, we carried out some experiments on four benchmark datasets to investigate how well can ChatGPT solve ASTE task with diverse prompt settings. The experimental results are shown in Table 6. Moreover, we list some examples of prompts for the experimental settings in Table 7. Note that we only list the zero-shot and one-shot prompts due to the limited length of the table. The only difference between few-shot prompts and one-shot prompts is the presence of more data samples.

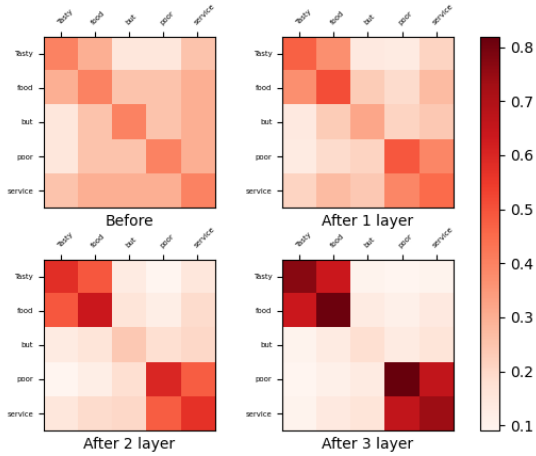
Specifically, we employ the following experimental setting to verify the performance of ChatGPT on the ASTE task: (1) zero-shot without task instruction, (2) zero-shot with task instruction, (3) one-shot ICL, (4) one-shot ICL with multi-view linguistic features, (5) 3-shot ICL, (6) 3-shot ICL with multi-view linguistic features, (7) 5-shot ICL and (8) 5-shot ICL with multi-view linguistic features. From the experimental results, we first observe that using the task instruction significantly improves the average F1 scores by 7.90%, which suggests it is effective in enabling ChatGPT to understand the purpose of the ASTE task. Second, prompting with training samples further improves the performance. We suppose the reason is that ChatGPT is able to learn from more training samples to extract sentiment triplets from different situations. Note that we also conduct additional experiments for each ICL setting by incorporating multi-view linguistic features of the given samples. The experimental results show that ChatGPT improves by a large margin with the addition of multi-view linguistic features, suggesting the effectiveness of the prior indication effect of multi-view linguistic features for ASTE.



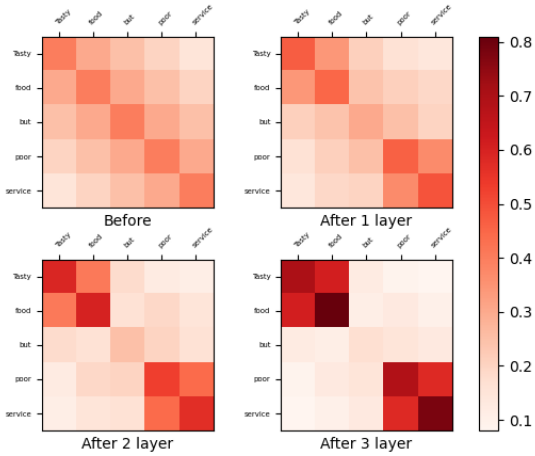

(a) Syntactic dependency type




(b) Part-of-speech relation




(c) Syntactic dependency distance




(d) Relative position distance

Figure 6: Heat maps of multi-view linguistic features after refining with different RGAT layers on the sentence "Tasty food but poor service".

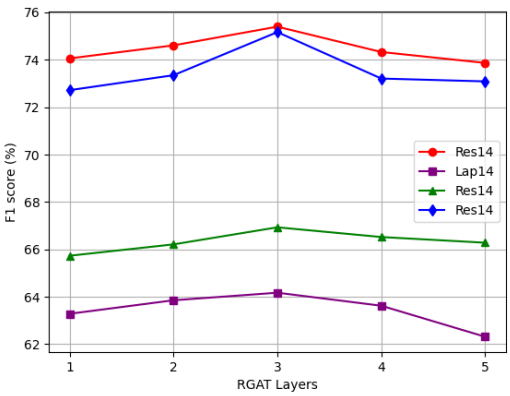



Figure 7: Impact of different RGAT layers on the results.

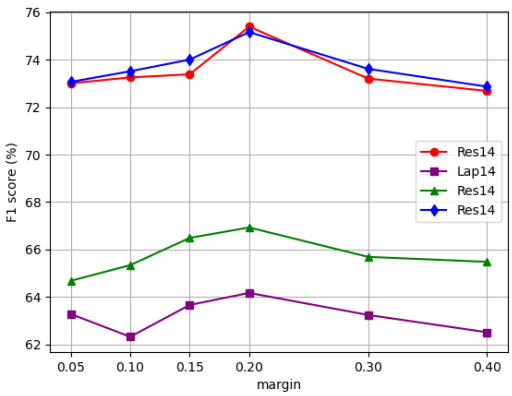



Figure 8: Sensitivity analysis of the margin $\gamma$.

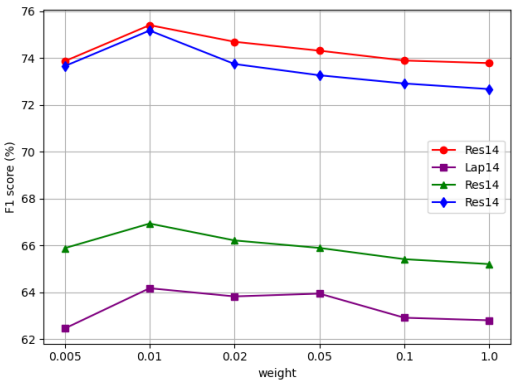



Figure 9: Sensitivity analysis of the weight $\beta$ of relation constraint loss.

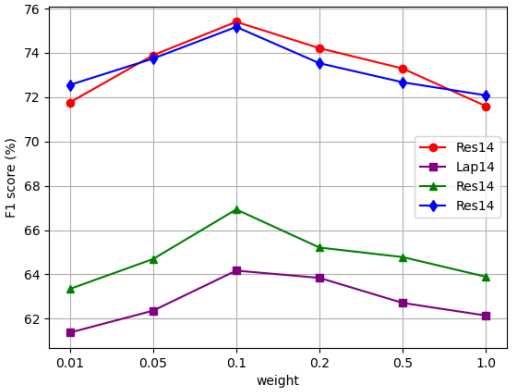



Figure 10: Sensitivity analysis of the weight $\mu$ of contrastive learning loss.

| Model | Res14 | | | Lap14 | | | Res15 | | | Res16 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **P** | **R** | **F1** | **P** | **R** | **F1** | **P** | **R** | **F1** | **P** | **R** | **F1** |
| zero-shot w/o task instruction | 13.96 | 18.42 | 15.88 | 11.28 | 13.59 | 12.33 | 12.36 | 14.84 | 13.49 | 14.37 | 16.33 | 15.29 |
| zero-shot w/ task instruction | 21.07 | 24.16 | 22.51 | 18.74 | 21.92 | 20.21 | 20.78 | 23.69 | 22.14 | 22.65 | 24.94 | 23.74 |
| 1-shot ICL | 25.54 | 29.37 | 27.32 | 21.29 | 24.79 | 22.91 | 24.91 | 28.85 | 26.74 | 26.23 | 30.08 | 28.02 |
| 1-shot ICL w/ MvLF | 31.24 | 33.98 | 32.55 | 26.38 | 29.49 | 27.85 | 30.72 | 31.92 | 31.31 | 32.47 | 33.81 | 33.13 |
| 3-shot ICL | 30.82 | 33.71 | 32.20 | 27.01 | 29.43 | 28.17 | 30.69 | 31.97 | 31.32 | 31.45 | 33.01 | 32.21 |
| 3-shot ICL w/ MvLF | 40.72 | 45.63 | 43.04 | 31.09 | 37.24 | 33.89 | 37.81 | 45.96 | 41.49 | 39.23 | 47.81 | 43.10 |
| 5-shot ICL | 41.27 | 46.09 | 43.55 | 31.16 | 37.33 | 33.97 | 37.98 | 46.83 | 41.94 | 39.55 | 48.49 | 43.57 |
| **5-shot ICL w/ MvLF** | **47.18** | **53.62** | **50.19** | **34.22** | **47.91** | **39.92** | **42.83** | **57.94** | **49.25** | **43.75** | **57.09** | **49.54** |

Table 6: Comparing ASTE results obtained using ChatGPT with different prompt settings. ICL means in-context learning and MvLF denotes multi-view linguistic features.

| Setting | Prompt |
|---|---|
| zero-shot w/o task instruction | **Given the review:** extract all the sentiment triplets in the review and return the result in JSON format. Remember that no explanation is required and there should be no irrelevant text replies!<br>**Review:** The cheese pizza is crispy and tasty, but the ambience is indeed dull. |
| zero-shot w/ task instruction | **Given the review for ASTE task:** please follow the task instruction and return the result in JSON format. Remember that no explanation is required and there should be no irrelevant text replies!<br>**Task instruction:** ASTE aims to extract all sentiment triplets from the review, and each triplet contains three elements, namely aspect term, opinion term and their associated sentiment.<br>The sentiment polarity belongs to the set {positive, neutral, negative}.<br>**Review:** The cheese pizza is crispy and tasty, but the ambience is indeed dull. |
| one-shot ICL | **Given the review and several extraction samples for ASTE task:** please follow the task instruction and several extraction samples, then return the result in JSON format. Remember that no explanation is required and there should be no irrelevant text replies!<br>**Task instruction:** ASTE aims to extract all sentiment triplets from the review, and each triplet contains three elements, namely aspect term, opinion term and their associated sentiment.<br>The sentiment polarity belongs to the set {positive, neutral, negative}.<br>**Sample1:** The food was just OK, at least for what food was available.<br>Result of sample1: Sentiment triplets: (food, ok, positive)<br>**Review:** The cheese pizza is crispy and tasty, but the ambience is indeed dull. |
| one-shot ICL w/ MvLF | **Given the review and several extraction samples with multi-view linguistic features for ASTE task:** please follow the task instruction and several extraction samples with multi-view linguistic features, then return the result in JSON format. Remember that no explanation is required and there should be no irrelevant text replies!<br>**Task instruction:** ASTE aims to extract all sentiment triplets from the review, and each triplet contains three elements, namely aspect term, opinion term and their associated sentiment.<br>The sentiment polarity belongs to the set {positive, neutral, negative}.<br>**The prior indication effect of multi-view linguistic features for ASTE:** (1) in the view of syntactic dependency type, the aspect term is the nominal subject (“nsubj”) of the opinion term, also the opinion term is adjectival modifier (“amod”) of the the aspect term. (2) in the view of part-of-speech relation, aspect terms are nouns while opinion terms are adjectives. Hence, the word pair with the “NN-JJ” part-of-speech combination tends to form an aspect-opinion pair. (3) in the view of syntactic dependency distance, the matched aspect and opinion terms are closer. (4) in the view of relative position distance, the matched aspect and opinion terms are closer.<br>**Sample1:** The food was just OK, at least for what food was available.<br>**Multi-view linguistic features for sample1:** We provide part-of-speech tagging labels for each word in the review, as well as syntactic dependency type between each word and its parent word. The "Head" indicates the position of the parent word in the review (starting from 1, with 0 representing the root node). Based on this information, you need to calculate the syntactic dependency type, part-of-speech relation, syntactic dependency distance, and relative position distance between words to obtain the multi-view linguistic features of the given comment.<br>**Part-of-speech tagging labels:** ["DT", "NN", "VBD", "RB", "JJ", ",", "RB", "RBS", "IN", "WDT", "NN", "VBD", "JJ", "."]<br>**Syntactic dependency type:** ["det", "nsubj", "cop", "advmod", "root", "punct", "advmod", "fixed", "mark", "det", "nsubj", "cop", "advcl", "punct"]<br>**Head:** [2, 5, 5, 5, 0, 5, 13, 7, 13, 11, 13, 13, 5, 5]<br>**Result of sample1:** Sentiment triplets: (food, ok, positive)<br>**Review:** The cheese pizza is crispy and tasty, but the ambience is indeed dull. |

Table 7: Some prompts for ChatGPT.