Implicit Sentiment Extraction Using Structure Generation with Sentiment Instructor Prompt Template

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Abstract. Aspect-Category-Opinion-Sentiment quadruple extraction (ACOS) is the novel and challenging sentiment analysis task, which aims to analyze the full range of emotional causes. Existing approaches focus on solving explicit sentiment, but struggle with analyzing implicit sentiment reviews. In this paper, to address the issue, we propose SI-TS, a framework that takes implicit sentiment extraction into account. Specifically, we design target structure (TS) to capture implicit sentiment by converting sentiment elements into a structured format. Furthermore, to adaptively generate appropriate TS according to different sentiment scenarios, we design an prompt template based sentiment instructor(SI). It assists the framework in effectively extracting implicit sentiment elements from the reviews. Extensive experiments were conducted on two widely used ACOS benchmarks, and improvements in F1 values were observed. Specifically, we achieved a 1.05% and 1.28% improvement in F1 values for Laptop-ACOS and Restaurant-ACOS, respectively. Notably, significant results were achieved in extracting implicit sentiment.

Keywords: The ACOS Task · Implicit Sentiment Extraction · Target Structure (TS) · Sentiment Instructor (SI) · Prompt Template

1 Introduction

Aspect-Category-Opinion-Sentiment quadruple extraction(ACOS) [1] is a challenging task in aspect-based sentiment analysis(ABSA) [2,3], This is a typical multitask with four sub-tasks, which are (1) identifying aspect term mentions, (2) detecting aspect categories, (3) extracting opinions linked to aspects, and (4) classifying the sentiments belonging to aspect. These help us to understand the aspect-level opinions in the reviews and provide a complete story. Give an example review "The ambience is wonderful for a date or group outing." The review can be extracted as a pair of four elements of aspect-category-opinion-sentiment (a, c, o, s), which are aspect (a): "service", category (c): "food quality", opinion (o): "wonderful", and sentiment (s): "positive".

The typical studies tackle this task by using either extractive or generative methods. (1) Extractive methods require designing specific sentiment element

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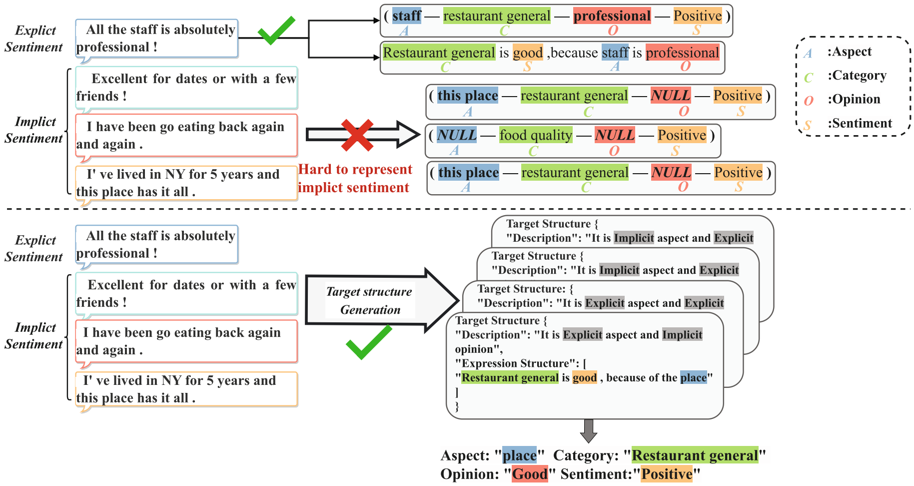

Fig. 1. Comparison between existing frameworks and our framework. Above the split dashed line is the existing framework. Below the split dashed line is our proposed framework. We believe that using target structure to represent sentiment quadruples in a unified way can comprehensively consider a variety of implicit sentiments, This approach allows better assisting the framework to mine implicit sentiments.

extraction modules to jointly model individual or multiple sentiment elements. Cai et al. [1] Perform category classification on candidate aspect-opinion pairs based on Peng et al. [4] and Wan et al. [5] for sentiment quadruplet extraction. They also extended the labeling model using a sequential labeling approach inspired by this work [6]. (2) Generative methods employ sequence generation approach to generate sentiment elements directly. For instance, Yan et al [7], proposed a generative framework. Meanwhile, models such as GAS [8], PARAPHRASE [9] and USI [10] generate sentiment elements or paraphrases directly in the task. The generative approach is preferred over the extractive approach for generating sentiment using generic knowledge, leading to a shift in research towards generative approaches for sentiment extraction.

However, existing approaches to the ACOS task struggle with cases where reviews include implicit aspects or implicit opinions. According to recent studies [11,12], a significant portion of reviews in the corpus contain implicit expressions, with over 30% including implicit aspects or opinions, and more than 8% containing both [1]. We observe that most of the current research focuses on explicit sentiment and neglects modeling implicit sentiment(aspects or opinions).

To address the above limitation, our focus is on addressing the ACOS task, with particular emphasis on the extraction of implicit sentiment in formulations. The major difference between our work and current work is shown in Fig. 1. Firstly, we re-examine the sentiment features in reviews and categorize them into different sentiment scenarios, including three types of implicit sentiment scenarios and one type of explicit sentiment scenario. Secondly, based on the above sentiment scenarios, we propose SI-TS, a generation framework that takes implicit sentiment into account, Specifically, for one, we design target structure (TS) that can effectively encode the sentiment elements in different sentiment scenarios into a unified natural text representation, so that the text-to-structure process can be completed in different sentiment scenarios through the generation framework. For the second, in order to generate appropriate TS according to different sentiment scenarios, we design an prompt template based sentiment instructor (SI), which consists of sentiment scenario prompt, category candidate, sentiment candidate and expression prompt candidate, which can fully exploit the potential of the language model. The framework is also instructed to generate the corresponding TS adaptively, which helps the framework to explore the implicit sentiment elements from reviews under different sentiment scenarios. Finally, we conduct experiments on two benchmark ACOS datasets, and the results demonstrate the effectiveness of our proposed approach, especially in extracting implicit sentiment elements.

In summary, our main contributions are as follows:

1. We propose SI-TS, an implicit sentiment generation framework that contains an elaborate target structure (TS) that represent reviews in a variety of implicit sentiment scenarios.
2. To instruct the framework to generate suitable target structure, we propose an prompt template based sentiment instructor (SI) to help the model effectively mine implicit sentiment elements from the reviews.
3. Our experiments on two popular benchmarks show F1 improvements of 1.05% and 1.28% for Laptop-ACOS and Restaurant-ACOS, respectively. In addition, we achieved significant results in implicit sentiment extraction.

2 Problem Statement

2.1 ACOS Task Definition

Given a review sentence r the ACOS task aims to extract aspect-level quadruples $Q_i = (a_i, c_i, o_i, s_i)$. The elements a_i, c_i, o_i, s_i, corresponding to the i-th aspect, aspect category, opinion, and sentiment in the review r, these elements are collectively referred to as sentiment elements. The sentiment polarity s_i and $s_i \in \{POS, NEU, NEG\}$, where $\{POS, NEU, NEG\}$ stands for positive, neutral, negative, respectively.

2.2 Types of Sentiment Scenario

As shown in Fig. 2, we define aspect terms and opinion terms with explicit sentiment representation in review as EA (Explicit Aspect) and EO (Explicit Opinion), and if there are no aspect terms or opinion terms with explicit sentiment representation, we define them as IA (Implicit Aspect) and IO (Implicit Opinion). Reviews are divided into four sentiment scenarios, i.e. $\varepsilon = \{EA\&EO, EA\&IO, IA\&EO, IA\&IO\}$, i.e. the explicit sentiment scenario containing both EA and EO, and the three implicit sentiment scenarios containing either a single IA or IO or both IA and IO $\{(EA\&IO, IA\&EO, IA\&IO)\}$.

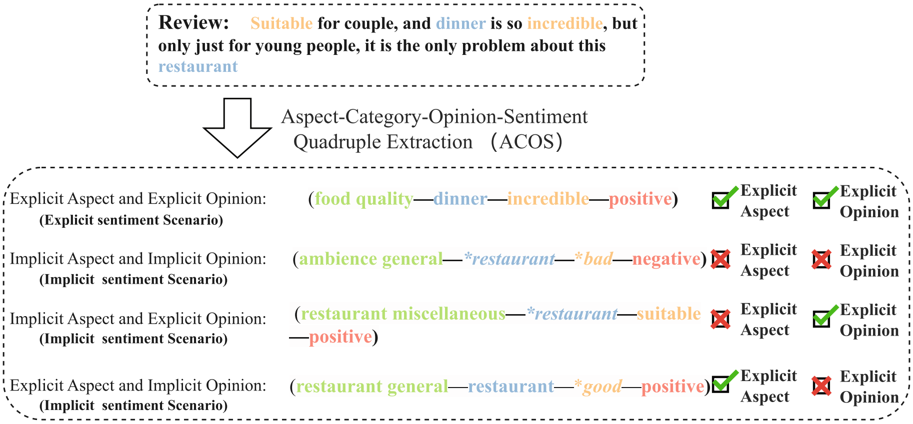

Fig. 2. The example review sentence in the figure contains four clauses, each of which contains a pair of sentiment quadruples. We define the clauses with explicit aspect and opinion as explicit sentiment scenarios (e.g. EA&EO) and the clauses without explicit aspect or opinion (with implicit aspect or opinion) as implicit sentiment scenarios (e.g. EA&IO, IA&EO, IA&IO). The cross in the figure means that it does not contain this item and the tick means that it does.

3 Methodology

In this section, we (1) introduce TS, a target structure that represents multiple implicit sentiment scenarios. And (2) propose SI, a prompt template based sentiment instructor, which controls the framework adaptively generating the corresponding target structure. The overall framework of SI-TS is shown in Fig. 3.

3.1 Sentiment Mapping

To better capture the semantics in the sentiment polarity set $\{s_i\}$, we first map the sentiment polarity s_i as follows.

$$P_s(s_i) = \begin{cases} great, & \text{if } \mathrm{s_i} = POS \\ ok, & \text{if } \mathrm{s_i} = NEU \\ bad, & \text{if } \mathrm{s_i} = NEG \end{cases} \tag{1}$$

After performing the sentiment mapping operation $P_s(.)$, The model is aware of selecting stronger semantics and more appropriate sentiments. Note that the particular mapping can be predefined using the commonsense knowledge in Eq. 1, or it can rely on the dataset, using the most common consensus terms for each sentiment polarity as sentiment expressions.

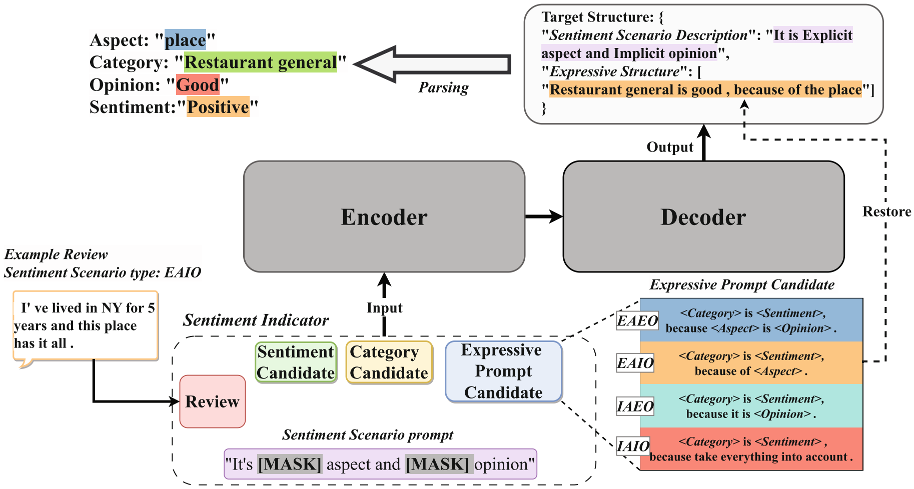

Fig. 3. The overall framework of SI-TS. Our framework first feeds the raw review into the encoder after a sentiment instructor (SI) transformation. Specifically, our sentiment instructor consists of Sentiment Scenario Prompt, Sentiment Candidate, Category Candidate, and Expression Prompt Candidate. After the transformation of the SI, decoder adaptively constructs the Target Structure (TS) based on the Sentiment Scenario Prompt, and the Expression Prompt Candidate. Finally, we parse the TS obtained from the output according to the location of the specific design to acquire the final quadruples. The expression structure we designed is shown in the bottom right part of the figure, and we design one expression prompt for each sentiment scenario (e.g., EA&EO, EA&IO, IA&EO, IA&IO).

3.2 Sentiment Instructor(SI) Components and Input Transformations

To leverage the capabilities of the language model and enable it to distinguish implicit sentiment scenarios, inspired by this paper [10], we employed a sentiment-instruction based prompting method to convert the input reviews r. The sentiment instructor we designed consist of the following components.

Sentiment Scenario Prompt. In order to allow the model to learn the discrepancy between sentiment scenarios, we designed the sentiment scenario prompt as part of the sentiment instructor. We define Sentiment Scenario prompt as I_{mask}. I_{mask} will be constructed for input in the following form:

$$I_{mask} = It's < extra\_id\_0 > aspect\ and < extra\_id\_1 > opinion \quad (2)$$

Here "$< extra\_id\_0 >$", "$< extra\_id\_1 >$" tokens are special mask tokens in the T5 model [29]. it allows better exploitation of the generic knowledge of language models by modeling downstream tasks as pre-trained targets. (i.e. mask language modeling). This approach, also called prompt learning [31], has shown powerful effectiveness on a wide range of NLP tasks.

Sentiment Candidate. We use the set of sentiment expressions $\{P_s(s_i)\}$ as candidates after sentiment mapping as described above. It enables the model to aware of which choice of sentiment expressions is required.

Category Candidate. The ACOS task also involves classifying aspect categories. Therefore, we also input all the set of categories $\{c\}$ as category candidates. It enables the model to be aware of which category choices are required.

Expressive Prompt Candidate. We designed the expression prompt T_{ep}, which makes the model aware of which expression structure may be generated. We designed four expression prompt corresponding to four sentiment scenarios, and combined together as expression prompt candidates as part of the sentiment instruction. Our expression prompt are shown in the bottom right corner of Fig. 3. To sum up, We concatenate the reviews r with all the instruction elements mentioned in the appeal, separated by separator, to obtain the input $\mathcal{X}$ refactored by the prompt template SI.

$$\mathcal{X} = [I_{mask}; [SSEP]; r; [SSEP]; \{P_s(s)\}; [SSEP]; \{c\}; [SSEP]; \{T_{ep}\}] \tag{3}$$

The input is represented by $\mathcal{X}$, with "$[SSEP]$" denoting the separator and ";" representing the connection operation.

3.3 Target Structure(TS) Generation for Implicit Sentiment

We adopt an encoder-decoder style architecture to compose our generative framework for extracting implicit sentiment. Our purposes are that:

(1) The corresponding target structures should be generated adaptively according to the implicit sentiment scenarios.
(2) In addition, to generate quadruples in one step and model multiple implicit sentiments scenarios, we adopt structures as output targets instead of sequential labels such as $< aspect >$, $< opinion >$, $< category >$, $< sentiment >$. Based on the above mentioned, inspired by this work. [32], we propose TS, a target structure that represent implicit sentiment. In the following we will describe our TS and its generation method.

Firstly, the decoder restores the special mask token (from SI) in I_{mask}, and during training, we restore the corresponding positions of the special mask token to "explicit" and "implicit". For the sentiment scenario $k/in/varepsilon$, the recovered I_{mask} we call the sentiment scenario description, which is defined as $I_{des}(k)$.

$$I_{des}(k) = \begin{cases} It's\ explicit\ aspect\ and\ explicit\ opinion. & \text{if } k\ is\ EA\&EO; \\ It's\ implicit\ aspect\ and\ explicit\ opinion. & \text{if } k\ is\ IA\&EO; \\ It's\ explicit\ aspect\ and\ implicit\ opinion. & \text{if } k\ is\ EA\&IO; \\ It's\ implicit\ aspect\ and\ implicit\ opinion. & \text{if } k\ is\ IA\&IO; \end{cases} \tag{4}$$

Second, we train to restore the special prompt tokens (e.g., $< category >$, $< emotion >$, $< view >$, $< opinion >$) which from the T_{ep} in the above SI.

During training. We employ the teacher forcing strategy to train the model to generate accurate sentiment elements corresponding to the special prompt tokens. We refer to the recovered T_{ep} as the expression structure, which is defined as $T_{et}(Q_i)$.

$$T_{aop}(a_i, o_i, k) = \begin{cases} because\ a_i\ is\ o_i. & \text{if } k \ \ is \ \ EA\&EO; \\ because\ it\ is\ o_i. & \text{if } k \ \ is \ \ IA\&EO; \\ because\ of\ the\ a_i. & \text{if } k \ \ is \ \ EA\&IO; \\ taking\ everything\ into\ account. & \text{if } k \ \ is \ \ IA\&IO; \end{cases} \tag{5}$$

$$T_{et}(Q_i) = c_i\ is\ P_s(s_i)\ T_{aop}(a_i, o_i, k) \tag{6}$$

$$T_{output}(Q_i, k) = I_{des}(k)\ ;\ T_{et}(Q_i) \tag{7}$$

Here, $T_{aop}(.)$ is a linear mapping function used to generate target structures for aspect-opinion pairs according to the sentiment scenario k. It maps different TS depending on the sentiment scenario. Considering that the review r probably contains more than one sentiment quadruple, we connect multiple sentiments using the special concatenation symbol "&&", and the final output TS form $\mathcal{Y}$ is:

$$\mathcal{Y} = T_{output}(Q_1, k)\ \&\&\cdots\ \&\&\ T_{output}(Q_n, k) \tag{8}$$

Notice that the target structure $T_{output}(Q_i, k)$ of our final output is reduced by $\mathcal{X}$. Also it is determined by the sentiment scenario k and the quadruplet $Q_i = a_i, c_i, o_i, s_i$. This indicates that the target structure we designed can be generated adaptively according to the sentiment scenario k, which achieves our purpose.

3.4 Model Architecture and Training

We employ the T5 [29], an encoder-decoder language model that utilizes an auto-regressive generation process to model the conditional probability of generating the next token y_i, based on the input sequence $\mathcal{X}$ and previously generated tokens $y_{<i}$. The model can calculate the entire probability $p(\mathcal{Y} \mid \mathcal{X})$ of generating the output sequence $\mathcal{Y}$, given the input sequence $\mathcal{X}$, which is expressed as follows: $\mathcal{Y}$ is:

$$p(\mathcal{Y} \mid \mathcal{X}) = \prod_{i=1}^{|\mathcal{Y}|} p\left(y_i \mid y_{<i}, \mathcal{X}\right) \tag{9}$$

The $\mathcal{X}$ and $\mathcal{Y}$ mentioned here are the same as those mentioned in Eq. 3and Eq. 8. Therefore, we will use expressions in the form of $\mathcal{X} = (x_1, x_2, \cdots, x_m)$ for ease of understanding.

In the training phase, the model parameters θ are initialized with the pre-trained weights. Our model is trained using the teacher-forcing strategy with both input $\mathcal{X}$ and ground truth target $\mathcal{Y}$. The loss function of the model is as follows:

$$\mathcal{L}(\mathcal{D}) = -\sum_{j=1}^{|\mathcal{D}|} \sum_{i=1}^{n} \log p_\theta\left(y_i \mid y_1, \ldots, y_{i-1}, \mathcal{X}_j\right) \tag{10}$$

θ represents all the trainable parameters, $\mathcal{D}$ represents the training set samples, $|\mathcal{D}|$ represents the number of training set samples, $\mathcal{X}_j$ denotes the input sequence from the jth sample transformed by the prompt template containing the SI, and n is the length of the output sequence. We use the Adam optimizer with weight decay [33] to update the model parameters during the training phase.

3.5 Inference and Parsing

After the training phase, we use beam search to generate predicted results in an autoregressive manner. Then, we segment the possible structures according to the special delimiter "[SSEP]" mentioned in Eq. 3, and obtain the segmented predicted TS. Finally, We employ the reverse parsing strategy of TS to obtain the predicted quadruple $Q' = (a', c', o', s')$ and evaluate it against the golden emotional quadruple Q.

4 Experiments Setup

We detail the experience setup for evaluating our techniques on the ACOS task.

4.1 Datasets

We employed two large-scale ACOS datasets, Restaurant-ACOS and Laptop-ACOS. Both were annotated by Cai et al [1] and cover various sentiment scenarios. Table 1 shows the statistics of sentiment quadruples in each dataset.

4.2 Implementation Details

We selected the T5-large model from huggingface [34] for training. The training process was executed on an NVIDIA RTX A6000 with 48Gbit memory and included a warm-up strategy for 10 epochs. We utilized the Adam optimizer with weight decay [33].

Table 1. Sentiment quadruplets statistics in different sentiment scenarios in the Restaurant-ACOS and Laptop-ACOS datasets.

Class	Restaurant-ACOS		Laptop-ACOS	
	train	test	train	test
Categories	13		121	
#Type				
EA&EO	971	366	1619	467
EA&IO	187	76	814	225
IA&EO	303	128	535	128
IA&IO	225	90	249	64
All	1686	660	3217	884

4.3 Baselines

We compared seven prevailing ACOS technologies as follows:

Double Propagation-ACOS is a representative rule-based ACOS method based on improved Double Propagation [35] by Cai et al. [1].

JET-ACOS was proposed by Cai et al. [1], which was improved from the JET model [6] for aspect-category-sentiment-opinion quadruple extraction.

TAS-BERT-ACOS is a two-step pipelined approach proposed by Cai et al. [1]. It utilizes TAS-BERTcite [22] to extract quaternions.

Extract-Classify-ACOS was proposed by Cai et al. [1]. It adopts a representative aspect-opinion co-extraction system to accommodate ACOS quadruple extraction.

GAS-ACOS was improved from GAS [8], a model for generating sentiment elements through annotated and extractive paradigms. We adapted GAS for the ACOS task and named the resulting model GAS-ACOS.

PARAPHRASE [9] is an effective aspect-category-sentiment-opinion quadratic generative model, which is a text-to-text paradigm based work.

USI was proposed by Wang et al. [10], aiming to accomplish the ACOS task with a generative approach, which is currently the state-of-the-art method in the field in terms of performance.

5 Result and Analysis

We evaluate the extraction task of the sentiment quadruplets using precision, recall, and F1 metrics, where a correct extraction requires that all components are correct.

Table 2. Main results of our model and baselines on the Restaurant-ACOS and the Laptop-ACOS. The one marked with † is the baseline we reproduce.

Model	Restaurant-ACOS			Laptop-ACOS		
	Pre	Rec	F1	Pre	Rec	F1
Double-Propagation-ACOS	34.67	15.08	21.04	13.04	5.71	8.01
JET-ACOS	59.81	28.94	39.01	44.52	16.25	23.81
TAS-BERT-ACOS	26.29	46.29	33.53	**47.15**	19.22	27.31
Extract-Classify-ACOS	38.54	52.96	44.61	45.56	29.48	35.8
GAS-ACOS †	56.01	56.01	56.01	42.04	40.91	41.47
PARAPHRASE †	58.76	59.3	59.08	45.06	41.88	43.47
USI	<u>60.07</u>	<u>61.14</u>	<u>60.61</u>	44.57	**43.91**	<u>44.24</u>
SI-TS	**62.36**	**61.41**	**61.89**	<u>46.71</u>	<u>43.58</u>	**45.29**

5.1 Main Results

Our experimental results are shown in Table 2, with some noteworthy observations. Firstly the performance of the extractive methods is far from satisfactory, likely due to error-accumulation over several sub-tasks and limited pre-training alignment. Secondly, in the generative methods, the GAS-ACOS, PARAPHRASE and USI largely outperform the previous extractive methods, which shows that sequence-sequence modeling is effective for the ACOS task. Thirdly, it can be observed that our proposed method demonstrates effective performance across all metrics in both datasets. Specifically, we achieved a 1.05% improvement in F1 value for Laptop-ACOS and a 1.28% improvement for Restaurant-ACOS.

5.2 Ablation Study

We conducted an ablation study to further quantify the contribution of each component of the proposed method. The Restaurant-ACOS dataset was chosen for this experiment. Our ablation experiment is shown in Table 3, where we explored the following different situations separately. We also eliminated all the modules we designed, and the average evaluation metric was reduced by 3.48.

Table 3. Ablation study of our method on Restaurant-ACOS dataset. The Avg.$\triangle$ represents the average difference in all evaluation metrics between removing the module and not removing it.

Model	Pre.	Rec.	F1	Avg.$\triangle$
Ours	62.36	61.41	61.89	-
-(TS)	60.33	59.87	60.11	-1.78
-(SI)	59.46	58.83	59.14	-2.74
-(All)	58.71	58.11	58.41	-3.48

Firstly, We eliminated the SI. We found that performance had a significant decrease, with an average decrease of 2.74 for all evaluation metrics. This indicates the necessity of our SI. Secondly, We also conducted experiments by excluding TS. Our results show that the overall performance of our framework decreases on average by 1.76 after excluding TS. This validates our intuition that changing the structure of our design can effectively model the sentiment elements. Also it is more adaptable to subsequent sentiment quadruplet parsing and is effective for sentiment quadruplet extraction.

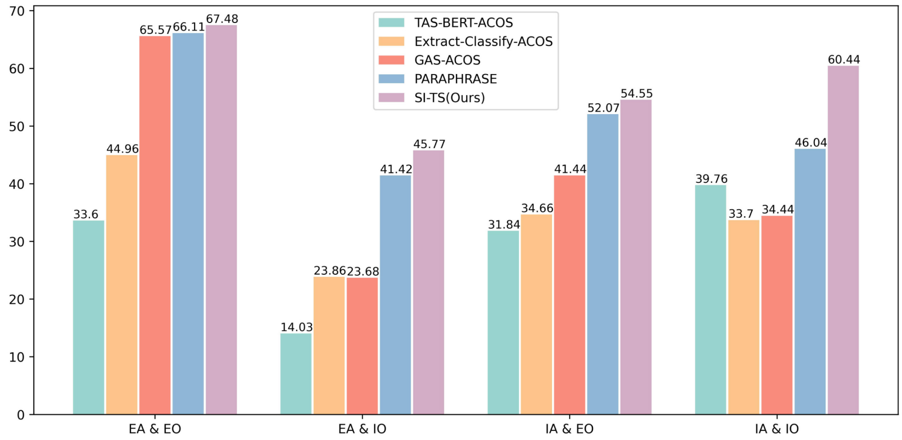

Fig. 4. The F1 performance of our model and a baseline in various sentiment scenarios, and compared the results.

5.3 Performance on Implicit Sentiment Scenarios

As we have mentioned, the ACOS task contains several different sentiment scenarios. Therefore, effective modeling of different sentiment scenarios is vital. To quantify the performance improvement of our approach under different sentiment scenarios, we explore the performance of our model. Specifically, we divided the testing set into four subsets and observed the performance on different subsets, while we compared the performance of our model with the baseline model, as shown in Fig. 4. For such situations we analyzed that previous researches such as Zhang et al [9]. and Wang et al [10]. only considered the distinction between EAEO and IAEO and only replaced the implicit aspect with it. However, we also considered the case of other implicit sentiment scenarios (e.g., EAIO and IAIO) and designed for them a suitable text structure TS, which can effectively model implicit sentiments not noticed by previous work. Meanwhile, under the guidance of SI, the model is trained to generate the corresponding TS.

5.4 The Effectiveness of Sentiment Instructor

To verify the effectiveness of SI in differentiating between four sentiment scenarios on the model, we generated t-SNE [36] visualizations of the average merged final encoder layer. Figure 5 shows the results on the Restaurant-ACOS dataset. Our findings indicate that SI is able to effectively distinguish implicit sentiment scenes. To a certain extent, the implicit sentiment scenes are distinguished secondarily. This also demonstrates that our SI can help the framework distinguish between explicit sentiment samples and implicit sentiment samples.

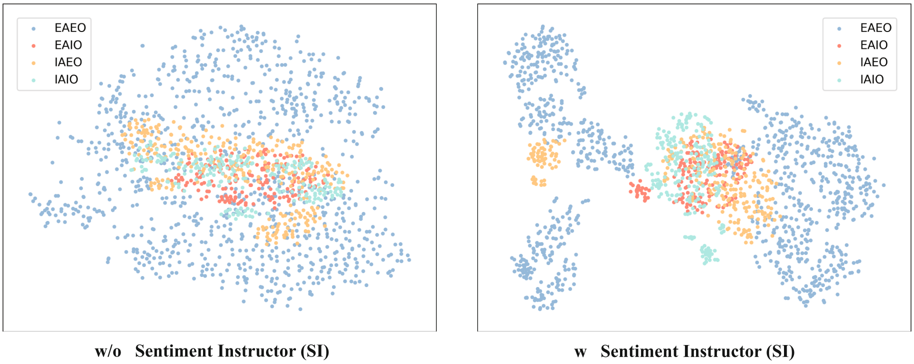

Fig. 5. T-SNE visualization of the last layer of the encoder on the Restaurant-ACOS dataset. Our SI indication model distinguishes four sentiment scenarios in the reviews.

6 Related Work

Implicit Sentiment Extraction. Implicit sentiment extraction aims to extract aspects and opinions that are not specifically described. Lazhar et al. [13] proposed a method based on dependency grammar to extract sentiment-opinion pairs obtaining implicit opinions. Fang et al. [14] developed a clustering algorithm to construct feature classes to extract the implicit opinions. Xu et al. [15] proposed the extracted aspect-specific opinion words to extract the implicit aspects. Zhang et al. [16] proposed an improved knowledge-based topic modeling KTM to extract the implicit aspects. Prasojo et al. [17] used a method based on adjective-to-aspect mapping to extract implicit aspects. Nandhini and Pradeep [18] proposed a co-occurrence and ranking-based algorithm to extract implicit aspects. However, implicit sentiment extraction remains a challenging task.

Aspect-Category-Opinion-Sentiment Quadruples. Recent researches [19–25]have shown that multiple extraction of sentiment elements can be effective in analyzing aspect-based reasons for sentiment. To fully analyze the sentiment in the review the Aspect-Category-Opinion-Sentiment quadruples(ACOS) task [1, 9] was proposed. Pre-trained transformer-based [26] models like BERT [27], BART [28], and T5 [29] are commonly used for the ACOS task. Xu et al. [6,30] used Bert for sentiment element extraction, while Cai et al. [1] improved the JET model for aspect-category-sentiment-opinion quadruple extraction. Yan et al. [7] and Zhang et al. [8] designed unified generative frameworks using Bart and T5 models, respectively. Zhang et al. [9] treated aspect-category-sentiment-opinion quadruple extraction as a paraphrase generation. Wang et al. [10] proposed a framework based on multi-task instruction tuning. However, in the ACOS task, current methods still struggle to extract implicit sentiment elements, which has motivated us to explore this direction.

7 Conclusions

In this work, we introduce TS, a modified target structure for ACOS generation. It effectively models a full range of implicit sentiment scenarios. We combine this with SI, our novel task-specific application of prompt learning that adaptively generate the corresponding target structures and assist the model in effectively mining implicit sentiment elements in reviews. Our proposed SI-TS framework demonstrate its effectiveness, especially in implicit sentiment scenarios.

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