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THE MULTI-TASK LEARNING MODEL FOR INDEX-BASED IMPLICIT ASPECT-LEVEL SENTIMENT ANALYSIS

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Abstract. *In order to effectively identify the aspect information that is not explicitly mentioned but implied in the semantics of the review text and its corresponding sentiment tendency, this paper defines implicit aspect-level sentiment analysis as an index-based sequence generation task. This paper adopted a generative pre-training model, T5, combined with prompt learning to capture the prompts and semantic information in the context to understand implicit sentiment. Additionally, it proposed a differentiated loss function with varying penalties for different types of errors. In order to improve the generalization performance of the model, this paper adopts a multi-task training method, which makes the model have stronger adaptability. Compared with the existing advanced models, the F1 value of the proposed model increases by 0.8% on the standard restaurantACOS dataset. It also shows an improvement of 1.01% on the LaptopACOS dataset. Ablation experiments show that each improvement is effective for aspect-level sentiment analysis.*
Keywords: Implicit aspect-level sentiment analysis, Index-based sequence generation task, Prompt learning, Differentiated loss, Multi-task learning

1. **Introduction.** Aspect-based sentiment analysis (ABSA) aims to extract one or more specific sentiment elements from a given text or sentence [1]. For massive text information, such fine-grained information is difficult to extract manually. Current aspect-level sentiment analysis tasks usually involve four sentiment elements, which are aspect term (A), opinion term (O), aspect category (C), and sentiment polarity (S) [2].

In practice, many comments lack explicit emotion words but still clearly convey emotions [3]. However, for computers, the lack of sentiment words will make it more difficult to understand the semantics. Compared with explicit sentiment, there are two main difficulties in the study of implicit sentiment: first, the lack of explicit sentiment words leads to semantic features that are not easy to recognize; second, implicit sentiment analysis usually requires deeper contextual understanding [4]. To address the shortcomings in implicit sentiment analysis, researchers have applied generative modeling to the aspect-based sentiment analysis (ABSA) task. Generative modeling leverages contextual information to enhance the understanding and generation of natural language texts that align more closely with human expressions [5]. In this paper, T5 (text-to-text transfer transformer)

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model developed by Google Research is used to generate target sequences in an end-to-end process [6]. Traditional generative models select the most probable text from a word list based on probabilistic predictions. This approach requires the model to choose from a large vocabulary, which increases the complexity of both training and inference. In order to reduce the search space and improve accuracy, this paper introduces an indexing mechanism to convert the generation process into an index form. The model can understand the relationship between sentiment and aspects based on these index values instead of relying on explicit sentiment words, thus getting rid of the strict dependence on sentiment words. Even in the absence of explicit sentiment words, the model can identify implicit sentiment in the text through these predefined index values. The indexing mechanism not only makes sentiment analysis no longer dependent on the explicit appearance of sentiment words, but also improves the generalization ability of the model, enabling the model to derive consistent sentiment representations from different contexts, thereby improving the robustness of the model. In addition, index generation usually requires less computational cost because the model only needs to generate indexes of task-related labels rather than complete text sequences.

In aspect-level sentiment analysis research, traditional methods may struggle to capture the latent contextual information in the text, leading to inaccurate identification of aspects and sentiment tendencies. To this end, this paper adopts a prompt learning approach that can infer implicit emotions based on the textual context. By designing appropriate prompts, the model can better capture the prompts and semantic information in the context, ensuring effective processing of implicit emotions. It can also enhance the adaptability of the model to new tasks or new data. Three tasks are used in this paper: ACOS task is used to extract "aspect terms-aspect category-opinion terms-sentiment polarity" from the quadruples, AOC task extracts "aspect terms-opinion terms-sentiment polarity" from the quadruples, and AS task focuses on extracting "aspect terms-sentiment polarity" from the quadruples to improve the generalization performance of the model.

Most of the existing sentiment analysis models use cross-entropy loss, but in the three-classification sentiment task, the distance between different sentiment labels is different, which cannot be treated equally. Implicit sentiment lacks clear emotion words and relies on context, so this difference needs to be strengthened in implicit sentiment classification. To this end, this paper proposes a differentiated cross-entropy loss function that selects varying punishment intensities based on the degree of error in the predicted emotional polarity. This approach aims to enhance implicit sentiment features.

The contributions of this paper are as follows.

- This paper introduces the indexing mechanism and combines it with prompt learning, treating aspect-level sentiment analysis as an index generation problem. This approach reduces the search space and improves the accuracy of implicit sentiment.
- This paper can be applied to any sub-task of aspect-level sentiment analysis without changing the model structure. It also realizes the joint learning of multiple tasks.
- A differentiated loss function is proposed to enhance the ability of the model to distinguish different prediction results and optimize the performance of the model.
- Experiments show that the F1 value of the proposed method is increased by 0.8% and 1.01% on the benchmark datasets restaurantACOS and LaptopACOS, respectively. The model has strong universality, which is not only suitable for implicit aspect-level sentiment text, but also has good results for explicit aspect-level sentiment text.

2. **Related Works.** In aspect-level sentiment analysis research, the pipeline approach was initially adopted [7]. Firstly, aspects related to sentiment analysis are extracted from the text, and then for each extracted aspect, the sentiment tendency (positive, negative

or neutral) describing the aspect in the text is identified [8]. This kind of serial separate processing method is relatively simple, and each module is more flexible. However, this method overlooks the relationship between aspect extraction and sentiment classification. The results of aspect extraction can influence sentiment classification, leading to potential error accumulation.

In order to solve the shortcomings of the serial method, researchers have proposed a unified labeling method [9]. This method creates a category label that encompasses both the position of aspect words and sentiment polarity. It transforms the two sequential tasks of aspect extraction and sentiment classification into a joint task based on sequence labeling. The classification labels include both aspect words and sentiment information. By classifying each element in the linear sequence based on contextual content, the method achieves joint annotation of evaluation aspects and sentiment classifications, resulting in sequence prediction outcomes.

With the wide use of sequence-to-sequence models, generative models have gradually become the focus of aspect-level sentiment analysis research. The generative model produces the target output in a single step, rather than relying on a preset question-and-answer format. This approach avoids the complexities of multiple question-answering, significantly reducing computational overhead. By utilizing pre-training and multi-level semantic modeling, the generative model enhances its understanding of complex contexts. This improvement allows it to generate outputs that contain implicit emotional information and adapt to a broader range of application scenarios. Yan et al. used the pre-trained model BART to solve seven subtasks of ABSA, and the framework achieved substantial performance improvement [10].

3. Methodology.

3.1. Problem definition.

The aspect-level sentiment analysis quadruple task is formalized below.

- Input: $X = [x_1, \ldots, x_i, \ldots, x_n]$, $i \in (1, n)$ where X is an input instance. n is the number of tokens in the instance, and x_i denotes the ith token in the input instance.
- Output: $Y = \left[a_1^b, a_1^e, o_1^b, o_1^e, c_1, s_1, \ldots, a_i^b, a_i^e, o_i^b, o_i^e, c_i, s_i, \ldots, a_m^b, a_m^e, o_m^b, o_m^e, c_m, s_m\right]$, $i \in (1, m)$, where a_i^b and a_i^e respectively represent the start index and end index of the ith aspect item, and the start index and end index of the implicit aspect item are denoted by 0. o_i^b and o_i^e denote the starting index and the ending index of the opinion item corresponding to the i aspect item, and the starting index and the ending index of the implied opinion item are also represented by 0. c_i said the first i aspects item belongs to category of index value, $c_i \in C$, C is a predefined category index value, the size of the collection for $|C|$, the scope of the index values for $[204, |C|]$; s_i represents the index value of the sentiment tendency corresponding to the ith aspect item $s_i \in \{201, 202, 203\}$, where 201, 202 and 203 represent positive, neutral and negative sentiment, respectively.

The goal of aspect-level sentiment analysis model is to automatically learn a mapping function f: $X \rightarrow Y$, so that for any input X' on the test data, it can generate a sequence of tuples describing the mention object and expressing the sentiment of X'.

3.2. Model structure.

In this paper, we treat the quadruple task as an index generation problem. This involves generating the aspect terms and opinion terms of the corresponding quadruples in index form, as well as the predefined aspect categories and sentiment polarity in index form. The model structure is shown in Figure 1.

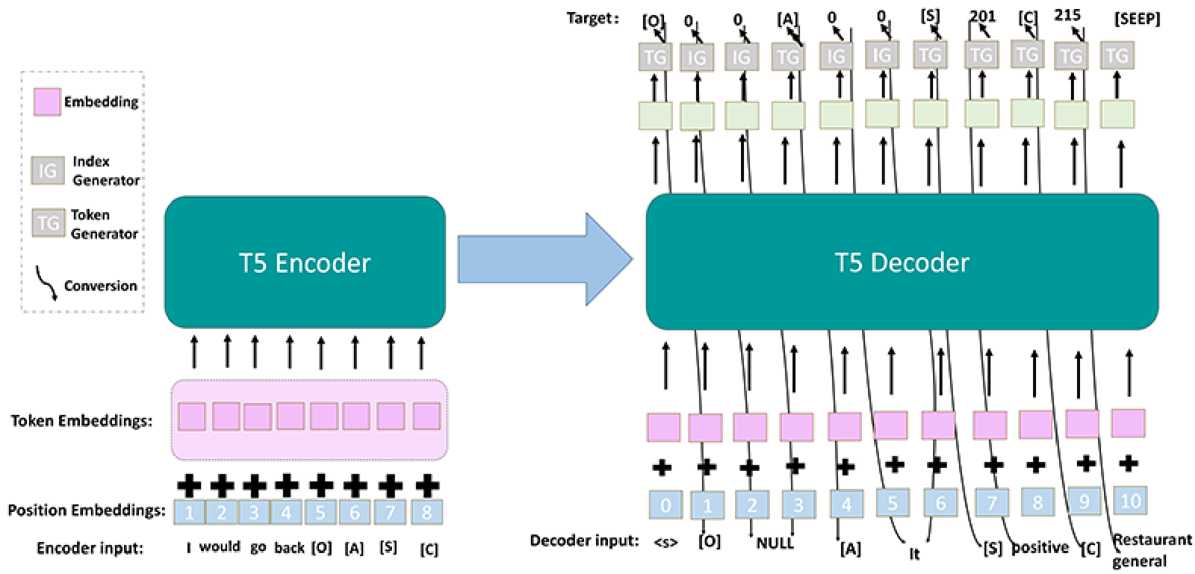

FIGURE 1. General architecture of the model

The 'Index Generator' in the figure converts the index value into the corresponding tokens in the original text. If the index of the opinion item is 0, the corresponding token is marked as It. If the index of an aspect item is 0, the corresponding tag is NULL. To achieve better generation performance, this paper uses relative position coding, and proposes that the model consists of two parts: encoder and decoder. We used relative position encoding for better generation performance.

3.3. **Pointer index.** This paper transforms the quadruple task into an index generation problem, reducing the output space from the size of the vocabulary to the number of task-related labels, thereby lowering the complexity of the task. The index generation problem generally requires less computational cost. This is because the model only needs to generate indexes of the labels relevant to the task, rather than producing the complete text sequence. Specifically, when the model generates aspect terms and opinion terms, we record their starting and ending subscripts in the original text. In this way, we can align the generated results with the original text, ensuring that the extracted sentiment components accurately reflect their position in the context. The sentiment polarity and aspect category are also converted into the index form to achieve consistency in data representation. This standardization helps the model maintain a consistent understanding across tasks. It not only improves the output quality of the model, but also enhances the interpretability of the final results. In multi-task learning scenarios, using a unified index form can also better facilitate information sharing and improve the synergy between different tasks.

The final output of this paper is the starting and ending position index corresponding to the aspect words and opinion words of the input sentence. For the implicit aspect items and opinion items, we set their index value to 0. For example, in the sentence "They complained to me about the small tip", there is no explicit aspect item, but there is a clear opinion item. The index corresponding to the aspect item is $[0, 0]$, indicating the absence of an explicit aspect. The index corresponding to the opinion item is $[2, 2]$, while the negative sentiment polarity is represented by the index [202], and the aspect category "service general" is indexed as [215]. The specific process is shown in Figure 2.

3.4. **Prompt learning.** In order to better infer implicit sentiment, we introduce the method of prompt learning and combine it with the indexing mechanism, as shown in

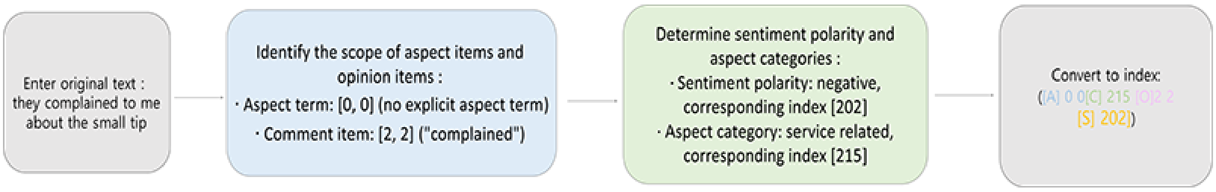

FIGURE 2. Pointer index conversion process

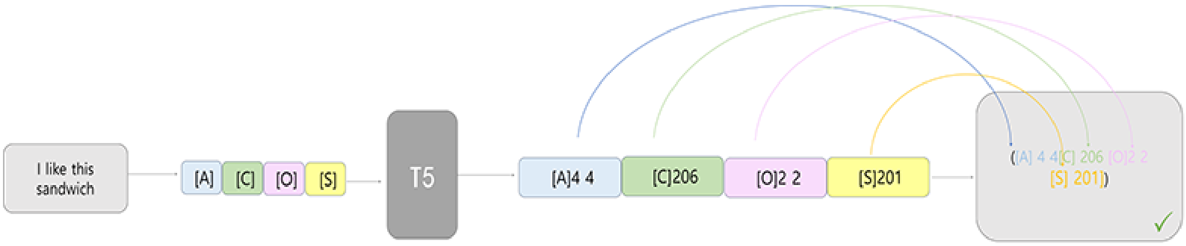

FIGURE 3. Prompt learning

Figure 3. Specifically, we design an ordered target template, where the target element is output according to the template words, using [A], [C], [O], and [S] as the prompt prefixes to generate the corresponding index values. For example, "$[A]a^b$, $a^e[O]o^b$, $o^e[C]c[S]s$".

If an input statement has more than one sentiment tuple, we use a special notation [SEP] to concatenate them into a final target sequence:

Input(x): The food is good, I would go back [O][A][S][C]

Output(y): [O]4 4[A]2 2[S] 201 [C]206 [SEP][O]0 0[A]0 0[S] 201[C] 215

Therefore, our task can be expressed as follows:

$$P(Y|X) = \prod_{t=1}^{m} p(y_t|X, Y < t) \tag{1}$$

In order to obtain the probability distribution $P(Y|X) = p(y_t|X, Y < t)$ for each step, we use T5 model for implementation.

3.5. **Multi-task joint learning.** In this paper, multi-task training is adopted [12], and ACOS is used as the main task, and AOS and AS are used as auxiliary tasks for joint training. The main task and auxiliary task share the model parameters by utilizing a common underlying data representation. The losses from both the main task and the auxiliary task are optimized together as the total loss of the model. By learning multiple tasks simultaneously, the intrinsic relationships and dependencies between different tasks can be discovered. This helps improve the model's understanding of complex correlations between tasks, which improves overall performance. The order of goals for each subtask is as follows:

- AS: $Y = \left[\left(a_1^b, a_1^e, s_1\right), \ldots, \left(a_i^b, a_i^e, s_i\right)\right]$
- AOS: $Y = \left[\left(a_1^b, a_1^e, o_1^b, o_1^e, s_1\right), \ldots, \left(a_i^b, a_i^e, o_i^b, o_i^e, s_i\right)\right]$
- $ACOS$: $Y = \left[\left(a_1^b, a_1^e, o_1^b, o_1^e, s_1, c_1\right), \ldots, \left(a_i^b, a_i^e, o_i^b, o_i^e, s_i, c_i\right)\right]$

In this paper, we deal with the three tasks jointly trained in this paper by sharing the encoder and decoder, and select different tasks by different prompts, as shown in Figure 4. Multi-task learning is a powerful training method for natural language processing tasks,

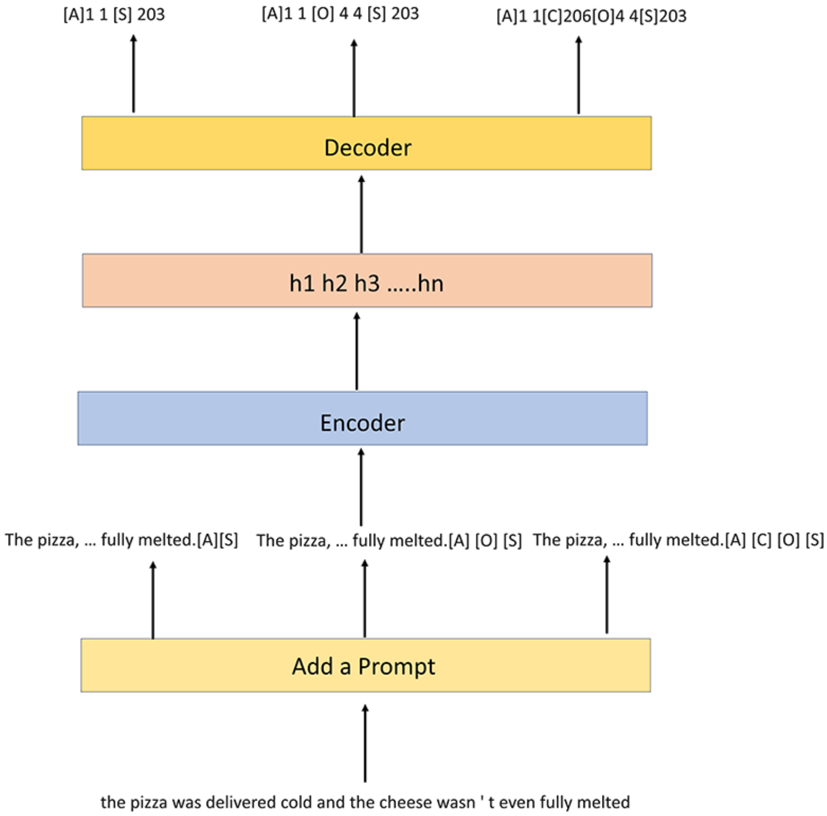

FIGURE 4. Multi-task learning

which provides higher efficiency, better generalization performance, and better resource management.

3.6. **Differentiated loss function.** The cross-entropy loss function is often used to measure the difference between the model's predicted value and the actual target value, represented as a scalar. This function compares the output probability distribution of the model to the true target distribution, with the negative log-likelihood frequently used to quantify this difference, as shown in Equation (2):

$$LCE(x,y) = -\sum_{t=1}^{T} \log_p(y_t|x, y < t) \tag{2}$$

where T is the length of the target sequence y and $y < t$ denotes the previously generated token.

In traditional sentiment categorization efforts, the positive, negative, and neutral sentiment categories are usually treated equally. However, for sentiment analysis tasks, the distinction between positive and negative sentiments is often greater than that between positive and neutral or negative and neutral. This means that if the model misclassifies positive text as negative sentiment, the model should give a heavier penalty for misclassifying it as neutral. This phenomenon needs to be especially considered and addressed in the context of implicit emotions. For implicit emotions, sentences often describe objective events without clear emotional words, making emotional characteristics less apparent. This results in a more blurred distinction between positive, negative, and neutral texts, making it more challenging to differentiate between neutral and positive-negative emotions. To this end, this paper proposes a class differentiated loss function, which is calculated as follows:

$$L_{diff} = \begin{cases} \sum_{i=0\&i\neq y}^{C-1} \max\left(0, m_b - p(\widehat{y})[y] + p(\widehat{y})[i],\ \text{if } (|y-i|) > 1\right) \\ \sum_{i=0\&i\neq y}^{C-1} \max\left(0, m_s - p(\widehat{y})[y] + p(\widehat{y})[i],\ \text{if } (|y-i|) \leq 1\right) \end{cases} \tag{3}$$

where, C is the total number of categories, $C = 3$ for sentiment triple classification, and in the training data of this paper positive category labels are 0, neutral is 1, and negative is 2. $p(\widehat{y})$ is the predicted category scores, and y is the true category labels, where $0 \leq y$, $i \leq C - 1$, $p(\widehat{y})[y]$ stands for predicted scores of the category y, and $p(\widehat{y})[i]$ represents the predicted scores of the category except that m_s and m_b represent two weight values differentiated for different labels, respectively. The aim of this paper is to make positive and negative more distant than positive and neutral. Therefore, a large and a small weight value m_s and m_b are used to control the different cases of $|y-i|$. If $|y-i| > 1$, this paper adopts a larger weight value, resulting in a larger penalty term. If $|y-i| \leq 1$, a smaller weight value is used. The final differentiated cross-entropy loss function in this paper is

$$L = \alpha LCE + \beta L_{diff} \tag{4}$$

4. Experiments.

4.1. **Datasets.** To solve the aspect-level sentiment analysis quadruple extraction task, Cai et al. constructed two benchmark datasets, restaurantACOS and LaptopACOS [11]. These datasets specifically focus on implicit aspects and opinions. This focus helps to comprehensively measure the effectiveness of the approach presented in this paper. The predefined aspect category of Restaurant has 13 categories. The predefined aspect category of Laptop has 121 categories. The specific details are given in Table 1.

Table 1. Statistics of samples and quadruples in the Restaurant and Laptop

Dataset # Cat		**Number of samples**	**Number of quadruples**
Laptop 121	**Train**	2934	4174
	Dev	326	440
	Test	816	1161
	Total	4076	5775
Restaurant 13	**Train**	1530	2484
	Dev	171	261
	Test	583	917
	Total	2284	3662

Implicit aspect items and opinion items are marked with NULL labels, for example:

Input	Target
our teenage kids love it , too .	[['NULL', 'restaurant general', 'positive', 'love']]
check this place out !	[['place', 'restaurant general', 'positive', 'NULL']]
you can't go wrong here.	[['NULL', 'restaurant general', 'positive', 'NULL']]

4.2. **Experimental environment and parameter setting.** The experimental environment is python3.8, pytorch 1.13.1, Cuda11.6, and the graphics card RTX3080Ti is used for model training. In this paper, the T5-BASE model from Huggingface Transformers library is used as the pre-trained model [13]. The epochs for dataset training are set to 20. The maximum length of sentences is set to 200. The batchsize is 2. The initial learning rate is 1e-4. m_s and m_b in the differentiated loss function are 0.5 and 0.2, and α and β are 0.8 and 0.2, respectively.

4.3. **Evaluation index.** Precision, recall and F1 score are used to measure the performance of the model and is calculated as shown in Equations (5), (6), (7):

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

where, TP is the number of quadruples for which the sample fully conforms to the label; FP is the number of quadruples for which the sample prediction does not conform to the label; FN is the number of quadruples that exist in the label itself but are not predicted.

4.4. **Comparative experiment.** We compare the proposed method with the following two methods on the Restaurant and Laptop datasets.

1) Extractive methods: **DP-ACOS:** Dependency parsing is used to capture syntactic relations between words in a sentence to extract aspect category, opinion, and sentiment quadruples [11]. **Extract-Classify-ACOS:** First jointly extract aspect-opinion and then predict category-sentiment pairs [11]. **SGTS:** The grid marking mechanism is used to jointly extract aspect category-opinion-emotion quadruples guided by sentence-level information [14].

2) Generative methods: **Paraphrase:** Design language template and generate final target by filling elements according to template [15]. **Seq2Path:** Generate tuples as paths for the tree and then select valid paths [16]. **BART-CRN:** Contrastive learning is used to distinguish similar aspects or opinions, and a retrospective mechanism is used to refine the prediction [17].

All experimental results in this paper are obtained based on the pre-trained model T5-BASE, and the results are shown in Table 2 and Table 3.

Table 2. Experimental results on the Restaurant dataset

	Methods	**Precision (%)**	**Recall (%)**	**F1 (%)**
Extractive methods	DP-ACOS	34.67	15.08	21.04
	Extract-Classify-ACOS	38.54	52.96	44.61
	SGTS	55.20	43.70	48.80
Generative	Paraphrase	N/A	N/A	<u>61.16</u>
	Seq2Path	N/A	N/A	58.41
	BART-CRN	50.84	47.10	48.90
	The approach in this paper	**61.96**	**61.96**	**61.96 (↑ 0.8)**

Table 3. Experimental results on the Laptop dataset

	Methods	Precision (%)	Recall (%)	F1 (%)
Extractive methods	DP-ACOS	13.0	5.70	8.0
	Extract-Classify-ACOS	45.56	29.48	35.80
	SGTS	41.40	32.30	36.30
Generative	Paraphrase	N/A	N/A	43.51
	Seq2Path	N/A	N/A	42.97
	BART-CRN	**48.16**	31.83	38.32
	The approach in this paper	44.93	**44.12**	**44.52 (↑ 1.01)**

Table 2 and Table 3 show the experimental results of our model and the baseline model on two datasets. The results highlight the superiority of the generative model over the extractive model as shown in the following table.

Method	Advantages	Disadvantages	Limitations in implicit sentiment analysis
Extractive methods	– Simple and easy to understand, directly extract key information from the original text – High computational efficiency	– Cannot generate new content, only select from existing text – Difficult to handle implicit information in the text	Cannot accurately capture implicit sentiment, as it relies on explicitly appearing sentiment words and sentences, and struggles with indirect emotional expressions
Generative methods	– Can generate new content, highly adaptable – Can understand complex semantics and implicit information through generative models	– High computational cost, generation quality limited by training data – May generate irrelevant or meaningless content	Can generate implicit sentiment information through context, but the generated content may lack accuracy or reliability

Seq2Path is one of the earlier generative models that relies on path generation methods. It effectively captures explicit quadruples and is well-suited for scenarios with clear explicit information. However, it often struggles with implicit quadruples, as there is usually no clear path or clue for their generation, resulting in a high miss rate. To improve the processing of implicit information, subsequent models have started to introduce additional mechanisms. These mechanisms include review processes and paraphrase strategies to enhance performance. The review mechanism of the BART-CRN model allows the model to correct its generated results by re-evaluating them after the first prediction. However, implicit quadruples lack explicit labels, making it challenging for the review mechanism to effectively capture implicit information. As a result, the experimental outcomes are not ideal. Paraphrase models generate new expressions by rephrasing the text, which enhances the model's ability to handle diverse inputs. This approach helps capture the information of quadruples in various expressions and improves the understanding of implicit quadruples. However, the paraphrase strategy can introduce noise in the implicit quadruple task. This may lead to misassociations with content that is not explicitly mentioned in the original sentence during the paraphrasing process.

In this paper, we propose a prompt learning-based generative model for aspect-level sentiment analysis. We introduce prompt learning to better focus on implicit aspects and sentiment during the generation process, avoiding the noise introduced by paraphrase models. This approach provides a more flexible implicit inference mechanism compared to explicit symbolic labeling. Experiments show that the proposed model is superior to other generative models on both datasets. Specifically, the F1 value of the proposed model is increased by 0.8% on the Restaurant dataset and 1.01% on the Laptop dataset. The results highlight the superiority of the proposed model in the generation of emotional quadruples.

Although there has been a significant improvement in performance compared to the baseline model, challenges remain in handling certain types of implicit sentiment. Specifically, in texts with subtle or mixed sentiments, the model may misclassify the sentiment polarity. This can be attributed to two main factors. First, due to the complexity of the task itself, the extraction and precise matching of four different types of sentiment elements increases the difficulty. Second, there are many aspect and opinion items in language that are difficult for computers to understand, which hinders the model's performance.

4.5. **Ablation experiment.** Ablation experiments were conducted to evaluate the impact of different combinations of methods on this task. These experiments were performed under the same experimental conditions to ensure consistency. Results of the ablation experiments are shown in Figure 5.

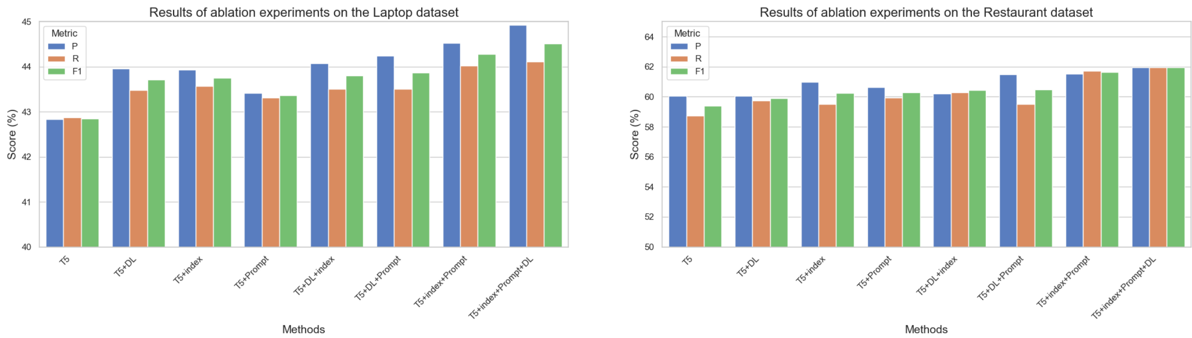

FIGURE 5. Results of ablation experiments on the Restaurant and Laptop datasets

According to the experimental results in Figure 5, T5 is the model using only T5-BASE with F1 values of 59.39% and 42.85%, respectively. DL is an improved differentiation loss function that results in an F1 value increase of 0.51% and 0.87% percentage points compared to T5-BASE. This indicates that the differentiation loss can make the distinctions among positive, negative, and neutral texts more apparent. To formulate the extraction task as an index generation problem, the F1 value for the index increased by 0.86% and 0.9% percentage points compared to T5-BASE after implementing this method. This indicates that using an index can reduce the vocabulary size of the output space to the number of task-related labels, thereby lowering the complexity of the task. For prompt learning, the F1 value for the prompt increased by 0.9% and 0.52% percentage points compared to T5-BASE after the introduction of prompt learning. This indicates that the appropriate prompts enable the model to better capture the clues and semantic information in the context, effectively allowing it to capture and process implicit emotions. This model integrates the three improvements into a single framework. It achieves an enhancement of 2.57% percentage points on the Restaurant dataset and 1.67% percentage points on the Laptop dataset. It proves that each improved method in this paper is effective for implicit aspect-level sentiment analysis.

This paper compares the loss values of the differentiated loss function and the cross-entropy loss. The results of this comparison are illustrated in Figure 6.

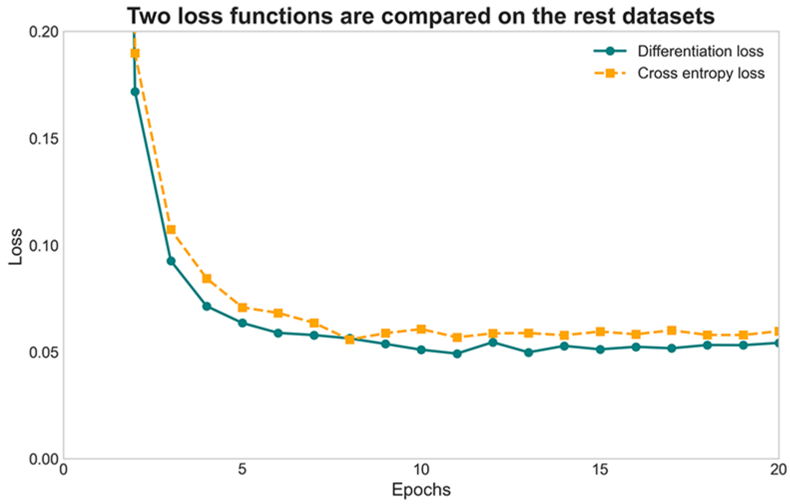

FIGURE 6. Comparison of loss

The results show that during the early stages of training, the decline rate of the differentiated loss is faster than that of the cross-entropy loss. This indicates that the differentiated loss adjusts the model's parameters more quickly. From the perspective of the entire training process, the value of the differentiated loss is generally lower than that of the cross-entropy loss function. This indicates that the differentiated loss function allows the model to achieve smaller errors during training, leading to better performance.

4.6. **Comparative experiments on multi-task learning.** The three tasks, ACOS, AOS and AS, are jointly learned to obtain generalized capabilities across different tasks. The proposed method can be naturally applied to multiple ABSA tasks and shows better stability, as shown in Table 4.

TABLE 4. Experimental results of multi-task learning on Restaurant and Laptop datasets

Methods	P (Res/Lap) %	R (Res/Lap) %	F1 (Res/Lap) %
ACOS	60.42/43.94	60.96/44.36	60.69/44.15
AOS	66.74/68.02	64.82/66.49	65.77/67.25
AS	78.08/74.60	67.22/64.51	72.24/69.19

5. **Conclusion.** To address the challenges in implicit aspect-level sentiment analysis, this paper proposes a multi-task learning model based on index generation for implicit aspect sentiment analysis and modifies the existing cross-entropy loss by introducing a differentiated loss function. Compared with the baseline model, the F1 value is increased by 0.8% and 1.01% on the Restaurant and Laptop datasets, respectively, improving the model's performance. Ablation studies verify the effectiveness of each improvement. In the proposed algorithm, the model is influenced by the different sequences of prompts, and selecting the appropriate sequence is a tedious process that requires further research and improvement in the future. The choice and combination of different prompt orders can significantly impact the model's performance. By exploring and optimizing the combinations of prompt sequences, along with automated methods and dynamic adjustment

mechanisms, the model's accuracy can be effectively improved. Therefore, researching how to design and optimize prompt orders rationally has become an important research direction for enhancing model performance.

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REFERENCES

[1] H. Liu, I. Chatterjee, M. C. Zhou et al., Aspect-based sentiment analysis: A survey of deep learning methods, *IEEE Transactions on Computational Social Systems*, vol.7, no.6, pp.1358-1375, 2020.
[2] W. Zhang, X. Li, Y. Deng et al., A survey on aspect-based sentiment analysis: Tasks, methods, and challenges, *IEEE Transactions on Knowledge and Data Engineering*, vol.35, no.11, pp.11019-11038, 2022.
[3] M. Tubishat, N. Idris and M. A. M. Abushariah, Implicit aspect extraction in sentiment analysis: Review, taxonomy, oppportunities, and open challenges, *Information Processing & Management*, vol.54, no.4, pp.545-563, 2018.
[4] C.-X. Yang, Y. Han, Q.-G. Chen et al., BERT with attention mechanism based on implicit emotional level analysis model, *Journal of Nanjing Information Engineering University (Natural Science Edition)*, vol.15, no.5, pp.551-560, 2023.
[5] M. Lewis, BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension, *arXiv Preprint*, arXiv: 1910.13461, 2019.
[6] C. Raffel, N. Shazeer, A. Roberts et al., Exploring the limits of transfer learning with a unified text-to-text transformer, *Journal of Machine Learning Research*, vol.21, no.140, 2020.
[7] S. Vanaja and M. Belwal, Aspect-level sentiment analysis on e-commerce data, *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, pp.1275-1279, 2018.
[8] X. Li, L. Bing, P. Li et al., A unified model for opinion target extraction and target sentiment prediction, *Proceedings of the AAAI Conference on Artificial Intelligence*, vol.33, no.1, pp.6714-6721, 2019.
[9] Y. Li, F. Wang and S. Zhong, A more fine-grained aspect-sentiment-opinion triplet extraction task, *Mathematics*, vol.11, no.14, 3165, 2023.
[10] H. Yan, J. Dai, X. Qiu et al., A unified generative framework for aspect-based sentiment analysis, *arXiv Preprint*, arXiv: 2106.04300, 2021.
[11] H. Cai, R. Xia and J. Yu, Aspect-category-opinion-sentiment quadruple extraction with implicit aspects and opinions, *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp.340-350, 2021.
[12] Y. Zhang and Q. Yang, An overview of multi-task learning, *National Science Review*, vol.5, no.1, pp.30-43, 2018.
[13] T. Wolf, HuggingFace's Transformers: State-of-the-art natural language processing, *arXiv Preprint*, arXiv: 1910.03771, 2019.
[14] L. Zhu, Y. Bao, M. Xu et al., Aspect sentiment quadruple extraction based on the sentence-guided grid tagging scheme, *World Wide Web*, vol.26, no.5, pp.3303-3320, 2023.
[15] W. Zhang, Y. Deng, X. Li et al., Aspect sentiment quad prediction as paraphrase generation, *arXiv Preprint*, arXiv: 2110.00796, 2021.
[16] Y. Mao, Y. Shen, J. Yang et al., Seq2path: Generating sentiment tuples as paths of a tree, *Findings of the Association for Computational Linguistics (ACL 2022)*, pp.2215-2225, 2022.
[17] H. Xiong, Z. Yan, C. Wu et al., BART-based contrastive and retrospective network for aspect-category-opinion-sentiment quadruple extraction, *International Journal of Machine Learning and Cybernetics*, vol.14, no.9, pp.3243-3255, 2023.

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