Learning Contrastive Interaction Relations for Aspect Sentiment Triplet Extraction

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***Abstract*—Aspect Sentiment Triplet Extraction (ASTE) aims to extract triplets consisting of an aspect, an opinion, and their corresponding sentiment polarity. A key challenge in ASTE is the presence of numerous Overlapping Triplets (OT), which increase the task's complexity. We categorize these OTs into three types based on their complexity: Single-OT, Multi-OT, and Conflicted-OT. While most existing approaches primarily focus on Single-OT, Multi-OT and Conflicted-OT remain relatively underexplored. To address this gap, we propose a novel ASTE method that effectively decodes complex relations between aspects and opinions to perform Multi-OT and Conflicted-OT. Specifically, we introduce a pointer network to locate aspect and opinion indexes, and then propose a Contrastive Sentiment-enhanced Mechanism (CSM) to enhance sentiment interaction. CSM integrates a Markov Graph Convolutional Network to capture syntactic dependencies for context enhancement and constructs contrastive pairs to enrich sentiment knowledge, improving performance on OTs. Extensive experiments demonstrate that our method achieves significant performance, especially in Multi-OT and Conflicted-OT.**

***Index Terms*—Triplet Extraction, Sentiment Analysis, Pointer Network**

I. Introduction

Aspect Sentiment Triplet Extraction (ASTE) [1], [2] is crucial for aspect-based sentiment analysis [3], which aims to extract aspects of the discussion from the text, make corresponding sentiment judgments, and provide opinion reasons for the sentiment. In recent years, ASTE has attracted increasing research attention due to its ability to offer a comprehensive and structured sentiment analysis picture. Consequently, ASTE plays an important role in various real-world applications, including recommendation systems [4] and social media analysis [5].

However, more than one aspect and opinion are hidden in texts. Therefore, Overlapping Triplets (OTs) complicate the ASTE task under multi-aspect and multi-opinion scenarios. For example, in the text, *"The ease of use and the excellent service are pleasant, but top quality comes with top price (e.g., dearer service)"*, as shown in Figure 1. There are four aspects and five opinions, and they generate seven triplets, all of which belong to OTs. Based on our observation, these OTs could be further categorized into Single-OT, Multi-OT, and Conflicted-OT based on their complexity. Specifically, (1) Single-OT represents single-Overlapping Triplets and is

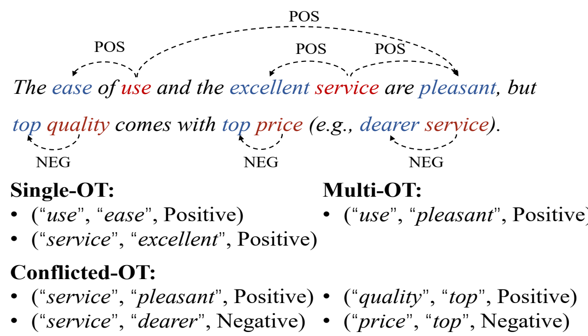

Fig. 1. The illustrative example for OTs. The red and blue fonts represent aspect terms and opinion terms, respectively. POS, NEU, and NEG represent the corresponding sentiment polarities.

also referred to as aspect-Overlapping Triplets or opinion-Overlapping Triplets. For example, the triplets ("*use*", "*ease*", Positive) and ("*service*", "*excellent*", Positive) share an aspect with other triplets. (2) Multi-OT represents multi-Overlapping Triplets, that is, triplets with an overlapping aspect and an overlapping opinion. For example, the triplet ("*use*", "*pleasant*", Positive) shares both an aspect and an opinion with others. (3) Conflicted-OT is more challenging than Single-OT and Multi-OT when an aspect has more than one sentiment or an opinion expresses two conflicted sentiments. For example, "*top*" has two different sentiments in triplets ("*quality*, "*top*", Positive) and ("*price*, "*top*", Negative).

Existing work on ASTE can be broadly divided into tag-level and span-level approaches. Tag-level schemes focus on sequence tagging [6] and grid-tagging methods [7]–[9]. Peng et al., [10] propose a two-stage sequence tagging method. However, it assigns a fixed sentiment to each aspect, making it hard to handle Conflicted-OT. Chen et al., [11] introduce a grid-tagging method with a multi-channel table-filling system. However, it primarily focuses on word-level interactions and overlooking multi-word aspect–opinion relations, which limit its performance on OTs. Span-level methods include question-driven [12], [13] and span detection strategies [14]. These methods model the start and end positions of aspects and opinion to learn span-based interactions. However, they often struggle with Multi-OT and Conflicted-OT due to the complex sentiment interactions between aspects and opinions. For instance, Mao et al., [15] and Zhai et al., [16] propose

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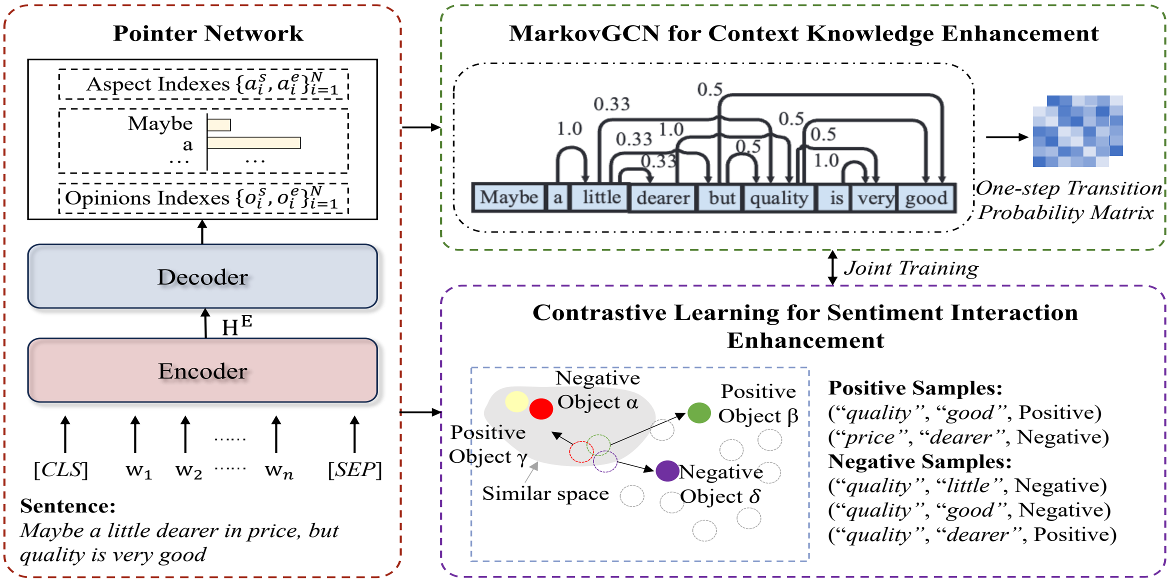

Fig. 2. The overall architecture of the proposed method.

question-driven methods based on reading comprehension, but they do not explicitly model aspect–opinion relations, limiting performance in OTs. Recently, span detection methods [1] enlarge the search space by enumerating all spans, but they have a high computational cost and struggle to capture sentiment knowledge. Chen et al., [17] are the first to handle OTs by learning cooperative interactions between aspects and opinions. However, they use a two-stage method based on syntax dependency, which relies on the quality of parser trees and leads to error propagation. These limitations highlight that ASTE is far from being solved and demands further research attention.

To solve the above issues, we propose a novel method for the ASTE task, as shown in Figure 2, which models contrastive sentiment interactions between aspects and opinions to effectively decode their complex relations in OTs. Specifically, we utilize an encoder-decoder framework, where a pointer network is adapted in the decoder to locate aspect and opinion indexes. We further design a Contrastive Sentiment-enhanced Mechanism (CSM) to learn the sentiment interaction between aspects and opinions by incorporating context knowledge and sentiment knowledge. To capture context knowledge, we introduce the One-step Transition Probability Matrix (OTPM) to describe the transition probability between words in a Markov chain, and then adjust the Graph Convolution Network (GCN) over dependency structures to build a MarkovGCN. Compared with directly applying GCN [17], the MarkovGCN is integrated into CSM to encode richer syntactic and structural information. For sentiment knowledge, we construct contrastive positive and negative pairs to better distinguish sentiment interactions between aspects and opinions. The contrastive objective encourages the model to capture subtle distinctions between gold pairs and their corrupted counterparts when handling complex triplets. Extensive experiments demonstrate that our proposed method achieves significant improvements, particularly on Multi-OT and Conflicted-OT. Code will be released upon acceptance. The main contributions are summarized as follows:

- We propose a novel ASTE method, which models contrastive sentiment interactions between aspects and opinions to effectively decode their complex relations in OTs. Our proposed method achieves promising performance on the ASTE task, especially Multi-OT and Conflicted-OT.
- We design a contrastive sentiment-enhanced mechanism, which integrates a MarkovGCN for context knowledge enhancement and a contrastive training object for sentiment knowledge enhancement to improve the performance for the ASTE task.
- Extensive experiments conducted on multiple benchmark datasets demonstrate that our proposed method significantly outperforms a set of strong baselines and obtains convincing performance.

II. Related Work

Recently, the ASTE task has received widespread attention in industry and academia. However, OTs make ASTE a significant challenge. Most existing works ignore OTs or only focus on Single-OT. Therefore, they have limited performance in the ASTE task. The research works on the ASTE task can be summarized into two groups: tag-level and span-level methods.

Tag-level methods contain sequence tagging and grid tagging. Peng et al. [10] utilize two sequence tagging systems (i.e., 'B-POS' and 'BIOES') to extract aspect terms with sentiments and the corresponding opinion terms. However, they only assign a fixed sentiment tag to an aspect term and fail to identify aspects with different sentiments. Therefore, they struggle to solve Conflicted-OT. Xu et al. [6] leverage a position-related sequence tagging scheme to extract aspects, opinions, and their corresponding sentiments. However, the position of an aspect could only be used one time due to position limitations, failing to extract OTs. Chen et al. [18], Li et al. [7], and Sun et al. [8] propose grid tagging schemes to tag the relations between word-word pairs to fill a relation table. They focus on interactions between single words and enumerate all possible word-word pairs. However, they perform poorly in aspects consisting of multiple words. Therefore, incompleteness of aspect terms or opinion terms may degrade the performance in triplets, esp. OTs.

Span-level methods identify aspect spans and opinion spans by considering the start and end boundaries. Question-driven [12], [13], [19], span identification [1], [14], [20], and Seq2seq generation [21] are major research lines on span-aware methods. Zhang et al. [12] propose a question-driven method based on a reading comprehension scheme. They design questions related to aspects and select one or more answers to a question to extract the corresponding opinion and sentiment. However, these methods focus on the interactions between a question and its answers. They may fail to explicitly model the relation between aspects and opinions, leading to suboptimal performance. To extract spans effectively, Liang et al. [1] and Li et al. [14] enumerate all possible spans in a given text. However, the method is high cost and increases the difficulty both in the training phase and the test phase. To decrease cost, Zhao et al. [17] and Dong et al. [22] propose generation methods to extract entire triplets. However, simple generative structures fail to handle complex sentiment information and perform poorly in Conflicted-OT. Inspired by the idea, we design a generative method with contrastive knowledge enhancement to capture sentiment information. The proposed method solves the ASTE task by learning contrastive sentiment interaction.

III. Methodology

A. Task Formulation

Given a sentence $X = \{w_1, w_2, ..., w_n\}$ consisting of n words, we define (a^s, a^e) and (o^s, o^e) as the position indexes of an aspect and an opinion, respectively. Therefore, an aspect sentiment triplet is defined as $(a^s, a^e, o^s, o^e, s^p)$, where s^p indicates sentiment polarity, including Positive, Neutral, and Negative. The ASTE task aims to extract all aspect sentiment triplets in the sentence.

B. Pointer Network Construction

We adopt a pointer network to predict the position indexes of aspects and opinions, as it directly models target spans as pointers to the input sequence. The pointer network follows an encoder–decoder architecture. Given a sentence $X = \{w_1, w_2, ..., w_n\}$, the encoder transforms X into hidden states H^E. At each decoding step t, the decoder takes H^E and previous predictions $\hat{Y}_{<t}$ to generate a hidden state h_t^D, which is used to compute the probability distribution P_t over token positions. To capture the interaction between aspects and opinions, we employ a shared decoder with the same structure and parameters to jointly predict both types of indexes. Specifically, the aspect target sequence $Y^a = \{y_i^a\}_{i=1}^{T_a}$ and the opinion target sequence $Y^o = \{y_i^o\}_{i=1}^{T_o}$ are optimized by the following loss:

$$\mathcal{L}_{PNC} = -\frac{1}{N}\sum_{i=1}^{N}(\sum_{t=1}^{T_a} y_t^a \log(\hat{y}_t^a) + \sum_{t=1}^{T_o} y_t^o \log(\hat{y}_t^o)) \tag{1}$$

C. Contrastive Sentiment-enhanced Mechanism

We introduce CSM to model sentiment interactions between aspects and opinions. Given encoder outputs H^E and the predicted aspect ($\hat{Y}^a$) and opinion ($\hat{Y}^o$) indexes, CSM predicts the sentiment polarity between an aspect and its associated opinion. It integrates a MarkovGCN to capture syntactic dependencies for context knowledge enhancement and employs contrastive learning objectives for sentiment knowledge enhancement, promoting effective aspect sentiment triplet extraction.

1) Context Knowledge Enhancement: To better model context, we utilize GCN [23] to capture syntactic dependency between aspects and opinions. However, previous works [17] heavily rely on the quality of parser trees, which may cause error propagation. To overcome the issue, we propose MarkovGCN to encode more information, where the adjacency matrix is defined by the One-step Transition Probability Matrix (OTPM) derived from a Markov chain [24], as shown in Eq. 2.

$$\begin{aligned} &P\{X(t_{m+1}) = i_{m+1}|X(t_1) = i_1, ..., X(t_m) = i_m\} \\ &= P\{X(t_{m+1}) = i_{m+1}|X(t_m) = i_m\}, \end{aligned} \tag{2}$$

where each state is a word, and the transition between states is equivalent to the transition between words. Therefore, OTPM describes the transition probability between words. Then, we leverage MarkovGCN to encode contexts:

$$h_i^{(l)} = \sigma(\sum_{j=1}^{n} A_{ij} W^{(l)} h_j^{(l-1)} + b^{(l)}), \tag{3}$$

where A is OTPM, and $h_i^{(l)}$ is the i^{th} node in the l^{th} layer. The initial representation $h_i^{(0)}$ derives from the encoder embedding H^E. $W^{(l)}$ and $b^{(l)}$ are learnable parameters. σ is an activation function. We use $h_i^{(l)}$ to learn the aspect and opinion representations. To represent multi-word terms, we apply self-attention to emphasize informative words and obtain a term-level vector r:

$$r = \sigma(W_r^1 f(W_r^2 M_r^T + b_r^2) + b_r^1) M_r \tag{4}$$

where $r \in R^d$. $M_r \in R^{L\times d}$ denotes all word representations of an aspect or an opinion. L represents the number of words. W_r^1, b_r^1, W_r^2, and b_r^2 are learnable parameters. σ and f are activation functions. We formulate that r_a and r_o denote the aspect representation and the opinion representation, respectively. The r_{ao} denotes the aspect-opinion pair representation: $r_{ao} = [r_a; r_o; r_a - r_o]$, where r_a - r_o denotes the difference value between an aspect and an opinion. Therefore, the sentiment prediction between an aspect-opinion pair is written as:

$$p(s|r_{ao}) = \sigma((f(W_s^1 r_{ao} + b_s^1) W_s^2 + b_s^2)) \tag{5}$$

where $s \in \{\text{Positive}, \text{Negative}, \text{Neutral}, \text{None}\}$. W_s^1, b_s^1,W_s^2, and b_s^2 are learnable parameters.

$$\mathcal{L}_{\text{CKE}} = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{|\mathcal{G}_i|}\sum_{r_{ao}\in\mathcal{G}_i}\log p(s^* \mid r_{ao}) \tag{6}$$

where N is the batch size. $\mathcal{G}_i$ is the set of aspect–opinion pairs in the i^{th} sentence. s^* is the gold label of each pair.

2) Sentiment Knowledge Enhancement: We design contrastive training objects [25]–[27] to enhance the sentiment interactions between aspects and opinions. Given a sentence, we use gold triplets as positive samples and generate corrupt triplets by replacing one aspect term or one opinion term with random spans in the sentence. We define the positive set as $\mathcal{G}^+$ and the negative set as $\mathcal{G}^-$. Using positive and negative samples, the contrastive training objective could inject sentiment knowledge regarding aspects and opinions into the model to further improve performance. The contrastive loss is written as:

$$A_i^{(a,o)} = \exp\left(\frac{\text{sim}(r_a^i, r_o^i)}{\tau}\right) \tag{7}$$

$$B_i^{(a,o)} = A_i^{(a,o)} + \sum_{(r'_a, r'_o)\in\mathcal{G}_i^-}\exp\left(\frac{\text{sim}(r'_a, r'_o)}{\tau}\right) \tag{8}$$

$$\mathcal{L}_{\text{SKE}} = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{|\mathcal{G}_i^+|}\sum_{(r_a, r_o)\in\mathcal{G}_i^+}\log\frac{A_i^{(a,o)}}{B_i^{(a,o)}} \tag{9}$$

where N is the batch size, τ is a temperature parameter, and $\text{sim}(\cdot,\cdot)$ denotes the similarity function (e.g., cosine similarity).

D. Training

The overall optimization objective is as follows:

$$\mathcal{L} = \alpha\mathcal{L}_{PNC} + \beta\mathcal{L}_{CKE} + \gamma\mathcal{L}_{SKE} \tag{10}$$

where α, β, and γ are hyperparameters.

IV. Experiment

A. Experimental Setup

Datasets and Parameter Settings. We conducted extensive experiments on the dataset released by Xu et al. [6]. It includes three sub-datasets (i.e., 14res, 15res, 16res) in a restaurant domain and a sub-dataset (i.e., 14lap) in a laptop domain, and has been widely employed for the ASTE task. To evaluate the performance of our model, we used three standard metrics: Precision, Recall, and F1-score. The English version of BART_{base} is our backbone. We used the validation set to determine some hyperparameters. Specifically, the number of MarkovGCN layers is set to 2. The hyperparameters α, β, and γ are set to 0.3, 0.6, and 0.1. For optimization, we adopted the AdamW optimizer with a learning rate of 5e-5. The model was trained for 30 epochs with a batch size of 8. Activation functions σ and f are Softmax(.) and Tanh(.), respectively.

Baselines. JET [6] designs a position-related sequence tagging method to identify the relations between three factors of a triplet. EMCGCN [11] and MiniConGTS [8] utilize grid tagging methods to fill a sentiment relation table. PASTE [28] constructs a generative structure to generate a triplet at each time step. BARTABSA [21] and UIE [29] utilize a Seq2Seq generation framework to generate triplets through a sequence output. ERNIE [30] proposes a knowledge-enhanced pre-trained language model. We experiment with ERNIE-Bot4.0. ERNIE uses in-context learning to handle ASTE without fine-tuning the whole model. TripleMRC [13] proposes a question-driven method based on multi-task shared cascade learning and machine reading comprehension.

B. Experimental Results

Main Result Analysis. Table I presents an effective evaluation for the ASTE task. The results show that our proposed method outperforms most baselines in all scenarios. While MiniConGTS achieves a convincing performance in 14res, it is inferior to our proposed method due to low performance in the other three scenarios. Our proposed method injects contrastive sentiment knowledge regarding aspects and opinions into the model while generating triplets. Therefore, our proposed method achieves significant improvement in the ASTE task. Furthermore, we further conduct experiments on large language models (i.e., ERNIE and UIE) by providing ten examples to guide their output. ERNIE struggles with aspect–opinion boundaries, while UIE, though trained on a large-scale structural text corpus, performs worse than our proposed method. In conclusion, all experimental results verify the effectiveness of our proposed method in the ASTE task.

Overlapped Triplet Analysis. Figure 3.1 presents the performance on sentences with OTs. Overall, our method outperforms PASTE and MiniConGTS in 14lap, 15res, and 16res. Besides, we observe that MiniConGTS shows a convincing performance on 14res, but it is worse than our proposed method due to low performance in other scenarios. Shortly, experimental results show that our proposed method achieves convincing improvement for OTs. Therefore, our proposed method can effectively decode the complex relations between aspects and opinions to solve OTs by learning contrastive sentiment knowledge. Then, we further investigate the performance in Multi-OT and Conflicted-OT.

Multi-overlapped Triplet Analysis. Figure 3.2 shows the performance on the sentences with Multi-OT. We directly conduct experiments on the restaurant and laptop domains because the number of Multi-OT is limited. 'Res' is a combined dataset from 14res, 15res, and 16res. 'Lap' comes from 14lap. Obviously, our proposed method can effectively handle Multi-OT. The reason is that they ignore task-related knowledge, whereas our proposed method considers contrastive knowledge enhancement to improve performance. Therefore, our proposed method performs well on Multi-OT. In conclusion, the experimental results demonstrate the effectiveness of our proposed method for Multi-OT.

TABLE I
COMPARISON P (PRECISION), R (RECALL), F1 FOR THE ASTE TASK.

Model	**14res**			**14lap**			**15res**			**16res**		
	P.	R.	F1.	P.	R.	F1.	P.	R.	F1.	P.	R.	F1.
ERNIE	58.02	44.23	50.24	40.97	42.33	41.64	48.17	46.19	47.16	48.53	44.94	46.67
UIE	67.03	49.90	57.21	62.03	46.21	52.96	54.11	44.74	48.98	61.99	53.31	57.32
JET	70.56	55.94	62.40	55.39	47.33	51.04	64.45	51.96	57.53	70.42	58.37	63.83
EMCGCN	71.21	72.39	71.78	61.70	56.26	58.81	61.54	62.47	61.93	65.62	71.30	68.33
BARTABSA	65.52	64.99	65.25	61.41	56.19	58.69	59.14	59.38	59.26	66.60	68.68	67.62
PASTE	68.70	63.80	66.10	59.70	55.30	57.40	63.60	59.80	61.60	68.00	67.70	67.80
Triple-MRC	-	-	72.45	-	-	60.72	-	-	62.86	-	-	68.65
MiniConGTS	76.10	75.08	**75.59**	66.82	60.68	<u>63.61</u>	66.50	63.86	<u>65.15</u>	75.52	74.14	<u>74.83</u>
Ours	73.46	72.82	<u>73.14</u>	65.20	63.00	**64.02**	65.78	64.80	**65.29**	76.43	73.85	**75.12**

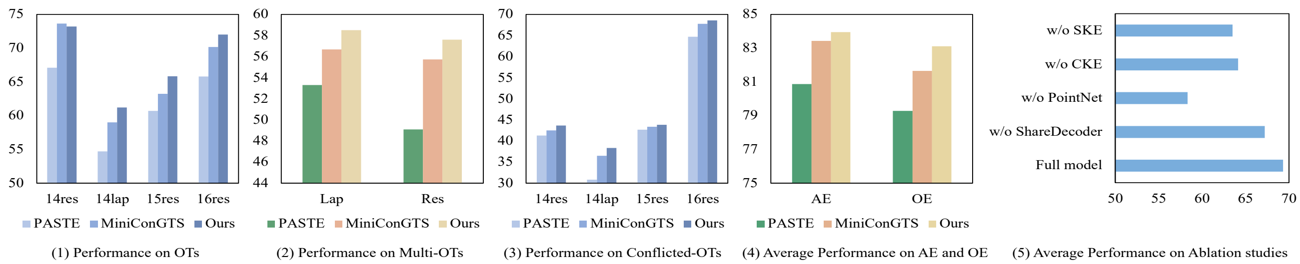

Fig. 3. F1 Performance on OTs, AE, and OE compared with PASTE and MiniConGTS (BERT Backbone), and Ablation Study.

TABLE II
ERROR ANALYSIS

Case 1	**Sentence #1:** STOPPED BOOTING UP less than a week after my one-year warranty was up. Extracted Triplets: (warranty, up, positive) Ground Truth: (BOOTING UP, STOPPED, negative), (one-year warranty, UP, neutral)
Case 2	**Sentence #2:** It just works out of the box and you have a lot of cool software included with the OS. Extracted Triplets: (works out, box, positive), (software, cool, positive), (OS, cool, positive) Ground Truth: (works, out of the box, positive),(software, cool, positive), (OS, cool, positive)
Case 3	**Sentence #3:** My favorite part of this computer is that it has a vga port so I can connect it to a bigger screen. Extracted Triplets: (vga port, favorite, positive), (screen, bigger, positive) Ground Truth:(vga port, favorite, positive), (screen, bigger, neutral)

Sentiment Robustness Analysis. Figure 3.3 reports experiment results on sentiment robustness. Considering Conflicted-OT samples are limited, we expand the evaluation area to sentences with at least two triplets with conflicted sentiments. The results indicate that our proposed method could effectively capture complex relations between aspects and opinions when predicting sentiment polarity by contrastive knowledge enhancement. In conclusion, our proposed method significantly improves the performance in sentences with conflicted sentiments. Therefore, our proposed method performs well on the ASTE task.

Pointer Network Analysis. We employ the pointer network to promote the generation of aspects and opinions. To evaluate the performance of the pointer network, we evaluate our model for Aspect Extraction (AE) and Opinion Extraction (OE) tasks, as shown in Figure 3.4. We observe that our proposed method outperforms PASTE and MiniConGTS. Therefore, it can locate the indexes of aspects and opinions effectively from contextual information. The overall performances verify the effectiveness of the pointer network.

C. Error Analysis

To further analyze the limitations of our proposed method and give future research directions, we conduct an error analysis, as shown in Table II. The sentence contains multiple triplets, and these triplets have different sentiments. The types of errors are divided as follows:

Wrong semantic awareness. In sentence #1, we observe that the proposed method suffers from complex semantic texts. With ambiguous contexts, the proposed method fails to learn the interaction between aspects and opinions.

Wrong multi-word boundaries. Sentence #2 shows that the proposed method fails to identify multi-word boundaries. Multi-word aspect/opinion boundaries are usually easily confused by other neighbor words. Affected by the noise of other words, it is challenging to identify correct triplets.

Wrong neutral sentiment. Regarding the classification of neutral sentiment for sentence #3, our method is weak in capturing sentiment features, and it tends to classify the neutral sentiment as positive or negative sentiment. The reason could be data unbalance for triplets with neutral sentiment.

D. Ablation Study

In Figure 3.5, we conduct an ablation study to examine the significance of the proposed method design. In "w/o Share-Decoder", removing the shared decoder reduces performance, showing its effectiveness in triplet extraction. In "w/o CKE" and "w/o SKE", removing CKE or SKE causes a sharp drop, confirming their role in enhancing aspect–opinion interactions. In "w/o PointNet", removing the pointer network also harms performance, indicating its importance in aspect and opinion location. Therefore, the absence of any part can decrease our performance. In conclusion, the design of our proposed method achieves the best performance.

V. Conclusion

We propose an effective method for ASTE that explicitly models contrastive sentiment interactions between aspects and opinions. The proposed method introduces a pointer network to locate aspect and opinion indexes, and designs a contrastive sentiment-enhanced mechanism to enhance their sentiment interactions. Extensive experimental results demonstrate the efficacy of our proposed method. In the future, we will consider more robust sentiment analysis technologies to generate sentiment knowledge from external resources.

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