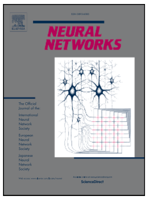
Neural Networks 192 (2025) 107894

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet



Full Length Article

MPGM:Multi-prompt generation model with self-supervised contrastive learning for aspect sentiment triplet extraction

Kun Yang[a], Liansong Zong[a], Mingwei Tang[a,*], Jie Hu[b], Yanxi Zheng[a], Yujun Chen[a], Mingfeng Zhao[c]

[a] School of Computer and Software Engineering, Xihua University, Chengdu, 610039, China
[b] School of Computing and Artificial Intelligence, Southwest Jiaotong University, Chengdu, 611756, China
[c] China Mobile Group Design Institute Co., Ltd. Sichuan Branch, Chengdu, 610045, Sichuan Province, China

ARTICLE INFO

Keywords:
Aspect sentiment triplet extraction
Generative model
Multiple prompt templates
Terminological affinity evaluation
Supervised contrastive learning

ABSTRACT

Generative models are widely used in natural language processing and achieve remarkable results in the Aspect Sentiment Triplet Extraction (ASTE) task. Although existing generative methods can effectively identify triplets within sentences, their performance still needs to be improved when dealing with complex sentences containing multi-span terms. The main issues are the insufficient recognition of long-span terms and the lack of comprehensive recognition of complete triplets. To address the limitations of generative models in the ASTE task, a multi-prompt generation model (MPGM) with self-supervised contrastive learning is proposed for aspect sentiment triplet extraction. Efforts are made to enhance the connections between terms and sentiment polarity from various perspectives. Initially, multiple prompt templates are proposed to integrate the generated triplets to mitigate potential errors in individual templates. In addition, a terminological affinity evaluation is designed, which incorporates term information during the training process to enhance the model's ability to recognize relationships between terms. Moreover, the dual-dimensional supervised contrastive learning strategy leverages multiple types of labels to enhance the representations of triplet spans. The enhanced triplet span representations facilitate more precise modeling of the relationships between terms and sentiment polarities. Extensive experiments have validated that the MPGM demonstrates superior performance to existing methods on two public datasets, proving its effectiveness and advancement in addressing the challenges of the ASTE task. Specifically, on the four subsets of the ASTE-DATA-v1 and ASTE-DATA-v2 datasets (14Lap, 14Res, 15Res, 16Res), the F1 scores of the MPGM method are 63.98 %, 76.63 %, 67.48 %, 75.61 % and 65.32 %, 76.80 %, 68.75 %, 75.49 %, respectively.

1. Introduction

Aspect-based sentiment analysis (ABSA) focuses on predicting the sentiment associated with specific aspect terms in a given sentence. It is an emerging and important research field within natural language processing (NLP). Unlike traditional document-level and sentence-level sentiment analysis (Cai et al., 2024; Maree & Eleyat, 2020; Phan & Nguyen, 2024; Rhanoui et al., 2019; Song et al., 2023), it offers a finer-grained sentiment analysis. Notably, the dimABSA task (Zhu et al., 2024) advances beyond basic sentiment polarity classification by modeling and predicting each aspect along multiple emotional dimensions.

Recent studies have introduced compound ABSA tasks that involve multiple related elements, such as ASC (Li et al., 2025; Xu & Wang, 2025), AOPE (Chen et al., 2020; Gao et al., 2021; Wu et al., 2021b), ASTE (Peng et al., 2020; Wu et al., 2020; Xu et al., 2020), TASD (Radi et al., 2024; Wan et al., 2020), and ASQP (Zhang et al., 2021a). The core of ABSA research revolves around four key emotional elements: aspect term (A), aspect category (C), opinion term (O), and sentiment polarity (S) (Ma et al., 2019; Zhang et al., 2023b; Zhou et al., 2015). Their formats are as shown in the Table 1. As shown in Fig. 1, it illustrates all the element types in the ABSA task for the sentence *'The décor needs to be upgraded but the food is amazing !'*. The sentence contains aspect terms such as '$decor$' and '$food$', aspect categories such as '*ambience general*' and '*food quality*', opinion terms such as '*upgraded*' and '$amazing$', and sentiment polarities of positive and negative, respectively.

As an important subtask of sentiment analysis, early research on Aspect Sentiment Triplet Extraction (ASTE) largely followed the methods of traditional Aspect-Based Sentiment Analysis. In the early stages of research, ASTE primarily relied on bidirectional long short-term memory networks (BiLSTMs) (Schuster & Paliwal, 1997), which enhanced

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* Corresponding author.
E-mail addresses: whichone276@gmail.com (K. Yang), lszong@my.swjtu.edu.cn (L. Zong), tang4415@126.com (M. Tang), jiehu@swjtu.edu.cn (J. Hu), 2746557318@qq.com (Y. Zheng), 2664223216@qq.com (Y. Chen), zhaomingfeng@cmdi.chinamobile.com (M. Zhao).

https://doi.org/10.1016/j.neunet.2025.107894
Received 16 February 2025; Received in revised form 26 May 2025; Accepted 20 July 2025

Table 1
Task classification and output results of aspect-based sentiment analysis task.

Task	Format	Output
Aspect-based Sentiment Classification (ASC)	*(a, s)*	(décor, negative), (food, positive)
Aspect-Opinion Pair Extraction (AOPE)	*(a, o)*	(décor, upgraded), (food, amazing)
Aspect Sentiment Triplet Extraction (ASTE)	*(a, o, s)*	(décor, upgraded, negative), (food, amazing, positive)
Target Aspect Sentiment (TASD)	*(a, c, s)*	(décor, ambience general, negative), (food, food quality, positive)
Aspect Sentiment Quad Prediction(ASQP)	*(a, s, o, c)*	(décor, negative, upgraded, ambience general), (food, positive, amazing, food quality)

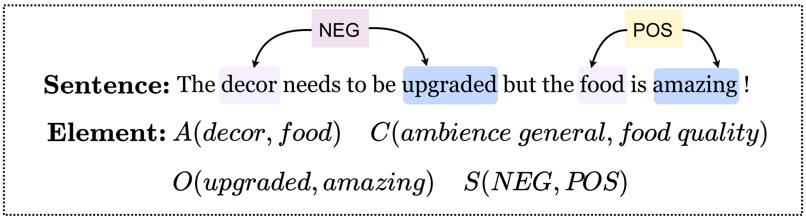


Fig. 1. An example of analyzing elements in aspect-based sentiment analysis task.

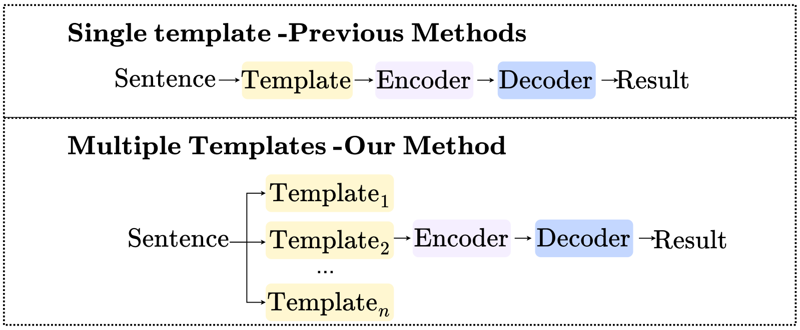


Fig. 2. The difference between our method and previous approaches.

the model's ability to capture contextual information and manage long-range dependencies. The incorporation of bidirectional information flow and gating mechanisms into the recurrent neural network (RNN) architecture (Kaur & Mohta, 2019) enables significant performance improvements. As the ASTE task evolved, the slow inference and low efficiency of BiLSTMs on long sequences began to limit the accuracy of triplet extraction. Subsequently, the release of BERT (Devlin et al., 2019) had a profound impact on the natural language processing field. Its bidirectional encoder structure utilized the Transformer architecture (Vaswani et al., 2017) to achieve bidirectional learning of context information, displaying excellent performance. The advancement spurred further research on the combination of various models based on BERT with graph neural networks (GNNs) (Wu et al., 2021a, 2023, 2019), knowledge graphs (Wan et al., 2023), and different decoding strategies (Liang et al., 2023; Wu et al., 2020; Zhang et al., 2022a). Recently, T5 (Raffel et al., 2019) unified all natural language processing tasks into a text-to-text framework, supporting multi-task learning (Akhtar et al., 2019; Yang et al., 2022), data augmentation (Hsu et al., 2021; Wang et al., 2022, 2024a), and self-supervised learning techniques (Qian et al., 2023; Tang et al., 2019). With its powerful generation capabilities and high flexibility, T5 has demonstrated significant advantages in handling complex language tasks and adapting to the needs of ASTE tasks in different domains.

Despite the strong performance of previous generative models, several shortcomings persist. A concise comparison between previous methods and our proposed approach is presented in Fig. 2. Past researches typically employed a single template, generating a single structure from left to right in a fixed manner. Existing approaches overlook the potential influence of template variations on generation performance and fail to account for the randomness introduced by relying on a single template. Such randomness could adversely affect the outcomes, ultimately impacting the overall performance of the model. The results show that there are significant performance differences among templates with different target orders Hu et al. (2022). Moreover, earlier models are typically constructed with a unified architecture that places primary emphasis on enhancing generation efficiency for triplet extraction. Adequate constraints are not imposed on the generated outputs, resulting in a remaining potential for improvement in the accuracy of the generated triplets.

To tackle the aforementioned challenges, a multi-prompt generation model is proposed. It integrates self-supervised contrastive learning to address key issues in the ASTE task through an enhanced generation process. By introducing different prompting templates into the model, a multi-template enhancement module is developed to address the limitations of a single template in prompting generation capabilities. The correct triplets are identified as those that occur most frequently across all templates, while others are regarded as misplaced. In addition, the accuracy of generated terms can be optimized by evaluating the similarity between the generated terms and the original terms. During the training process, positional and span information of the terms is utilized by the terminological affinity evaluation module to reduce the training loss, and the accuracy of term prediction is thereby improved. Furthermore, the dual-dimensional supervised contrastive learning (D2SCL) strategy is introduced to improve the model's ability to distinguish subtle sentiment types and handle varying triplet counts. D2SCL analyzes triplet features across multiple dimensions and assigns distinct labels to enhance the distinction between elements, bringing the predicted number of triplets and their sentiment classifications closer to the true values. The main contributions of this study are summarized as follows:

- We propose an innovative multi-prompt generation model with self-supervised contrastive learning. A diverse set of high-quality prompt templates is utilized to annotate the dataset. By systematically evaluating and comparing the results generated by each template, the optimal triplets are selected as the final output.
- Term affinity is evaluated by incorporating the position and span information of aspect and opinion terms. Incorporating such information enhances the identification and interpretation of semantic relationships.
- A dual-dimensional supervised contrastive learning framework is proposed, assigning labels based on triplet count and sentiment type. The framework enhances the ability to handle ambiguous sentiment expressions and accurately process sentences containing multiple triplets.
- Extensive experiments are conducted on two public datasets, and the results show that MPGM consistently outperformed the baseline models. Furthermore, the effectiveness of each individual module is confirmed through ablation studies, and the overall framework's superiority in addressing the ASTE task is demonstrated.

The remainder is organized in the following manner. In Section 2, related work is reviewed, with a focus on analyzing previous ASTE methods from three perspectives. A detailed explanation of the different components and their roles within the overall model architecture is provided in Section 3. Subsequently, experiments are conducted in Section 4 to demonstrate the effectiveness of the model on the ASTE task. Finally, the paper is concluded in Section 5 by summarizing the key findings and discussing directions for future research.

2. Related work

In the early stages, RNNs or CNNs were commonly used in most research papers on ABSA. Later, with the development of pretrained language models, models like BERT or T5 have been widely used in natural language processing tasks (Li et al., 2024). Existing research methods can be categorized into three main types: BERT-based methods, T5-based methods, and hybrid transformer methods.

2.1. BERT-based methods

In recent years, researchers have widely adopted pretrained language models to cope with sentiment analysis tasks. BERT has become the most frequently used pretrained language model in this field due to its excellent ability to capture contextual information.

Syntactic and semantic information are often combined with BERT models via GCNs to enhance feature extraction. In line with this approach, Li et al. (2021) considered both the syntactic structure and semantic association of sentences to mitigate dependency parsing errors and better capture semantic relevance. By integrating the two types of information, greater accuracy is achieved in analyzing the emotional expressions within the text. A multiple syntactic structure (MSS) fusion encoder is designed, which contains semantic and syntactic graph networks Shi et al. (2023). While the semantic graph network captures contextual information from adjacent tokens, the syntactic graph network encodes structural relations derived from syntax. Furthermore, an aspect-aware attention mechanism combined with self-attention was proposed to generate attention score matrices for sentences, enabling deeper exploration of syntactic and semantic information Zhang et al. (2022b). In a related vein, separation and contrastive learning strategies are employed for syntax and semantics in Zhao et al. (2024) and Guan et al. (2024), respectively. A2SMvCL (Chai et al., 2023) introduced a multi-view contrastive framework that combines syntactic and semantic cues for aspect-dependent sentiment representation. Several approaches were designed to further enhance the model's ability to distinguish and amplify syntactic and semantic information. Collectively, the aforementioned techniques successfully captured more distinctive syntactic and semantic features while reducing redundant interference.

In addition to the aforementioned methods, the decoding strategy is a crucial component of BERT-based models. The labels are employed to indicate the start and end positions of opinion and aspect terms within the table Chen et al. (2022). Additionally, they utilized multi-channel graph techniques to capture complex word relationships and thoroughly explore linguistic features. In recent research, table filling-based (Zhang et al., 2022a) and greedy inference decoding strategies (Liang et al., 2023) have achieved remarkable results. The Span-ASTE model initially introduced to extracts aspect terms and opinion terms, subsequently predicts the sentiment relationships between them (Xu et al., 2021). Subsequently, Liang et al. designed a span tagging and greedy inference scheme to extract sentiment triplets at the span level Liang et al. (2023). Each span, composed of multiple words, can simultaneously serve different roles. To maintain a separate table for each sentiment polarity, Zhang et al. proposed a table filling strategy. The elements in these tables represent the sentiment strength of the given aspect's span Zhang et al. (2023a). The table filling method builds a relation table for each tagged sentence and is an efficient decoding strategy. The BDTF was proposed, in which each triplet is represented as a relation region in a two-dimensional table, thereby transforming the ASTE task into the detection and classification of relation regions Zhang et al. (2022a).

2.2. T5-based methods

Since the T5 model (Raffel et al., 2019) is pretrained on a vast corpus of unsupervised text data, it acquires rich linguistic knowledge and diverse expression styles, which contribute to its exceptional performance across various NLP tasks. The T5 model unifies all NLP tasks as text-to-text conversion problems. For tasks such as text classification, translation, summarization generation, or question answering, both the input and output are represented as text sequences. The unified framework simplifies the training and fine-tuning process of the model, making it capable of adapting to various different NLP tasks.

Previous work has found that models struggle to handle implicit sentiment expressions and multi-span term prediction common in reviews. Supervised contrastive learning was employed to distinguish between key attributes Peper and Wang (2022), Xu et al. (2024). Xu et al. (2024) first applied graph attention networks to generative models, integrating dependency syntactic information to enhance the parsing of complex sentences. To allow generative models to capture boundary information of terms and provide prompts for decoding multiple triplets using shared labels, Zhou and Qian (2023) introduced a span-aware sequence labeling module. At the same time, the generative model BGCA was trained by Deng et al. (2023) in both text-to-label and label-to-text directions. The former reformulates tasks into a unified format to support domain-independent feature extraction. The latter generates natural language from noisy labels for data augmentation, which helps train more accurate models. In order to improve the prediction effect of sentiment triplets, Gou et al. (2023) proposed MvP to use multiple prompt templates in different orders to annotate the same sentence, which enhances the model's adaptability to diverse expressions.

2.3. Hybrid transformer methods

Some researchers have also explored the use of models such as XLNet, BART, and GPT for ABSA tasks, which represent extensions and innovations of the Transformer architecture. Yang et al. (2019) proposed XLNet by integrating the state-of-the-art self-attention model

Transformer-XL into pre-training through maximizing the expected likelihood of all permutations. XLNet overcomes the limitations of BERT's formula by learning bidirectional contexts. To address all ABSA subtasks within an end-to-end framework, Yan et al. (2021) utilized a pretrained sequence-to-sequence model BART. Additionally, the heuristic candidate selection strategy and the All-in-One model were proposed by Jiang et al. (2024) to address the challenges in few-shot aspect-based sentiment analysis. Chumakov et al. (2023) structured the output triplets by simplifying terms without losing meaningful information and successfully analyzed data from unknown domains. To improve the ability to learn sentiment information, SoftMCL (Wang et al., 2024b) introduced momentum queues to model representations at both the word level and the sentence level, allowing for the storage of more negative samples and the expansion of comparison sample size. Zheng et al. (2024) divided candidates into positive and negative examples based on the log-likelihood of a language model, and combined contrastive learning to promote samples to approach positive examples and stay away from negative examples. They further fine-tuned the language model through high-quality instruction generation targets to enhance generation performance. ChatABSA (Bai et al., 2024) reformulates five complex subtasks using constrained prompts and employs post-processing strategies to leverage LLMs' reasoning abilities, addressing limitations in implicit information prediction.

3. Method

3.1. Model overview

The framework of the MPGM model proposed in this paper is illustrated in the Fig. 3. It is divided into three main components: the Multi-Template Enhancement module (MTE), the Terminological Affinity Evaluation module (TAE), and the Dual-Dimensional Supervised Contrastive Learning module (D2SCL). Specifically, the T5 model is utilized as the core architecture, where the encoder captures contextual semantic representations, and the decoder generates the triplets. Reviews annotated with aspect and opinion terms are provided as input, and the correct triplets are extracted through the joint operation of multiple modules.

3.2. Task definition

Given a sentence $S = \{w_1, w_2, \dots, w_n\}$ with $n (n \geqslant 1)$ words, the goal of the ASTE task is to extract aspect-opinion-sentiment triplets from the sentence, where a, o, and s represent the aspect term, opinion term, and sentiment polarity, respectively. $s \in \{POS, NEU, NEG\}$, POS denotes positive sentiment, NEU denotes neutral sentiment, and NEG denotes negative sentiment.

3.3. Multi-template enhancement MTE

3.3.1. Prompt template design

Owing to the distinctive design of the T5 pretrained language model, the attention mechanism can be flexibly adjusted based on different input templates. As a result, significant variations are observed in the outputs generated by T5 decoding, depending on the input templates. As a result of its flexible architecture, different information hierarchies and content segments within the input text can be attended to during the execution of multiple tasks.

In the Fig. 4, n high-performance prompt templates $(T_1, T_2, T_3, T_4, \dots, T_n)$ are designed for the ASTE task. When using template $T_i (i \geqslant 1)$, the model will give priority to focusing on task-related keywords in the sentence, which will influence its comprehension and decoding process of the context.

For instance, given a $Sentence$ = '*The pizza is delicious*', the generation model $\mathbb{G}$ will adjust its attention to the $keywords$ = {'*pizza*','*delicious*'}. A template-based mechanism enhances the adaptability of the model and contributes to improved performance across a range of natural language processing tasks.

$$\mathbb{G} : T_i \oplus Sentence \cdot w(keywords) \Rightarrow \mathcal{T}_i, \quad i = 1, 2, \cdots, n \tag{1}$$

where w is the influence weight of the template on the keyword, and $\mathcal{T}_i$ represents the triplet generated by the i-th template.

3.3.2. Results aggregation

As can be observed from the generation results, different templates may yield varying triplets. If a single template is employed like in traditional methods, the most accurate triplet may not be obtained, leading to

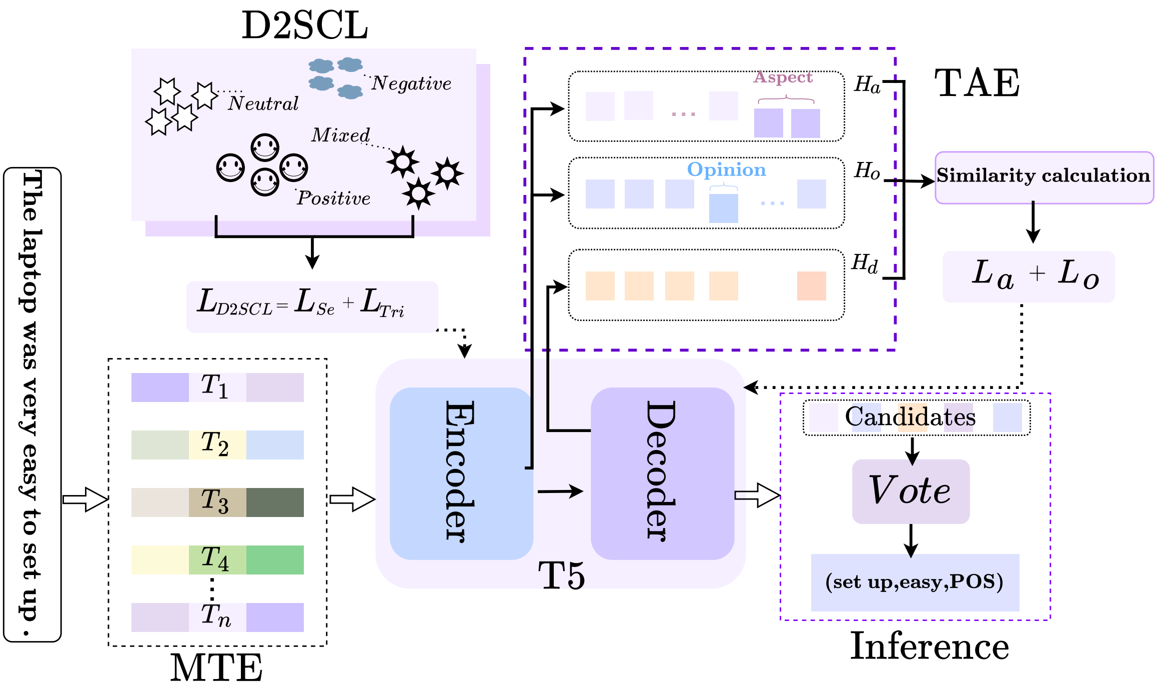


Fig. 3. The overall architecture of our MPGM model.

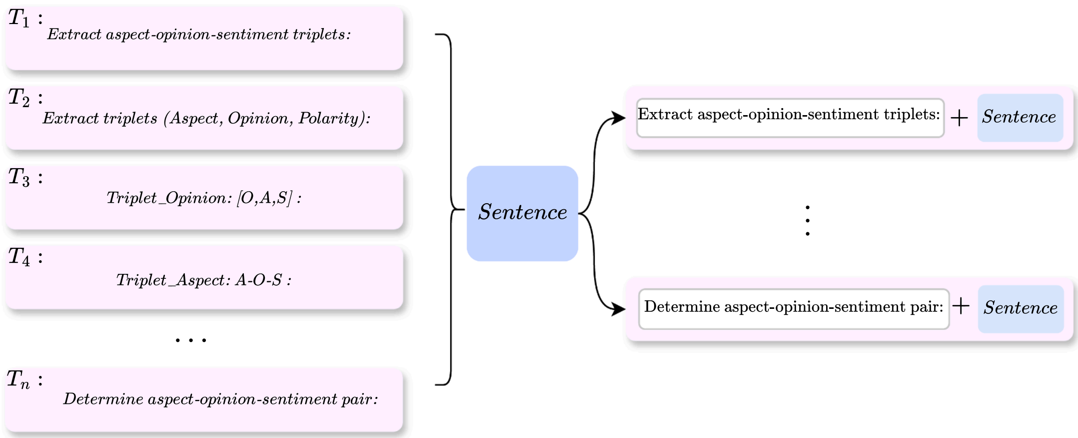


Fig. 4. A sentence combined with five prompt templates.

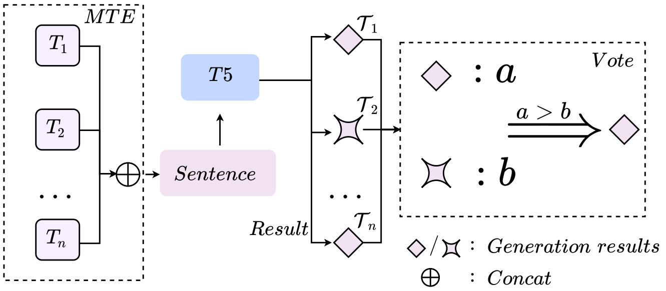


Fig. 5. Voting mechanism for final result selection.

unsatisfactory model performance. By aggregating triplets from diverse templates, the extracted outcomes not only capture the primary viewpoint and sentiment of the sentence but also take into account a range of contextual information, thus ensuring higher representativeness and accuracy.

A comprehensive description of the implementation details is provided, as illustrated in Fig. 5. Once all the triplets $\Gamma = \{\mathcal{T}_1, \mathcal{T}_2, \dots, \mathcal{T}_n\}$ are generated, a systematic statistical analysis is performed on these results. Firstly, the frequency $\mathcal{F}$ of occurrence for each triplet $\mathcal{T}_i$ is calculated during the generation process, helping identify triplets that are repeatedly mentioned in the decoding phase. Subsequently, $ArgMax(\cdot)$ is employed to select the triplet $\mathcal{T}_{correct}$ with the highest frequency as the correct one.

$$\mathcal{F}(\mathcal{T}_i) = \sum_{j=1}^{n} \mathbb{I}(\mathcal{T}_i = \mathcal{T}_j) \tag{2}$$

$$\mathcal{T}_{correct} = \underset{\mathcal{T}_i \in \Gamma}{ArgMax}(\mathcal{F}(\mathcal{T}_i)) \tag{3}$$

where $\mathbb{I}(\cdot)$ is an indicator function and n is the total number of generated triplets.

3.4. Terminological affinity evaluation TAE

Since aspect terms and opinion terms usually involve multiple spans rather than simple single words, boundary extraction errors often occur when extracting terms. The design goal of TAE is to integrate the span information of aspects and opinion items with the hidden state during term generation to improve the effectiveness of term generation. The enhancement of aspect term and opinion term information is divided into two independent parts, with each type of term handled separately and its affinity with the corresponding real labels calculated. The processing flow of the TAE module is shown in Fig. 6.

First, it is essential to accurately capture the positioning information of terms within their context. Term position features $\mathbf{H}^{pos} = \{h_1^{pos}, h_2^{pos}, \dots, h_N^{pos}\} \in \mathbb{R}^{N \times d}$ (N is the sum of all term lengths and d is the hidden dimension) are extracted by filtering term position elements $\mathbf{Pos} = \{\mathrm{p}_1, \mathrm{p}_2, \dots, \mathrm{p}_n\} \in \mathbb{R}^{n \times L}$ (L is the sentence length and n is the batch size) from the last hidden state of the decoder $\mathbf{H}^{dec} = \{h_1^d, h_2^d, \dots, h_n^d\} \in \mathbb{R}^{n \times L \times d}$.

$$\begin{aligned} \mathbf{H}_a^{pos} &= \mathbf{H}^{dec} \cap \mathbf{Pos}_a, \\ \mathbf{H}_o^{pos} &= \mathbf{H}^{dec} \cap \mathbf{Pos}_o \end{aligned} \tag{4}$$

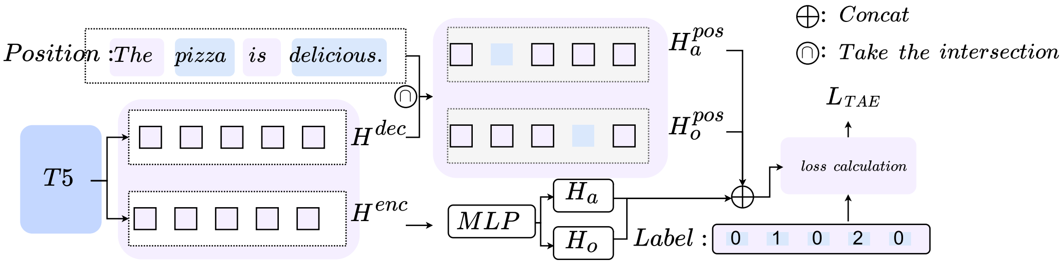


Fig. 6. The internal structure of TAE module.

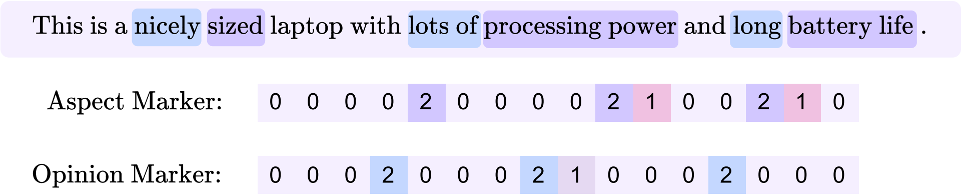


Fig. 7. An example of term information annotation.

Note that during the training phase, position information for each term is annotated, including its start and end positions. As illustrated in Fig. 7, the start position of the term is labeled as 2, positions within the term are marked as 1, and all other positions are labeled as 0. Using the mechanism, the text generation module can better capture term boundary information. When the input sentence contains multiple triplets, aspects and opinions at different positions have their own different position information. Identical tokens in the generation module are assigned distinct pointers for different aspect-opinion pairs, enabling information sharing without ambiguity. With this design, sentences containing multiple triplets can be decoded more efficiently.

Next, the hidden states of aspect $\mathbf{H}^a = \{h_1^a, h_2^a, \ldots, h_n^a\} \in \mathbb{R}^{L\times d}$ and opinion $\mathbf{H}^o = \{h_1^o, h_2^o, \ldots, h_n^o\} \in \mathbb{R}^{L\times d}$, containing the semantic representation of the term, are obtained. To ensure that the term features can be further utilized for computation, the hidden states are reshaped to adapt to different token lengths and batch requirements.

$$\mathbf{H}_a = \mathbf{Reshape}_a(H^{enc}), \mathbf{H}_o = \mathbf{Reshape}_o(H^{enc}) \tag{5}$$

The term position feature $\mathbf{H}^{pos}$ is concatenated with the term semantic feature $\mathbf{H}_a$, $\mathbf{H}_o$, and a more representative hidden state $\mathbf{S}^a$, $\mathbf{S}^o$ $\in \mathbb{R}^{n\times L\times d}$ is generated through linear projection and activation function. Then, the concatenated features are passed through a fully connected layer to predict the labels for the aspect and opinion terms, producing the predicted probabilities for the label set:

$$\mathbf{S}_{ij} = \mathbf{ReLU}(\mathbf{W}_1(h_j^{pos} \oplus h_i) + b_1) \tag{6}$$

$$\mathbf{P}_{ij} = \mathbf{softmax}(\mathbf{W}_2\mathbf{S}_{ij} + b_2) \tag{7}$$

Finally, terminological affinity evaluation is calculated using cross-entropy loss, and the accuracy of aspect terms and opinion terms extraction is enhanced through loss reduction in the training phase.

$$\mathcal{L}_{TAE} = -\sum_{i=1}^{N}\sum_{j=1}^{L}\sum_{c\in C}\left[\mathbb{I}(y_{ij}^a = C)\cdot\log(\mathbf{p}_{i,j}^a|C) + \mathbb{I}(y_{ij}^o = C)\cdot\log(\mathbf{p}_{i,j}^o|C)\right] \tag{8}$$

where $\mathbb{I}(\cdot)$ is the indicator function, y_{ij}^a and y_{ij}^o are the gold-standard labels, and C refers to the $\{B, I, O\}$ classification labels.

3.5. Dual-Dimensional supervised contrastive learning D2SCL

A robust learning framework is established by D2SCL to strengthen the relationships among related instances and minimize those among irrelevant ones, which facilitates the acquisition of highly discriminative feature representations. The interaction between instances and labels during the training process is illustrated in Fig. 8. Instances are influenced by the interactions with all labels, but only the same label causes the instances to cluster together, ensuring that instances with the same label are grouped during training. During model training, the loss function is minimized through multiple iterations. Feature extraction is gradually refined during the process, resulting in improved triplet extraction performance.

In the D2SCL module, two types of supervised contrastive learning modules are designed to improve model performance. First, labels for sentiment types are constructed. A fine-grained label setting is adopted to enhance the model's understanding of sentiment diversity and facilitate the identification of subtle differences in emotional expressions. Second, labels are constructed built on the count of triplets to resolve the challenge of insufficient triplet extraction. Sentences containing multiple triplets in reviews are typically more complex, making triplet extraction from such sentences more challenging compared to shorter ones.

The input feature representation $\mathbf{H}^{enc} = \{h_1, h_2, \ldots, h_n\}$ uses the inner product $(\cdot)$ to evaluate the similarity score between two feature vectors h_m and h_n. Through the application of the softmax function, the similarity scores are transformed into a probability distribution, ensuring that each score falls between 0 and 1, and the sum of all scores is 1. An intuitive representation of the similarity and importance of each sample is provided.

$$score(m, n) = h_m \cdot h_n/\tau \tag{9}$$

$$p(m, n) = \frac{e^{\mathrm{score(m,n)}}}{\sum_{a\in\mathcal{A}(i)} e^{\mathrm{score(m,a)}}} \tag{10}$$

where τ represents the temperature coefficient, which is used to scale the similarity values. $\mathcal{A}(i)$ is the total number of instances, and the

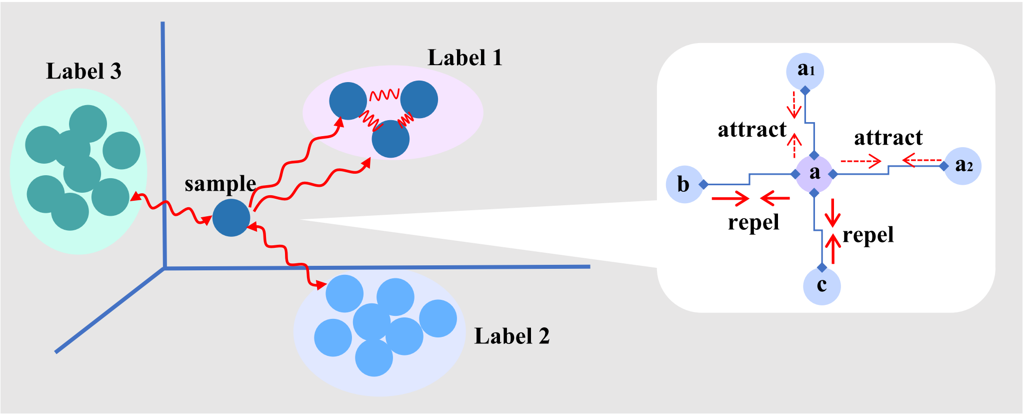


Fig. 8. Interactions between instances and labels in contrastive learning.

probability $p(m, n)$ represents the probability corresponding to the similarity between instance m and instance n.

In the end, for each sample i, find the other instances of the same category (positive instances) and instances of different categories (negative instances). The supervised contrastive loss $\mathcal{L}_{SCL}$ is obtained by accumulating the similarity between all instances.

$$\mathcal{L}_{SCL} = \sum_{i \in \mathcal{I}} \frac{1}{|\mathcal{P}(i)|} \sum_{p \in \mathcal{P}(i)} -\log p(i, p) \tag{11}$$

where $\mathcal{I}$ represents the collection of indices of all instances in a batch, and $\mathcal{P}(i)$ represents the collection of indices of positive instances that belong to the same category as sample p, excluding itself.

3.6. Model training

The T5 generation process uses a cross-entropy loss to calculate the degree of match between the words generated by the model and the target words. If the probability of the word generated by the model is close to that of the target word, the loss is smaller; otherwise, the loss is larger.

$$\mathcal{L}_{\mathrm{T5}} = -\sum_{t=1}^{T} \log P\left(y_t \mid x, y_{<t}\right) \tag{12}$$

where y_t represents the target word at time step t, and $P\left(y_t \mid x, y_{<t}\right)$ denotes the probability of generating the t-th word given the input sentence x and the previously generated words $y_{<t}$.

During the model training process, multiple loss functions are incorporated and comprehensively optimized. The total loss of the model $\mathcal{L}_{total}$ is the sum of the TAE loss $\mathcal{L}_{TAE}$, D2SCL loss $\mathcal{L}_{D2SCL}$, and T5 triplet extraction loss $\mathcal{L}_{T5}$.

$$\mathcal{L}_{total} = \mathcal{L}_{TAE} + \mathcal{L}_{D2SCL} + \mathcal{L}_{T5} \tag{13}$$

In Algorithm 1, the specific steps of our model for triplet extraction are described in detail. The first is data preprocessing, which is related to all the data required for model training. In the 2 to 4 lines, five designed prompt templates are introduced for use to process each sentence in the dataset. Each prompt template is added to the beginning of the sentence to form a new dataset, with the aim of using these templates to process the sentences in the dataset. As shown in lines 7 to 14, the loss calculation of the model during training is described, and the losses of multiple modules are added together for gradient update. In the evaluation stage, dictionary and statistical methods are used to calculate the triplets with the highest frequency and this result is used as the final one.

Algorithm 1 Extracting triplets using multiple templates.

```
Input: Datasets required for training.
Output: Correct triplets.
 1: ⊡ Data Processing
 2: for sentence in Dataset do
 3:     for $T_i$ in Templates: do
 4:         newDataset ← ($T_i$ + sentence,Gold)
 5:     end for
 6: end for
 7: ⊡ Training
 8: for step in steps do
 9:     $\mathcal{L}_{T5}$ = T5 ← (newDataset)
10:     $\mathcal{L}_{TAE}$ = Similarity_Computing(hidden_state,marker)
11:     $\mathcal{L}_{D2SCL}$ = Contrastive_loss_Computing(hidden_state,label)
12:     $\mathcal{L}_{total}$ = $\mathcal{L}_{TAE}$ + $\mathcal{L}_{D2SCL}$ + $\mathcal{L}_{T5}$
13: end for
14: Save best model
15: ⊡ Evaluating
16: Results = model ← (Dataset)
17: for i in range(0,len(Gold)) do
18:     id = i * 5
19:     outputs = Results[id:id+5]     ⌜ Get all predictions for one sentence ⌟
20:     counter = dict(Counter(outputs))     ⌜ Count predicted triplets ⌟
21:     Triplets = ArgMax ← counter     ⌜ Final predicted triplets ⌟
22: end for
```

Table 2
Dataset statistics. *S and *Γ indicate the number of sentences and triplets in the dataset. **Pos*, **Neu*, and **Neg* indicate the number of triplets with positive, neutral, and negative sentiment polarity. **TCC* (Triplet Count Categorization) is used to represent the number of sentences with a specified range of triplet counts.

Dataset		* *S*	* *Γ*	**Pos*	**Neu*	**Neg*	**TCC*		
							<2	2 ∼ 3	> 3
14Lap	Train	906	1460	817	126	517	545	321	40
	Dev	219	345	169	36	140	133	76	10
	Test	328	541	364	63	114	184	124	20
14Res	Train	1266	2337	1691	166	480	605	562	99
	Dev	310	577	404	54	119	153	130	27
	Test	492	944	773	66	155	206	232	54
15Res	Train	605	1013	783	25	205	338	230	37
	Dev	148	249	185	11	53	76	66	6
	Test	322	485	317	25	143	210	99	13
16Res	Train	857	1394	1015	50	329	504	303	50
	Dev	210	339	252	11	76	118	86	6
	Test	326	514	407	29	78	192	120	14

4. Experiment

4.1. Datasets

To assess the effectiveness of the proposed model, experiments are conducted on two datasets, $\mathcal{D}_1$ and $\mathcal{D}_2$. Both datasets contain sentiment analysis datasets in the laptop and restaurant domains (including *14Lap*, *14Res*, *15Res*, and *16Res*). Aspect terms, opinion terms, as well as sentiment polarity are used to annotate each review in these datasets. $\mathcal{D}_2$ shows considerable improvement in both the quality and completeness of its annotations. As a result, it overcomes several issues present in $\mathcal{D}_1$. For instance, when an opinion term is linked to multiple aspect terms, $\mathcal{D}_1$ annotates only one of the aspect terms. In contrast, $\mathcal{D}_2$ annotates all instances where an opinion term is linked to multiple aspect terms, providing a more comprehensive representation of the actual scenarios and improving the dataset's usability and completeness. Comprehensive statistics are provided in Table 2. Based on the statistical data presented in the table, appropriate labels for supervised contrastive learning are designed.

4.2. Experiment setting

The T5-BASE model from Huggingface Transformers is used as the pretrained model, with greedy search employed for decoding by default. In the experiments, consistent parameters are applied across all tasks and datasets, with the default number of prompt templates set to 5. Multiple experiments are included, such as those conducted on two datasets, ablation studies, and visualization analysis. To simplify, the number of prompt templates used during inference matches that of the training phase. Additionally, the learning rate is set to 1e-4, and adam_epsilon is set to 1e-8. All experiments are conducted on NVIDIA RTX 3090 GPUs and NVIDIA A40 Tensor Core GPUs.

4.3. Baselines

The baseline methods are categorized according to different model types, including traditional methods, advanced BERT-based methods, and generative methods. Our model is compared with several innovative approaches from recent years. The details of each method are as follows:

1. Traditional methods

- **CMLA+, RINANTE+, Li-unified-R+ and Peng-two-stage** (Peng et al., 2020) are all pipeline methods, with the first three models being adaptations of their original versions as modified by Peng et al. CMLA (Wang et al., 2017) is a coupled multi-layer attention network designed to jointly extract aspects and opinions by capturing direct relationships and dependencies. RINANTE (Dai & Song, 2019) introduces an algorithm that utilizes inter-word dependencies to automatically mine co-extraction rules for aspect and opinion terms. Li-unified-R (Li et al., 2019) employs two stacked recurrent neural networks and targets goal-oriented sentiment analysis tasks.
- **GTS** (Wu et al., 2020) proposes a novel grid tagging scheme, using it in an end-to-end manner for more accurate extraction, marking the first work focused on aspect-oriented fine-grained opinion extraction.
- **JET** (Xu et al., 2020) puts forward the initial end-to-end model that is characterized by a completely new position aware tagging method. More expressive label semantics are utilized to define the structural details of triplets.
- **Biston** (Hao et al., 2024) proposes an end-to-end dual syntax-guided transformer network designed to explicitly model the complex relationships between aspects and opinions, as well as the boundaries of multi-word aspects and opinions.
- **COM-MRC** (Zhai et al., 2022) applies a strategy to enrich the context for expanding the training corpus. Meanwhile, it creates a discriminative model composed of four collaborative modules. This model performs inference by means of iterative aspect masking.
- **SA-Transformer** (Yuan et al., 2024) incorporates knowledge of dependency types into graph neural networks to expand the ASTE task, using edge dependency types to prevent inappropriate propagation.

2. Advanced BERT-based methods

- **EMC-GCN** (Chen et al., 2022) proposes an enhanced multi-channel graph convolutional network to fully exploit the relationships between words. It also utilizes a dual-radiative attention mechanism to embed these relationships into adjacent tensors between words in a sentence.
- **Dual-Span** (Li et al., 2023) constructs two relational graph attention networks to capture linguistic features from syntactic dependency and part-of-speech graphs, effectively using both channels to reduce noise and computational cost in the ASTE task.
- **D2E2S** (Zhao et al., 2024) proposes a dual-encoder model. This model maximizes syntactic and semantic connections between words by introducing a heterogeneous feature interaction module. It also dynamically selects key nodes to capture complex interactions between dependency syntax and attention semantics.
- **MiniConGTS** (Sun et al., 2024) initiates with a re-evaluation process. Based on this evaluation, it presents an approach designed to enhance and utilize pretrained representations. The approach incorporates a minimalist labeling scheme and an innovative token-level contrastive learning strategy. By adopting a specific algorithm, the model aims to reduce redundancy and strengthen the internal representations.
- **PT-GCN** (Peng et al., 2024) builds a target-aware grid graph using table cells as nodes, weighted by hint attention scores, and applies a three-channel convolution to precisely extract emotional knowledge.
- **SAAG** (Sun et al., 2025) is an AttentionGate semantic framework driven by SenticNet and AMR, designed to highlight emotional intent in word representations and balance word pair expressions across different semantic contexts.
- **SKen** (Lu et al., 2025) uses commonsense and syntactic dependency knowledge to enhance context representation and improve interpretability in sentiment extraction. It also employs an orthogonal loss-based self-attention mechanism to better capture word interactions.

3. Generative methods

- **ASTE-BART** (Yan et al., 2021) converts all ABSA subtasks into a unified generation task and achieves the generation of target sequences in an end-to-end process based on the unified task formulation.
- **GAS** (Zhang et al., 2021b) transforms the ABSA problem into a text generation problem and proposes two paradigms (annotation modeling and extractive modeling) to define each task as a text generation problem.
- **PARAPHRASE** (Zhang et al., 2021a) proposes a novel paradigm of paraphrase-based modeling, which converts quadruplet prediction into paraphrase generation. It predicts sentiment tuples at once, effectively utilizes semantic information, and facilitates knowledge transfer in low-resource environments.
- **MvP** (Gou et al., 2023) employs element-order-based prompts to predict sentiment elements in a controlled sequence, enhancing expression diversity and mitigating issues from fixed orders and error propagation.
- **CONTRASTE** (Mukherjee et al., 2023) introduces a more versatile placeholder template for fine-tuning T5 on ASTE than **PARAPHRASE** (Zhang et al., 2021a) and applies supervised contrastive learning to the decoder's output for aspect-level sentiment embeddings.

4.4. Main results

We compare our proposed method with traditional approaches, advanced BERT-based models, and generative methods. As shown in Tables 3 and 4, evaluations are conducted using precision, recall, and F1 score. Notably, the proposed model achieves the highest F1 scores across all four datasets in both experimental settings. Specifically, improvements of 1.18 %, 1.16 %, 0.44 %, and 0.93 % are observed on the $\mathcal{D}_1$ subsets, and 0.83 %, 1.21 %, 1.62 %, and 0.66 % on the $\mathcal{D}_2$ subsets, compared to the best-performing existing methods. These results demonstrate the exceptional performance and strong stability of MPGM in triplet extraction tasks.

The above results indicate that our model significantly outperforms traditional methods. Traditional approaches, such as grid tagging, position-aware tagging, transformers, and machine reading comprehension, show limited capability in accurately extracting triplets, particularly in handling complex and multi-span triplets. While advanced BERT-based methods demonstrate notable improvements across all three evaluation metrics, the T5 model inherently holds advantages over BERT in triplet prediction. With the integration of the TAE module, more accurate term representations are learned through training on labeled aspect and opinion terms, leading to performance that surpasses all BERT-based models. Compared to other generative-based approaches, the proposed design demonstrates greater robustness. By meticulously optimizing various components of the triplet extraction process and leveraging the combined effects of TAE and D2SCL, generation errors related to aspect terms, opinion terms, and sentiment polarity are effectively reduced. As a consequence, superior performance is consistently achieved in both precision and recall compared to most other models.

4.5. Ablation study

To assess the impact of individual components on the model's performance, ablation experiments are conducted using the MPGM model on the $\mathcal{D}_2$ dataset. The experimental results, presented in the Table 5, use the F1 score to evaluate model performance and analyze the changes in different components across various datasets. The average magnitude of these changes provides a more accurate reflection of the model's performance trends. Specifically, the MTE and Vote mechanisms have the

Table 3
Experimental results on $\mathcal{D}_2$. The best results are indicated in bold, while the second-best results are underlined.

Methods	Lap 14			Rest 14			Rest15			Rest 16		
	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1
Traditional.												
GTS-BERT[a]	57.82	51.32	54.36	67.76	67.29	67.50	62.50	57.94	60.15	66.08	66.91	67.93
JET-BERT[a]	55.39	47.33	51.04	70.56	55.94	62.40	64.45	51.96	57.53	70.42	58.37	63.83
Biston	65.99	53.59	59.15	70.03	68.41	69.21	65.25	56.91	60.79	66.85	69.84	68.32
COM-MRC	62.35	58.16	60.17	75.46	68.91	72.01	68.35	61.24	64.53	71.55	71.59	71.57
Advanced BERT.												
Dual-Span	67.14	62.13	64.49	77.01	74.00	75.47	67.97	66.34	67.13	73.56	73.48	73.49
D2E2S	67.38	60.31	63.65	75.92	74.36	75.13	70.09	62.11	65.86	**77.97**	71.77	74.74
MiniConGTS	66.82	60.68	63.61	76.10	75.08	75.59	66.50	63.86	65.15	75.52	74.14	74.83
PT-GCN	67.69	57.30	62.06	77.85	72.13	74.88	69.76	65.15	67.38	74.39	71.21	72.76
SAAG	62.63	56.88	59.62	76.03	70.75	73.30	61.51	62.26	61.38	69.26	71.51	70.37
SKen	67.22	59.89	63.34	74.48	**75.15**	74.81	66.67	65.98	66.32	72.83	73.54	73.18
Generative.												
ASTE-BART[a]	61.41	56.19	58.69	65.52	64.99	65.25	59.14	59.38	59.26	66.60	68.68	67.62
GAS[a]	61.65	58.19	59.87	71.08	71.67	71.37	60.01	63.67	61.78	67.76	71.67	69.66
PARAPHRASE[a]	62.99	58.30	60.55	70.87	70.90	70.89	60.80	64.98	62.82	70.35	74.04	72.15
MvP	-	-	63.33	-	-	74.05	-	-	65.89	-	-	73.48
ContrASTE	64.20	61.70	62.90	73.60	74.40	74.00	65.30	66.70	66.10	72.20	**76.30**	74.20
Ours												
MPGM	**68.00**	**62.85**	**65.32**	**78.75**	74.95	**76.80**	69.70	**67.84**	**68.75**	76.09	74.90	**75.49**

[a] means the experiment results comes from Xu et al. (2024)

Table 4
Experimental results on $\mathcal{D}_1$. The best results are indicated in bold, while the second-best results are underlined.

Methods	Lap 14			Rest 14			Rest15			Rest 16		
	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1	Pre	Rec	F1
CMLA + [a]	30.09	36.92	33.16	39.18	47.13	42.79	34.56	39.84	37.01	41.34	42.10	41.72
RINANTE + [a]	27.71	18.66	20.07	31.42	39.38	34.95	29.88	30.06	29.97	25.68	22.30	23.87
Li-unified-R + [a]	40.56	44.28	42.34	41.04	67.35	51.00	44.72	51.39	47.82	37.33	54.51	44.31
Peng-two-stage[a]	37.38	50.38	42.87	43.24	63.66	51.46	48.07	57.51	52.32	46.96	64.24	54.21
GTS-BERT[b]	57.52	51.92	54.58	70.92	69.49	70.20	59.29	58.07	58.67	68.58	66.60	67.58
JET-BERT[b]	58.47	43.67	50.00	67.97	60.32	63.92	58.35	51.43	54.67	64.77	61.29	62.98
EMC-GCN	61.46	55.56	58.32	71.85	72.12	71.98	59.89	61.05	60.38	65.08	71.66	68.18
Dual-Span	64.50	58.59	61.36	77.55	73.52	75.47	67.66	66.14	66.85	72.44	73.47	72.94
PT-GCN	**71.36**	56.08	62.80	76.62	71.96	74.22	**71.29**	63.26	67.04	74.03	**75.35**	74.68
SAAG	61.83	57.49	59.58	72.70	74.85	73.76	65.43	61.65	63.48	68.86	73.29	71.01
GAS	-	-	60.78	-	-	72.16	-	-	62.10	-	-	70.10
COM-MRC	64.73	56.09	60.09	76.45	69.67	72.89	68.50	59.74	63.65	72.80	70.85	71.79
SA-Transformer	61.28	48.98	54.44	70.76	65.85	61.28	62.82	58.31	60.48	72.01	62.87	67.13
Ours												
MPGM	66.40	**61.74**	**63.98**	**79.40**	**74.04**	**76.63**	66.33	**68.66**	**67.48**	**78.61**	72.84	**75.61**

[a] means the experiment results comes from Sun et al. (2025)

[b] means the experiment results comes from Xu et al. (2024)

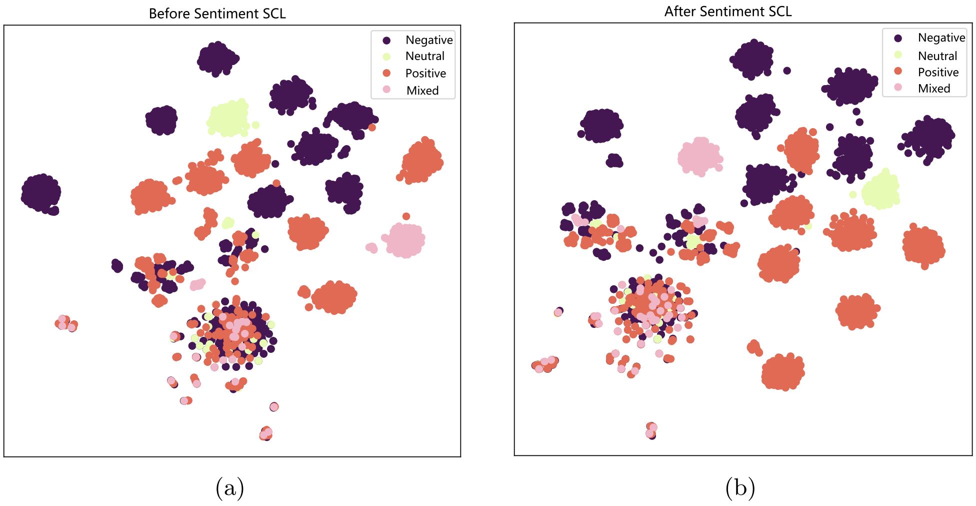
Table 5
Results of ablation experiments.

Model	Lap14	Rest14	Reat15	Rest16	Average
MPGM	65.32	76.80	68.75	75.49	
w/o MTE	$63.98_{\downarrow 1.34}$	$75.18_{\downarrow 1.62}$	$67.26_{\downarrow 1.49}$	$73.79_{\downarrow 1.71}$	$\triangle\downarrow$ 1.54
w/o TAE	$64.45_{\downarrow 0.87}$	$75.05_{\downarrow 1.75}$	$67.22_{\downarrow 1.53}$	$74.62_{\downarrow 0.87}$	$\triangle\downarrow$ 1.26
w/o SCL	$64.52_{\downarrow 0.80}$	$76.05_{\downarrow 0.75}$	$68.34_{\downarrow 0.41}$	$74.58_{\downarrow 0.91}$	$\triangle\downarrow$ 0.72
w/o Vote	$63.36_{\downarrow 1.96}$	$74.21_{\downarrow 2.59}$	$65.97_{\downarrow 2.78}$	$73.77_{\downarrow 1.72}$	$\triangle\downarrow$ 2.26

most significant impact on performance. Across four datasets, the performance drops are notable, with MTE averaging a 1.54 % decrease and Vote averaging a 2.26 % decrease. The model integrates MTE with a voting strategy for enhanced performance. When only the MTE module is used without the voting strategy, the model exhibits the lowest performance. The design of each template affects the decoding process, which can lead to an increased number of incorrect triplets in the case of complex sentences. Furthermore, removing the TAE module results in performance drops of 0.87 %, 1.75 %, 1.53 %, and 0.87 % across the four datasets, respectively. The critical role of incorporating aspect and opinion terms within each training batch is highlighted by these results, as the model's ability to generate accurate predictions is substantially enhanced by their presence. Due to factors such as the span and position of aspect and opinion terms, performance impacts vary across experiments and datasets. Finally, SCL also influences model performance. Removing the SCL module leads to an average performance drop of 0.72 %. The designed labels are leveraged by the SCL module for contrastive learning, with similar labels being clustered and differences between dissimilar ones being increased. The rationality of the label design is validated by the observed performance decline.

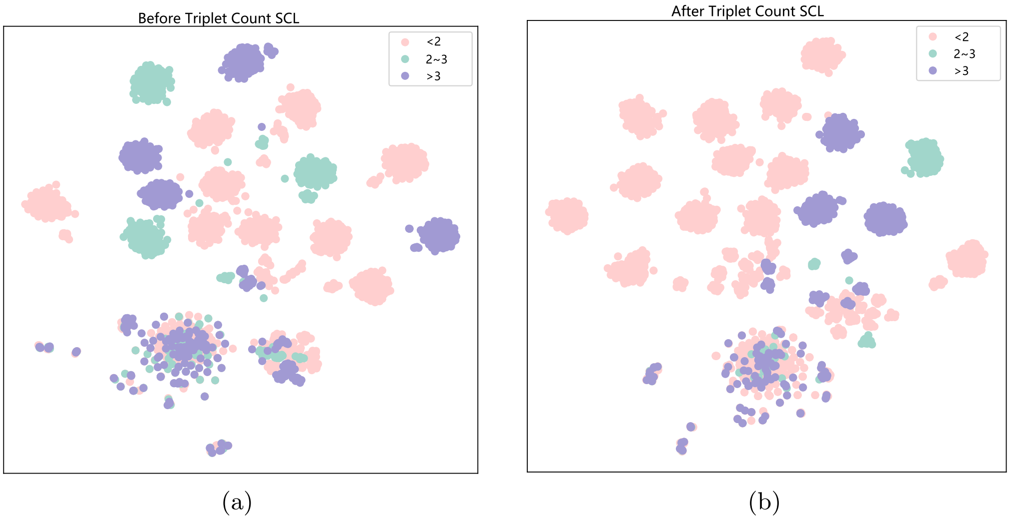
4.6. Model analysis and visualization

In this section, a detailed analysis is provided regarding how various components in the model design influence the overall architecture. To better present the analysis results, visualization techniques are utilized.



(a) (b)

Fig. 9. Visualization of sentiment SCL feature distributions.



(a) (b)

Fig. 10. Visualization of triplet count SCL feature distributions.

The analysis focuses on three key aspects: the effects of supervised contrastive learning, the influence of the number of prompt templates, and the role of the TAE module.

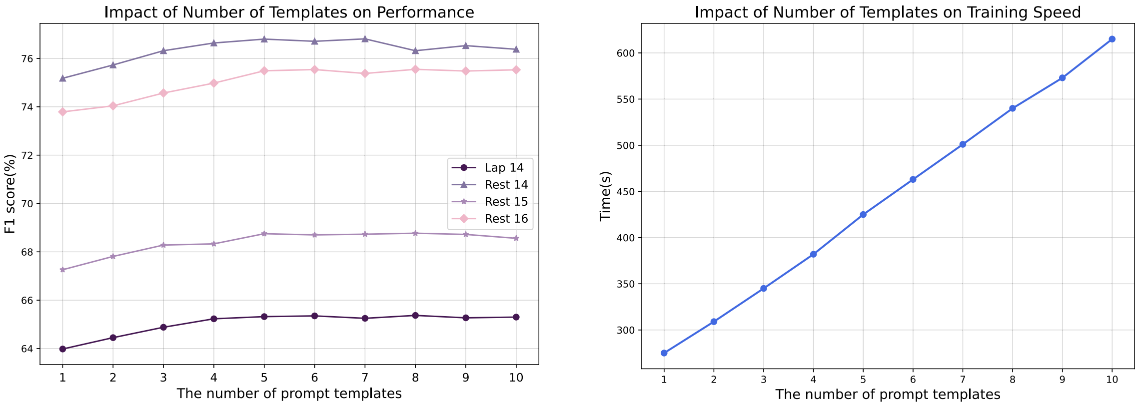
4.6.1. SCL feature visualization

The goal of supervised contrastive learning design is to adjust the feature distribution in high-dimensional space so that features with the same label are clustered together, while features with different labels are pushed apart. The spatial distribution is more regular, thus improving the effectiveness of feature extraction. To visually demonstrate this change, t-SNE is used to project high-dimensional features into a two-dimensional space. In the Figs. 9 and 10, different colors correspond to different labels. Following training within the contrastive learning framework, the initially disordered label distribution gradually transforms into a more structured and clearly organized pattern. In particular, the visualization results of Sentiment SCL clearly demonstrate a separation between features associated with positive and negative sentiments, with a well-defined boundary observed in the feature space. It shows that the model exhibits enhanced ability in distinguishing different emotion polarities. In contrast, the visualization for Triplet Count SCL shows that only the features of sentences containing a single triplet are effectively extracted, while distributional differences between other labels are also observed. Experimental results demonstrate that the designed supervised contrastive learning method contributes positively to the extraction of triples.

4.6.2. The impact of the number of prompt templates

The impact of the number of prompt templates on ASTE task performance is analyzed. In addition, the influence of increasing template quantity on model complexity is examined based on the trend observed in training time.

As shown in Fig. 11(a), an increase in the number of prompt templates leads to a gradual improvement in the model's performance across the four datasets. It proves the effectiveness of our use of multiple templates in the task, and the multi-template design can indeed improve the model's ability to extract correct triplets. Greater performance gains are observed in the initial stages, but the improvement rate diminishes as more templates are introduced. When the number of templates increased to six, a performance decline is observed on certain datasets. Moreover, further increases in template count led to non-monotonic and inconsistent performance fluctuations. In fact, when the number of templates is large enough, the quality of the templates begins to play a crucial role in determining the model's performance. If quality control is overlooked during the expansion of the template set, model performance will not improve and may even degrade due to the inefficient utilization of training resources. Additionally, training costs will increase



(a) (b)

Fig. 11. The impact of the number of prompt templates.

substantially. Increasing the number of templates substantially elevates training overhead, including memory consumption and computational time. Under existing hardware limitations, the feasibility of scaling to larger template sets is restricted, which in turn hinders further improvements in model performance.

As the number of templates increases, the time required for the model in the data preprocessing and training phases also increases accordingly. As shown in Fig. 11(b), the training time of a single epoch increases roughly linearly with the increase in the number of templates. In theory, when using m templates, the training time should be approximately m times that of using a single template. Since MPGM is based on T5-base, its overall training complexity is $\mathcal{O}(L \times (N_{template} + N_{text})^2 \times d)$. Among them, L is the total number of layers, N_{text} is the text length, $N_{template}$ is the template length, and d is the hidden layer dimension. MPGM needs to run all m templates once, so the total training complexity is $\mathcal{O}(m \times L \times (N_{template} + N_{text})^2 \times d)$. Experimental results on training speed further corroborate this finding.

4.6.3. Affinity analysis of different terms

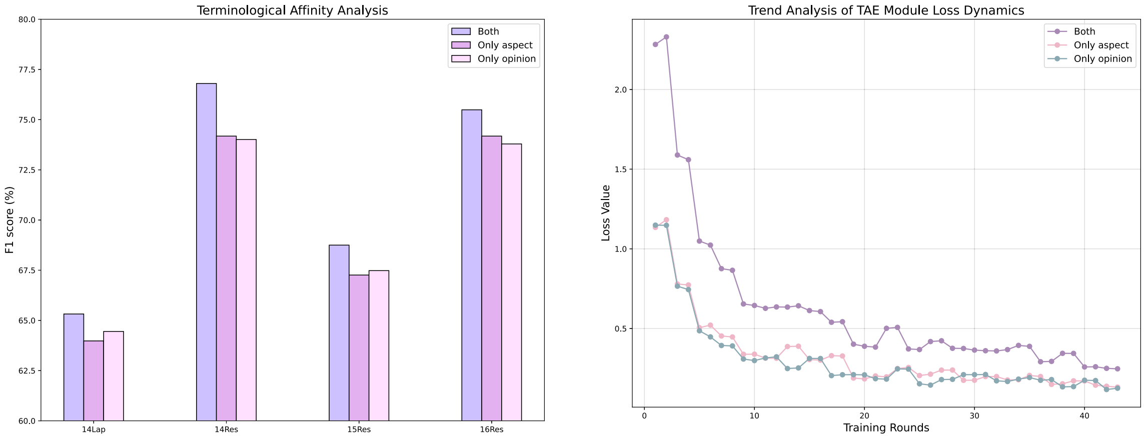
In this section, the influence of aspect and opinion terms within the TAE module on overall model performance is examined, and the corresponding trends in module loss are investigated. Optimal performance across all datasets is achieved when both aspect terms and opinion terms are incorporated into the TAE module, as shown in Fig. 12(a). However, when the span or positional information of either aspect terms or opinion terms is absent, the model's ability to recognize triplets declines significantly. Notably, comparable performance is achieved when only aspect terms or only opinion terms are provided, as reduced recognition accuracy of either component directly impacts the overall effectiveness of triplet extraction.

In Fig. 12(b), each point represents the loss value computed by the TAE module during each training round. As training progresses, the loss value demonstrates a steady downward trend, indicating that the predicted values are increasingly aligned with the true values of the terms. Furthermore, the loss value is lower when using only single-term information. It can be explained by the relatively simpler task of predicting a single term (either an aspect term or opinion term) as opposed to jointly predicting both terms. Consequently, the enhancement effect achieved by using single-term information falls short of expectations.

4.7. Case study

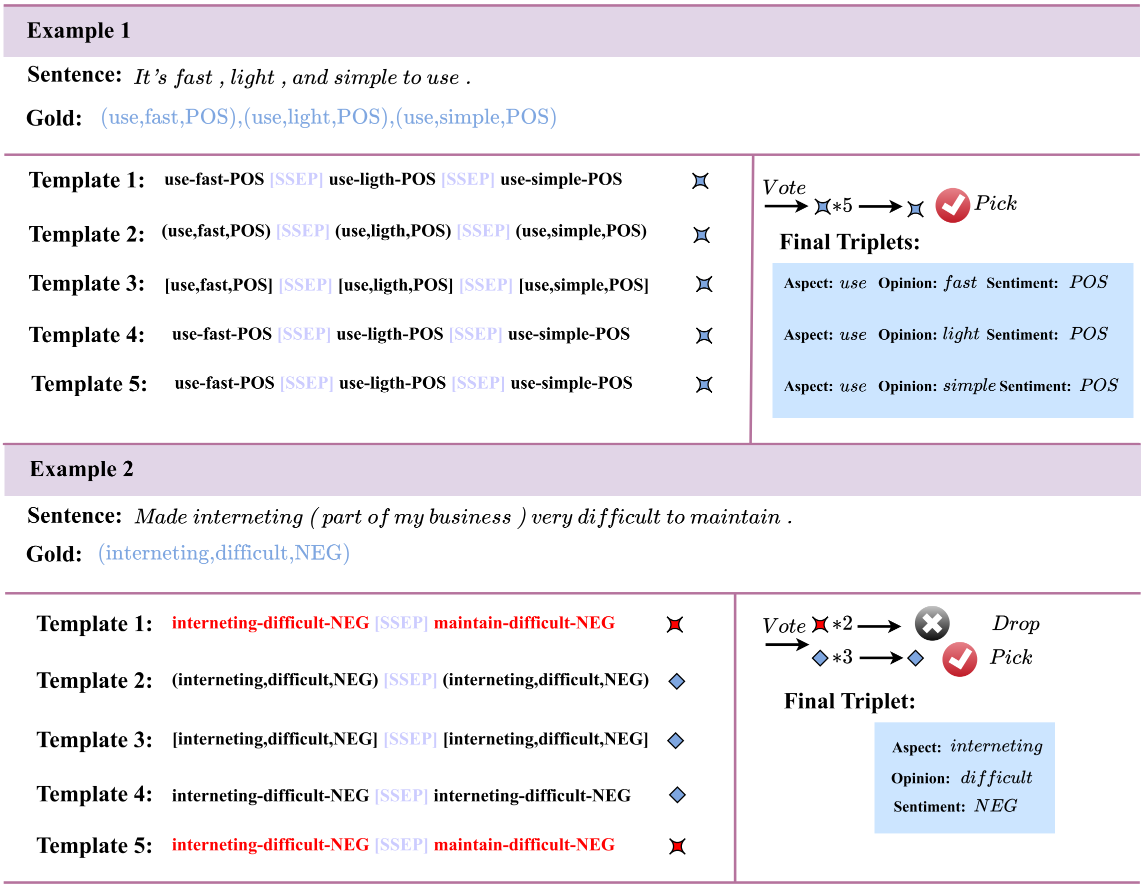
To further explore the performance of the model in actual datasets, two types of sentences are analyzed: single triplet and multiple triplets, as shown in Fig. 13, to verify the effectiveness of the model in triplet extraction.

In example 1, a sentence containing multiple triplets is a very common phenomenon in daily comments. The generation results after multi-template enhancement are shown in the figure. In the generation results of each template, the model accurately generated three correct triplets. Through the comprehensive selection of five templates, the final triplet



(a) (b)

Fig. 12. Terminological afinity analysis.



Example 1

Sentence: *It's fast , light , and simple to use .*

Gold: (use,fast,POS),(use,light,POS),(use,simple,POS)

Template 1: use-fast-POS [SSEP] use-ligth-POS [SSEP] use-simple-POS

Template 2: (use,fast,POS) [SSEP] (use,ligth,POS) [SSEP] (use,simple,POS)

Template 3: [use,fast,POS] [SSEP] [use,ligth,POS] [SSEP] [use,simple,POS]

Template 4: use-fast-POS [SSEP] use-ligth-POS [SSEP] use-simple-POS

Template 5: use-fast-POS [SSEP] use-ligth-POS [SSEP] use-simple-POS

Vote *5 *Pick*

Final Triplets:

Aspect: *use* **Opinion:** *fast* **Sentiment:** *POS*

Aspect: *use* **Opinion:** *light* **Sentiment:** *POS*

Aspect: *use* **Opinion:** *simple* **Sentiment:** *POS*

Example 2

Sentence: *Made interneting (part of my business) very difficult to maintain .*

Gold: (interneting,difficult,NEG)

Template 1: interneting-difficult-NEG [SSEP] maintain-difficult-NEG

Template 2: (interneting,difficult,NEG) [SSEP] (interneting,difficult,NEG)

Template 3: [interneting,difficult,NEG] [SSEP] [interneting,difficult,NEG]

Template 4: interneting-difficult-NEG [SSEP] interneting-difficult-NEG

Template 5: interneting-difficult-NEG [SSEP] maintain-difficult-NEG

Vote *2 *Drop*

*3 *Pick*

Final Triplet:

Aspect: *interneting*
Opinion: *difficult*
Sentiment: *NEG*

Fig. 13. Case study of MPGM. Generated triplets are annotated with distinct symbols and selected via voting.

obtained through the voting mechanism is completely correct and accurately reflects the content of the original sentence.

In example 2, the example sentence contains a triplet, but its syntactic structure is more complex and includes bracketed explanation components. Due to the different designs of the templates, the generation effects of each template vary significantly. It should be noted that each template generates two triplets, and the generated results of template 1 and template 5 both contain an incorrect triplet *(maintain, difficult, NEG)*. However, the results generated by template 2, template 3, and template 4 are all two identical and correct triplets. Therefore, in the voting, the generated results of templates 2, 3, and 4 received 3 votes more than the remaining two votes and are selected as the final correct triplet extraction results, and the final triplets are obtained after removing duplicates.

5. Conclusion

In this paper, we have proposed a new model MPGM. It embeds multiple high-quality prompt templates with strong generation capabilities into the model and combines the triplets generated by different templates using a voting mechanism. The TAE module incorporates prompt information for aspect terms and opinion terms into the training process. It accurately processes term features through position annotation and a masking mechanism, ensuring the model can effectively capture the semantic features of both aspect and opinion terms. In addition, D2SCL is designed to further enhance the model's ability to capture similarities and differences between triplets, improving the learning of more discriminative feature representations. During the experiment, the model demonstrates superior performance when tested on two publicly available ASTE datasets. Ablation experiments demonstrate the efficacy of every component within the model for performance improvement. In particular, the adoption of multi-template prompts leads to a significant improvement in model performance. Finally, visualization experiments are conducted to analyze the impact of each module on model performance, further confirming the superiority of the proposed model in addressing ASTE tasks. Future research will focus on a more in-depth exploration of generative models. Particular attention will be given to the impact of template quality on model performance, with the goal of guiding the design of more effective and efficient prompting strategies. Further efforts will focus on filtering out invalid triplets to enhance the model's applicability to ASTE tasks.

CRediT authorship contribution statement

Kun Yang: Writing – review & editing, Visualization, Conceptualization, Writing – original draft, Methodology; **Liansong Zong:** Supervision, Formal analysis; **Mingwei Tang:** Funding acquisition, Supervision, Conceptualization; **Jie Hu:** Supervision, Validation; **Yanxi Zheng:** Visualization, Conceptualization, Investigation; **Yujun Chen:** Visualization, Methodology; **Mingfeng Zhao:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported by Sichuan Science and Technology Program (No. 25LHJJ0133), the Scientic Research Funds project of Science and Technology Department of SichuanProvince (Nos. 2019YFG0508, 2019GFW131, 2026**), Sichuan Key R&D project (No. 2023YFG0354), the National Natural Science Foundation of China (No. 61902324), Funds Project of Chengdu Science and Technology Bureau (Nos. 2017-RK00-00026-ZF, 2022-YF04-00065-JH, 2023-JB00-00020-GX) and the Xihua University Education and teaching reform project (No: xjjg2021049, xjjg2021115).

References

Akhtar, M. S., Chauhan, D. S., Ghosal, D., Poria, S., Ekbal, A., & Bhattacharyya, P. (2019). Multi-task learning for multi-modal emotion recognition and sentiment analysis. In J. Burstein, C. Doran, & T. Solorio (Eds.), *Proceedings of the 2019 conference of the north american chapter of the association for computational linguistics: Human language technologies, NAACL-HLT 2019, Minneapolis, MN, USA, june 2–7, 2019, volume 1 (long and short papers)* (pp. 370–379). Association for Computational Linguistics. https://doi.org/10.18653/V1/N19-1034.

Bai, Y., Han, Z., Zhao, Y., Gao, H., Zhang, Z., Wang, X., & Hu, M. (2024). Is compound aspect-based sentiment analysis addressed by LLMs? In Y. Al-Onaizan, M. Bansal, & Y. Chen (Eds.), *Findings of the association for computational linguistics: EMNLP 2024, miami, Florida, USA, november 12–16, 2024* (pp. 7836–7861). Association for Computational Linguistics. https://aclanthology.org/2024.findings-emnlp.460.

Cai, H., Ma, H., Yu, J., & Xia, R. (2024). A joint coreference-aware approach to document-level target sentiment analysis. In L. Ku, A. Martins, & V. Srikumar (Eds.), *Proceedings of the 62nd annual meeting of the association for computational linguistics (volume 1: Long papers), ACL 2024, Bangkok, Thailand, august 11–16, 2024* (pp. 12149–12160). Association for Computational Linguistics. https://doi.org/10.18653/V1/2024.ACL-LONG.657.

Chai, H., Yao, Z., Tang, S., Wang, Y., Nie, L., Fang, B., & Liao, Q. (2023). Aspect-to-scope oriented multi-view contrastive learning for aspect-based sentiment analysis. In H. Bouamor, J. Pino, & K. Bali (Eds.), *Findings of the association for computational linguistics: EMNLP 2023, Singapore, december 6–10, 2023* (pp. 10902–10913). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.FINDINGS-EMNLP.727.

Chen, H., Zhai, Z., Feng, F., Li, R., & Wang, X. (2022). Enhanced multi-channel graph convolutional network for aspect sentiment triplet extraction. In S. Muresan, P. Nakov, & A. Villavicencio (Eds.), *Proceedings of the 60th annual meeting of the association for computational linguistics (volume 1: Long papers), ACL 2022, Dublin, Ireland, may 22–27, 2022* (pp. 2974–2985). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.ACL-LONG.212.

Chen, S., Liu, J., Wang, Y., Zhang, W., & Chi, Z. (2020). Synchronous double-channel recurrent network for aspect-opinion pair extraction. In D. Jurafsky, J. Chai, N. Schluter, & J. R. Tetreault (Eds.), *Proceedings of the 58th annual meeting of the association for computational linguistics, ACL 2020, online, july 5–10, 2020* (pp. 6515–6524). Association for Computational Linguistics. https://doi.org/10.18653/V1/2020.ACL-MAIN.582.

Chumakov, S., Kovantsev, A., & Surikov, A. (2023). Generative approach to aspect based sentiment analysis with GPT language models. *12th international young scientists conference in computational science, YSC2023* (pp. 284–293). (*229*). https://doi.org/10.1016/j.procs.2023.12.030

Dai, H., & Song, Y. (2019). Neural aspect and opinion term extraction with mined rules as weak supervision. In A. Korhonen, D. R. Traum, & L. Màrquez (Eds.), *Proceedings of the 57th conference of the association for computational linguistics, ACL 2019, Florence, Italy, july 28- august 2, 2019, volume 1: Long papers* (pp. 5268–5277). Association for Computational Linguistics. https://doi.org/10.18653/V1/P19-1520.

Deng, Y., Zhang, W., Pan, S. J., & Bing, L. (2023). Bidirectional generative framework for cross-domain aspect-based sentiment analysis. In A. Rogers, J. L. Boyd-Graber, & N. Okazaki (Eds.), *Proceedings of the 61st annual meeting of the association for computational linguistics (volume 1: Long papers), ACL 2023, Toronto, Canada, july 9–14, 2023* (pp. 12272–12285). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.ACL-LONG.686.

Devlin, J., Chang, M., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In J. Burstein, C. Doran, & T. Solorio (Eds.), *Proceedings of the 2019 conference of the north american chapter of the association for computational linguistics: Human language technologies, NAACL-HLT 2019, Minneapolis, MN, USA, june 2–7, 2019, volume 1 (long and short papers)* (pp. 4171–4186). Association for Computational Linguistics. https://doi.org/10.18653/V1/N19-1423.

Gao, L., Wang, Y., Liu, T., Wang, J., Zhang, L., & Liao, J. (2021). Question-driven span labeling model for aspect-opinion pair extraction. In *Thirty-fifth AAAI conference on artificial intelligence, AAAI 2021, thirty-third conference on innovative applications of artificial intelligence, IAAI 2021, the eleventh symposium on educational advances in artificial intelligence, EAAI 2021, virtual event, february 2–9, 2021* (pp. 12875–12883). AAAI Press. https://doi.org/10.1609/AAAI.V35I14.17523.

Gou, Z., Guo, Q., & Yang, Y. (2023). Mvp: Multi-view prompting improves aspect sentiment tuple prediction. In A. Rogers, J. L. Boyd-Graber, & N. Okazaki (Eds.), *Proceedings of the 61st annual meeting of the association for computational linguistics (volume 1: Long papers), ACL 2023, Toronto, Canada, july 9–14, 2023* (pp. 4380–4397). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.ACL-LONG.240.

Guan, M., Li, F., & Xue, Y. (2024). Enhanced syntactic and semantic graph convolutional network with contrastive learning for aspect-based sentiment analysis. *IEEE Transactions on Computational Social Systems*, *11*(1), 859–870. https://doi.org/10.1109/TCSS.2023.3296476.

Hao, S., Zhou, Y., Liu, P., & Xu, S. (2024). Bi-syntax guided transformer network for aspect sentiment triplet extraction. *Neurocomputing*, *594*, 127880. https://doi.org/10.1016/J.NEUCOM.2024.127880.

Hsu, T., Chen, C., Huang, H., & Chen, H. (2021). Semantics-preserved data augmentation for aspect-based sentiment analysis. In M. Moens, X. Huang, L. Specia, & S. W. Yih (Eds.), *Proceedings of the 2021 conference on empirical methods in natural language processing, EMNLP 2021, virtual event / Punta Cana, Dominican Republic, 7–11 november, 2021* (pp. 4417–4422). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.EMNLP-MAIN.362.

Hu, M., Wu, Y., Gao, H., Bai, Y., & Zhao, S. (2022). Improving aspect sentiment quad prediction via template-order data augmentation. In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Proceedings of the 2022 conference on empirical methods in natural language processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, december 7–11, 2022* (pp. 7889–7900). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.EMNLP-MAIN.538.

Jiang, B., Wan, Y., & Ju, S. (2024). Heuristic-enhanced candidates selection strategy for GPTs tackle few-shot aspect-based sentiment analysis. arXiv:2404.06063.

Kaur, M., & Mohta, A. (2019). A review of deep learning with recurrent neural network. In *2019 international conference on smart systems and inventive technology (ICSSIT)* (pp. 460–465). https://doi.org/10.1109/ICSSIT46314.2019.8987837

Li, P., Li, P., & Zhang, K. (2023). Dual-channel span for aspect sentiment triplet extraction. In H. Bouamor, J. Pino, & K. Bali (Eds.), *Proceedings of the 2023 conference on empirical methods in natural language processing, EMNLP 2023, Singapore, december 6–10, 2023* (pp. 248–261). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.EMNLP-MAIN.17.

Li, R., Chen, H., Feng, F., Ma, Z., Wang, X., & Hovy, E. H. (2021). Dual graph convolutional networks for aspect-based sentiment analysis. In C. Zong, F. Xia, W. Li, & R. Navigli (Eds.), *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing, ACL/IJCNLP 2021, (volume 1: Long papers), virtual event, august 1–6, 2021* (pp. 6319–6329). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.ACL-LONG.494.

Li, S., Wang, Z., Zhao, Z., Zhang, Y., & Li, P. (2025). Exploring model editing for LLM-based aspect-based sentiment classification. In T. Walsh, J. Shah, & Z. Kolter (Eds.), *Aaai-25, sponsored by the association for the advancement of artificial intelligence, february 25, - march 4, 2025, Philadelphia, PA, USA* (pp. 24467–24475). AAAI Press. https://doi.org/10.1609/AAAI.V39I23.34625.

Li, X., Bing, L., Li, P., & Lam, W. (2019). A unified model for opinion target extraction and target sentiment prediction. In *The thirty-third AAAI conference on artificial intelligence, AAAI 2019, the thirty-first innovative applications of artificial intelligence conference, IAAI 2019, the ninth AAAI symposium on educational advances in artificial intelligence, EAAI 2019, Honolulu, Hawaii, USA, january 27, - february 1, 2019* (pp. 6714–6721). AAAI Press. https://doi.org/10.1609/AAAI.V33I01.33016714.

Li, Z., Song, Y., Lu, X., & Liu, M. (2024). Twin towers end to end model for aspect-based sentiment analysis. *Expert Systems with Applications*, *249*, 123713. https://doi.org/10.1016/J.ESWA.2024.123713.

Liang, S., Wei, W., Mao, X., Fu, Y., Fang, R., & Chen, D. (2023). STAGE: Span tagging and greedy inference scheme for aspect sentiment triplet extraction. In B. Williams, Y. Chen, & J. Neville (Eds.), *Thirty-seventh AAAI conference on artificial intelligence, AAAI 2023, thirty-fifth conference on innovative applications of artificial intelligence, IAAI 2023, thirteenth symposium on educational advances in artificial intelligence, EAAI 2023, Washington, DC, USA, february 7–14, 2023* (pp. 13174–13182). AAAI Press. https://doi.org/10.1609/AAAI.V37I11.26547.

Lu, H., Cong, R., Nie, W., Liu, T., & Fang, W. (2025). A novel span-based knowledge-enhanced framework for aspect sentiment triplet extraction. *Neurocomputing*, *619*, 129145. https://doi.org/10.1016/J.NEUCOM.2024.129145.

Ma, D., Li, S., Wu, F., Xie, X., & Wang, H. (2019). Exploring sequence-to-sequence learning in aspect term extraction. In A. Korhonen, D. R. Traum, & L. Màrquez (Eds.), *Proceedings of the 57th conference of the association for computational linguistics, ACL 2019, Florence, Italy, july 28- august 2, 2019, volume 1: Long papers* (pp. 3538–3547). Association for Computational Linguistics. https://doi.org/10.18653/V1/P19-1344.

Maree, M., & Eleyat, M. (2020). Semantic graph based term expansion for sentence-level sentiment analysis. *International Journal of Computer Vision*, *19*, 647–655. https://doi.org/10.47839/IJC.19.4.2000.

Mukherjee, R., Kannen, N., Pandey, S. K., & Goyal, P. (2023). CONTRASTE: Supervised contrastive pre-training with aspect-based prompts for aspect sentiment triplet extraction. In H. Bouamor, J. Pino, & K. Bali (Eds.), *Findings of the association for computational linguistics: EMNLP 2023, Singapore, december 6–10, 2023* (pp. 12065–12080). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.FINDINGS-EMNLP.807.

Peng, H., Xu, L., Bing, L., Huang, F., Lu, W., & Si, L. (2020). Knowing what, how and why: A near complete solution for aspect-based sentiment analysis. In *The thirty-fourth AAAI conference on artificial intelligence, AAAI 2020, the thirty-second innovative applications of artificial intelligence conference, IAAI 2020, the tenth AAAI symposium on educational advances in artificial intelligence, EAAI 2020, New York, NY, USA, february 7–12, 2020* (pp. 8600–8607). AAAI Press. https://doi.org/10.1609/AAAI.V34I05.6383.

Peng, K., Jiang, L., Peng, H., Liu, R., Yu, Z., Ren, J., Hao, Z., & Yu, P. S. (2024). Prompt based tri-channel graph convolution neural network for aspect sentiment triplet extraction. In S. Shekhar, V. Papalexakis, J. Gao, Z. Jiang, & M. Riondato (Eds.), *Proceedings of the 2024 SIAM international conference on data mining, SDM 2024, Houston, TX, USA, april 18–20, 2024* (pp. 145–153). SIAM. https://doi.org/10.1137/1.9781611978032.17.

Peper, J., & Wang, L. (2022). Generative aspect-based sentiment analysis with contrastive learning and expressive structure. In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Findings of the association for computational linguistics: EMNLP 2022, Abu Dhabi, United*

Arab Emirates, december 7–11, 2022 (pp. 6089–6095). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.FINDINGS-EMNLP.451.

Phan, H. T., & Nguyen, N. T. (2024). A fuzzy graph convolutional network model for sentence-level sentiment analysis. *Trans. Fuzzy Syst.*IEEE Transactions on Fuzzy Systems, *32*(5), 2953–2965. https://doi.org/10.1109/TFUZZ.2024.3364694.

Qian, F., Han, J., He, Y., Zheng, T., & Zheng, G. (2023). Sentiment knowledge enhanced self-supervised learning for multimodal sentiment analysis. In A. Rogers, J. L. Boyd-Graber, & N. Okazaki (Eds.), *Findings of the association for computational linguistics: ACL 2023, Toronto, Canada, july 9–14, 2023* (pp. 12966–12978). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.FINDINGS-ACL.821.

Radi, M., Omar, N., & Kaur, W. (2024). Target-aspect-sentiment joint detection: Uncovering explicit and implicit targets through aspect-target-context-aware detection. *Access, 12*, 100689–100699.

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., & Liu, P. J. (2019). Exploring the limits of transfer learning with a unified text-to-text transformer. CoRR abs/1910.10683. http://arxiv.org/abs/1910.10683.

Rhanoui, M., Mikram, M., Yousfi, S., & Barzali, S. (2019). A CNN-biLSTM model for document-level sentiment analysis. *Machine Learning and Knowledge Extraction* , *1*(3), 832–847. https://doi.org/10.3390/MAKE1030048.

Schuster, M., & Paliwal, K. K. (1997). Bidirectional recurrent neural networks. *IEEE Transactions on Signal Processing, 45*(11), 2673–2681.

Shi, J., Li, W., Bai, Q., Yang, Y., & Jiang, J. (2023). Syntax-enhanced aspect-based sentiment analysis with multi-layer attention. *Neurocomputing*, *557*, 126730. https://doi.org/10.1016/J.NEUCOM.2023.126730.

Song, N., Cai, H., Xia, R., Yu, J., Wu, Z., & Dai, X. (2023). A sequence-to-structure approach to document-level targeted sentiment analysis. In H. Bouamor, J. Pino, & K. Bali (Eds.), *Findings of the association for computational linguistics: EMNLP 2023, Singapore, december 6–10, 2023* (pp. 7687–7698). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.FINDINGS-EMNLP.515.

Sun, Q., Yang, L., Ma, M., Ye, N., & Gu, Q. (2024). Rethinking ASTE: A minimalist tagging scheme alongside contrastive learning. CoRR abs/2403.07342. https://doi.org/10.48550/arXiv.2403.07342.

Sun, X., Qi, J., Zhu, Z., Li, M., Pei, H., & Meng, J. (2025). Senticnet and abstract meaning representation driven attention-gate semantic framework for aspect sentiment triplet extraction. *Engineering Applications of Artificial Intelligence*, *139*, 109625. https://doi.org/10.1016/J.ENGAPPAI.2024.109625.

Tang, J., Lu, Z., Su, J., Ge, Y., Song, L., Sun, L., & Luo, J. (2019). Progressive self-supervised attention learning for aspect-level sentiment analysis. In A. Korhonen, D. R. Traum, & L. Màrquez (Eds.), *Proceedings of the 57th conference of the association for computational linguistics, ACL 2019, Florence, Italy, july 28- august 2, 2019, volume 1: Long papers* (pp. 557–566). Association for Computational Linguistics. https://doi.org/10.18653/V1/P19-1053.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. In I. Guyon, U. von Luxburg, S. Bengio, H. M. Wallach, R. Fergus, S. V. N. Vishwanathan, & R. Garnett (Eds.), *Advances in neural information processing systems 30: Annual conference on neural information processing systems 2017, december 4–9, 2017, Long Beach, CA, USA* (pp. 5998–6008). https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html.

Wan, H., Yang, Y., Du, J., Liu, Y., Qi, K., & Pan, J. Z. (2020). Target-aspect-sentiment joint detection for aspect-based sentiment analysis. In *The thirty-fourth AAAI conference on artificial intelligence, AAAI 2020, the thirty-second innovative applications of artificial intelligence conference, IAAI 2020, the tenth AAAI symposium on educational advances in artificial intelligence, EAAI 2020, New York, NY, USA, february 7–12, 2020* (pp. 9122–9129). AAAI Press. https://doi.org/10.1609/AAAI.V34I05.6447.

Wan, Y., Chen, Y., Shi, L., & Liu, L. (2023). A knowledge-enhanced interactive graph convolutional network for aspect-based sentiment analysis. *Journal of Intelligent Information Systems*, *61*(2), 343–365. https://doi.org/10.1007/S10844-022-00761-1.

Wang, B., Ding, L., Zhong, Q., Li, X., & Tao, D. (2022). A contrastive cross-channel data augmentation framework for aspect-based sentiment analysis. In N. Calzolari, C. Huang, H. Kim, J. Pustejovsky, L. Wanner, K. Choi, P. Ryu, H. Chen, L. Donatelli, H. Ji, S. Kurohashi, P. Paggio, N. Xue, S. Kim, Y. Hahm, Z. He, T. K. Lee, E. Santus, F. Bond, & S. Na (Eds.), *Proceedings of the 29th international conference on computational linguistics, COLING 2022, Gyeongju, Republic of Korea, october 12–17, 2022* (pp. 6691–6704). International Committee on Computational Linguistics. https://aclanthology.org/2022.coling-1.581.

Wang, H., He, K., Li, B., Chen, L., Li, F., Han, X., Teng, C., & Ji, D. (2024a). Refining and synthesis: A simple yet effective data augmentation framework for cross-domain aspect-based sentiment analysis. In L. Ku, A. Martins, & V. Srikumar (Eds.), *Findings of the association for computational linguistics, ACL 2024, Bangkok, Thailand and virtual meeting, august 11–16, 2024* (pp. 10318–10329). Association for Computational Linguistics. https://doi.org/10.18653/V1/2024.FINDINGS-ACL.615.

Wang, J., Yu, L., & Zhang, X. (2024b). SoftMCL: Soft momentum contrastive learning for fine-grained sentiment-aware pre-training. In N. Calzolari, M. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.), *Proceedings of the 2024 joint international conference on computational linguistics, language resources and evaluation, LREC/COLING 2024, 20–25 may, 2024, Torino, Italy* (pp. 15012–15023). ELRA and ICCL. https://aclanthology.org/2024.lrec-main.1305.

Wang, W., Pan, S. J., Dahlmeier, D., & Xiao, X. (2017). Coupled multi-layer attentions for co-extraction of aspect and opinion terms. In S. Singh, & S. Markovitch (Eds.), *Proceedings of the thirty-first AAAI conference on artificial intelligence, february 4–9, 2017, San Francisco, California, USA* (pp. 3316–3322). AAAI Press. https://doi.org/10.1609/AAAI.V31I1.10974.

Wu, L., Chen, Y., Ji, H., & Liu, B. (2021a). Deep learning on graphs for natural language processing. In F. Zhu, B. C. Ooi, & C. Miao (Eds.), *KDD '21: The 27th ACM SIGKDD conference on knowledge discovery and data mining, virtual event, Singapore, august 14–18, 2021* (pp. 4084–4085). ACM. https://doi.org/10.1145/3447548.3470820.

Wu, L., Chen, Y., Shen, K., Guo, X., Gao, H., Li, S., Pei, J., & Long, B. (2023). Graph neural networks for natural language processing: A survey. *Foundations and Trends in Machine Learning*, *16*(2), 119–328. https://doi.org/10.1561/2200000096.

Wu, S., Fei, H., Ren, Y., Ji, D., & Li, J. (2021b). Learn from syntax: Improving pair-wise aspect and opinion terms extractionwith rich syntactic knowledge. CoRR abs/2105.02520. https://arxiv.org/abs/2105.02520.

Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2019). A comprehensive survey on graph neural networks. CoRR abs/1901.00596. http://arxiv.org/abs/1901.00596.

Wu, Z., Ying, C., Zhao, F., Fan, Z., Dai, X., & Xia, R. (2020). Grid tagging scheme for aspect-oriented fine-grained opinion extraction. CoRR abs/2010.04640. https://arxiv.org/abs/2010.04640.

Xu, H., Tang, M., Cai, T., Hu, J., & Zhao, M. (2024). Dual-enhanced generative model with graph attention network and contrastive learning for aspect sentiment triplet extraction. *Knowledge-Based Systems*, *301*, 112342. https://doi.org/10.1016/J.KNOSYS.2024.112342.

Xu, L., Chia, Y. K., & Bing, L. (2021). Learning span-level interactions for aspect sentiment triplet extraction. In C. Zong, F. Xia, W. Li, & R. Navigli (Eds.), *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing, ACL/IJCNLP 2021, (volume 1: Long papers), virtual event, august 1–6, 2021* (pp. 4755–4766). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.ACL-LONG.367.

Xu, L., Li, H., Lu, W., & Bing, L. (2020). Position-aware tagging for aspect sentiment triplet extraction. In B. Webber, T. Cohn, Y. He, & Y. Liu (Eds.), *Proceedings of the 2020 conference on empirical methods in natural language processing, EMNLP 2020, online, november 16–20, 2020* (pp. 2339–2349). Association for Computational Linguistics. https://doi.org/10.18653/V1/2020.EMNLP-MAIN.183.

Xu, L., & Wang, W. (2025). Aspect-based sentiment classification with BERT and AI feedback. *Natural Language Processing Journal*, *10*, 100136. https://doi.org/10.1016/J.NLP.2025.100136.

Yan, H., Dai, J., Ji, T., Qiu, X., & Zhang, Z. (2021). A unified generative framework for aspect-based sentiment analysis. In C. Zong, F. Xia, W. Li, & R. Navigli (Eds.), *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing, ACL/IJCNLP 2021, (volume 1: Long papers), virtual event, august 1–6, 2021* (pp. 2416–2429). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.ACL-LONG.188.

Yang, B., Wu, L., Zhu, J., Shao, B., Lin, X., & Liu, T. (2022). Multimodal sentiment analysis with two-phase multi-task learning. *IEEE ACM Transactions on Audio, Speech and Language Processing*, *30*, 2015–2024. https://doi.org/10.1109/TASLP.2022.3178204.

Yang, Z., Dai, Z., Yang, Y., Carbonell, J. G., Salakhutdinov, R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In H. M. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. B. Fox, & R. Garnett (Eds.), *Advances in neural information processing systems 32: Annual conference on neural information processing systems 2019, neurIPS 2019, december 8–14, 2019, Vancouver, BC, Canada* (pp. 5754–5764). https://proceedings.neurips.cc/paper/2019/hash/dc6a7e655d7e5840e66733e9ee67cc69-Abstract.html.

Yuan, L., Wang, J., Yu, L., & Zhang, X. (2024). Encoding syntactic information into transformers for aspect-based sentiment triplet extraction. *IEEE Transactions on Affective Computing, 15*(2), 722–735.

Zhai, Z., Chen, H., Feng, F., Li, R., & Wang, X. (2022). COM-MRC: A context-masked machine reading comprehension framework for aspect sentiment triplet extraction. In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Proceedings of the 2022 conference on empirical methods in natural language processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, december 7–11, 2022* (pp. 3230–3241). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.EMNLP-MAIN.212.

Zhang, M., Zhu, Y., Liu, Z., Bao, Z., Wu, Y., Sun, X., & Xu, L. (2023a). Span-level aspect-based sentiment analysis via table filling. In A. Rogers, J. L. Boyd-Graber, & N. Okazaki (Eds.), *Proceedings of the 61st annual meeting of the association for computational linguistics (volume 1: Long papers), ACL 2023, toronto, canada, july 9–14, 2023* (pp. 9273–9284). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.ACL-LONG.515

Zhang, W., Deng, Y., Li, X., Yuan, Y., Bing, L., & Lam, W. (2021a). Aspect sentiment quad prediction as paraphrase generation. In M. Moens, X. Huang, L. Specia, & S. W. Yih (Eds.), *Proceedings of the 2021 conference on empirical methods in natural language processing, EMNLP 2021, virtual event / Punta Cana, Dominican Republic, 7–11 november, 2021* (pp. 9209–9219). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.EMNLP-MAIN.726.

Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2021b). Towards generative aspect-based sentiment analysis. In C. Zong, F. Xia, W. Li, & R. Navigli (Eds.), *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing, ACL/IJCNLP 2021, (volume 2: Short papers), virtual event, august 1–6, 2021* (pp. 504–510). Association for Computational Linguistics. https://doi.org/10.18653/V1/2021.ACL-SHORT.64.

Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2023b). A survey on aspect-based sentiment analysis: Tasks, methods, and challenges. *IEEE Transactions on Knowledge and Data Engineering, 35*(11), 11019–11038.

Zhang, Y., Yang, Y., Li, Y., Liang, B., Chen, S., Dang, Y., Yang, M., & Xu, R. (2022a). Boundary-driven table-filling for aspect sentiment triplet extraction. In Y. Goldberg, Z. Kozareva, & Y. Zhang (Eds.), *Proceedings of the 2022 conference on empirical methods in natural language processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, december 7–11, 2022* (pp. 6485–6498). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.EMNLP-MAIN.435.

Zhang, Z., Zhou, Z., & Wang, Y. (2022b). SSEGCN: Syntactic and semantic enhanced graph convolutional network for aspect-based sentiment analysis. In M. Carpuat, M. de Marneffe, & I. V. M. Ruíz (Eds.), *Proceedings of the 2022 conference of the north american chapter of the association for computational linguistics: Human language technologies, NAACL 2022, Seattle, WA, United States, july 10–15, 2022* (pp. 4916–4925). Association for Computational Linguistics. https://doi.org/10.18653/V1/2022.NAACL-MAIN.362.

Zhao, X., Zhou, Y., & Xu, X. (2024). Dual encoder: Exploiting the potential of syntactic and semantic for aspect sentiment triplet extraction. In N. Calzolari, M. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.), *Proceedings of the 2024 joint international conference on computational linguistics, language resources and evaluation, LREC/COLING 2024, 20–25 may, 2024, Torino, Italy* (pp. 5401–5413). ELRA and ICCL. https://aclanthology.org/2024.lrec-main.480.

Zheng, G., Wang, J., Yu, L., & Zhang, X. (2024). Instruction tuning with retrieval-based examples ranking for aspect-based sentiment analysis. In L. Ku, A. Martins, & V. Srikumar (Eds.), *Findings of the association for computational linguistics, ACL 2024, Bangkok, Thailand and virtual meeting, august 11–16, 2024* (pp. 4777–4788). Association for Computational Linguistics. https://doi.org/10.18653/V1/2024.FINDINGS-ACL.284.

Zhou, S., & Qian, T. (2023). On the strength of sequence labeling and generative models for aspect sentiment triplet extraction. In A. Rogers, J. L. Boyd-Graber, & N. Okazaki (Eds.), *Findings of the association for computational linguistics: ACL 2023, Toronto, Canada, july 9–14, 2023* (pp. 12038–12050). Association for Computational Linguistics. https://doi.org/10.18653/V1/2023.FINDINGS-ACL.762.

Zhou, X., Wan, X., & Xiao, J. (2015). Representation learning for aspect category detection in online reviews. In B. Bonet, & S. Koenig (Eds.), *Proceedings of the twenty-ninth AAAI conference on artificial intelligence, january 25–30, 2015, Austin, Texas, USA* (pp. 417–424). AAAI Press. https://doi.org/10.1609/AAAI.V29I1.9194.

Zhu, S., Zhao, H., Wang, X., Liu, S., Jia, Y., & Zan, H. (2024). ZZU-NLP at SIGHAN-2024 dimabsa task: Aspect-based sentiment analysis with coarse-to-fine in-context learning. CoRR abs/2407.15341. https://doi.org/10.48550/arXiv.2407.15341.