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An Aspect-Category-Opinion-Sentiment Quadruple Extraction with Distance Information for Implicit Sentiment Analysis

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The aspect-category-opinion-sentiment (ACOS) quadruples play an essential role in implicit sentiment analysis. Considering the distances between aspects and opinions in sentences, a novel Distance-Extract-Classify-ACOS quadruple extraction method with distance information between aspects and opinions is proposed. Compared with Double-Propagation-ACOS, JET-BERT-ACOS, and Extract-Classify-ACOS quadruple extraction models, the recall and F1 scores of the Distance-Extract-Classify-ACOS quadruple extraction model respectively increase by 2.08%-35.81% and 1.47%-36.7% on the Restaurant-ACOS and Laptop-ACOS datasets. Using the extracted quadruples for implicit sentiment analysis, the performance of the LSTM, GRU, TextCNN, and BERT models significantly outperform these models with original sentences, aspects-opinions pairs, and aspects-categories-opinions triples on Restaurant-ACOS and Laptop-ACOS datasets.

KEYWORDS: Aspect-Category-Opinion-Sentiment (ACOS) Quadruple Extraction, Distance Information, Distance-Extract-Classify-ACOS, Implicit Sentiment Analysis, BERT.

1. Introduction

With the development of online shopping platforms, sentiment analysis has attracted academic and business communities. By analyzing the review sentences of customers, the platforms can improve product quality to meet the needs of consumers and further enhance consumer recognition. Generally, sentiment divides into explicit and implicit sentiments for sentences [20]. If a sentence contains sentiment words, then it is an explicit sentiment sentence. Conversely, it is an implicit sentiment sentence. Negation, the most common language phenomenon, always applies in auxiliary sentiment analysis tasks to improve the accuracy of explicit sentiment analysis [2]. Li et al. [15] proposed a bidirectional emotion recurrent unit to process the context information for conversation sentiment. Zhao et al. [37] integrated the a priori sentiment information into a language model. Their model obtained good performance in a few datasets. Thus, explicit and implicit sentiment analyses have essential applications in real life.

In natural language processing, sentiment analysis tasks include phrase-level, sentence-level, and text-level sentiment classifications. The task of phrase-level sentiment analysis is to divide a sentiment sentence into several phrases. Then, their sentiment polarities are identified one by one. Wilson [32] first used a priori-polarity classifier and a sentence dependency tree to disambiguate contextual polarity. This method adopted phrase-level sentiment analysis to achieve good classification results. For sentence-level and document-level sentiment analyses, they mainly handled the sentiment of sentences, paragraphs, and chapters. By sentence-level sentiment analysis methods, Yang et al. [34] obtained some specific sentiment polarities to extract user preferences. Their method is used very well in personalized recommendation tasks. Khanam et al. [9] applied text-level topics in the task of summary generation. Their experimental results showed that document-level topic information played a certain role in summary generation.

Aspect-based sentiment analysis (ABSA) is a fine-grained sentiment classification [1, 10, 16, 30, 35]. Aspects are different attributes of an object entity for review texts. For example, in reviews on laptops, aspects are the quality, price, and service of laptops. The core task of ABSA is to extract the opinion target described by an entity and its aspects from product reviews, distinguishing the aspect sentiments [21]. The ABSA task concerns two basic subtasks: aspect extraction (AE) and aspect polarity prediction (AP). Liang et al. [18] integrated external sentiment information, contextual sentiment information, contextual sentiment words, and aspect words with syntax dependency graphs of sentences. They further proposed an aspect-based sentiment classification method based on the graph convolution network. Their method improved the performance of the ABSA task.

Considering that aspect terms may be explicitly or implicitly mentioned in texts, ABSA is subdivided into aspect term sentiment analysis (ATSA), and aspect category sentiment analysis (ACSA) [3, 25]. The ATSA mainly judged sentiment polarities of given aspect terms [13]. Many neural network-based methods have been applied to ATSA. To make up for some limitations of the word embedding method, Song et al. [27] proposed an ATSA method based on one sentiment dictionary. Their method improved the effect of text sentiment classification. Pham et al. [24] fused multi-word embeddings and one-hot feature vectors into final word embeddings. This method greatly promoted the performance of aspect-based sentiment classification.

Aspect category sentiment analysis aims to identify sentiment polarities of sentences without aspect terms. Because there are no explicit aspect terms, the classification task of ACSA faces great challenges. Wei et al. [31] fused aspect term extraction and aspect category detection into one task. They further proposed a convolutional neural network model to infer aspect categories through explicit aspect terms. The aspect term extraction and aspect category detection in their model shared common vectors. These vectors were more accurate than other models. Considering that a review sentence may contain multiple aspect categories, and an aspect category may correspond to multiple sentiment polarities, Li et al. [16] constructed a neural network based on multiple-label learning. They analyzed different situations of aspect categories in a sentence. They finally got the sentence's final sentiment polarities of these aspect categories.

Currently, aspect and opinion extraction, aspect-opinion-sentiment triplet extraction, and aspect-category-opinion-sentiment (ACOS) quadruple extraction [4] have become research hotspots. The existing studies have only focused on aspects, opinions, and sentiments in a part of a sentence. For example, a review sentence "Everything is always cooked to perfection, the service is excellent, the decor cool and understated." contains four ACOS quadruples including "null-FOOD#QUALITY-perfection-positive", "service-SERVICE#GENERAL-excellent-positive", "decor-AMBIENCE#GENERAL-cool-positive" and "decor-AMBIENCE#GENERAL-understated-positive". Based on these ACOS quadruples, it easily concludes that the sentiment polarity of the sentence is positive. Another review sentence "Bagels are OK, but be sure not to make any special requests!" includes two ACOS quadruples, i.e., "bagels-FOOD#QUALITY-OK-positive" and "null-SERVICE#GENERAL-null-negative", where "null" represents that there does not exist aspect terms or opinion words in the sentence. Based on the two ACOS quadruples about the review sentence, they have different sentiment polarities. However, the sentiment polarity of the whole sentence is negative. Since this sentence contains implicit aspect terms and opinions, it is more difficult to determine the sentiment polarity of this sentence. Taken a complex example, the sentence "A little overpriced but worth it once you take a bite." contains two ACOS quadruples: "null-FOOD#PRICES-overpriced-negative" and "null-FOOD#QUALITY-worth-positive". The meaning of the sentence is that although "food" is costly, it tastes good. The whole sentence expresses a positive sentiment. However, suppose the sentence is directly input into a neural network. In that case, the output result of the neural network will express that "price" is good but "taste" is bad, contrary to the original meaning of the sentence. Thus, ACOS quadruples are very important to analyze the implicit sentiment of sentences.

A review text often contains multiple aspects and implicit words, and the aspects may hold different sentiment polarities. Identifying the sentiment polarity of the whole review text has become a challenge. This paper aims to extract aspect-category-opinion-sentiment quadruples for implicit sentiment analysis. It proposes a Distance-Extract-Classify-ACOS quadruple extraction method with distance information between aspects and opinions. Using the ACOS quadruples, the implicit sentiment analysis models' performance will be improved. The main contributions of this paper are summarized as follows:

1. Considering the distances of aspects and opinion terms, a Distance-Extract-Classify-ACOS quadruple extraction method is proposed.
2. Experiments confirm that the performance of the Distance-Extract-Classify-ACOS quadruple extraction method outperforms the Double-Propagation-ACOS, JET-BERT-ACOS, TAS-BERT-ACOS, and Extract-Classify-ACOS models.
3. Using the Distance-Extract-Classify-ACOS quadruples, the sentiment classification abilities of GRU, LSTM, TextCNN, and BERT models are superior to these models with original sentences, aspects-opinions (AO) pairs, and aspects-categories-opinions (ACO) triplets.

The remainder of this paper is organized as follows: Section 2 introduces the related work. The details of the proposed Distance-Extract-Classify-ACOS quadruple extraction method are presented in Section 3. The experiments of quadruple extraction and its application in sentiment classification models are shown in Section 4. Finally, the conclusions of the paper are presented in Section 5.

2. Related Work

2.1. ACOS Quadruple Extraction

In an aspect-category-opinion-sentiment quadruple, the aspect stands for some explicit aspect term in a sentence. The category represents the classification of the aspect term. Each aspect term may belong to different categories. In a sentence, aspect category usually expresses implicitly. The opinion represents opinion terms [23]. An opinion term is often a sentiment word in explicit sentiment sentences, but there may be no explicit term in implicit sentiment sentences. Sentiment refers to the sentiment polarities of the triplet of aspect term, aspect category, and aspect opinion [22].

Inspired by pair and triplet extractions, Cai et al. [4] proposed ACOS quadruple extraction. The pair extraction task included aspect-sentiment pair extraction [7, 11, 12] and aspect-opinion pair extraction [36, 38]. The former focused on extracting aspects and their sentiment pairs, while the latter focused on extracting aspects and their corresponding opinion expression word pairs. Considering the methods of pair extractions do not apply to the situation where aspect words are not in the text, Wan et al. [5] proposed the aspect-category-opinion triplet extraction method. In the review texts, aspect and opinion terms may not explicitly arise. Cai et al. [4] proposed a quadruple extraction method to solve this problem. However, few researchers have noticed the distances between aspect and opinion terms in sentences.

2.2. Implicit Sentiment Analysis

In recent, implicit sentiment analysis [8, 19, 29] has attracted much attention from academia and industry. Unlike explicit sentiment analysis, the biggest challenge of implicit sentiment analysis is that there are no fixed sentiment words as hints. Therefore, various sentiment analysis methods based on different sentiment dictionaries are no longer applicable for implicit sentiment analysis. Wei et al. [29] used the orthogonal attention mechanism to integrate the external sentiment dictionary into the attention mechanism. Their method paid orthogonal attention to the different sentiments of sentences. The performance of their method is better than other models in the SMP2019 dataset. Liao et al. [19] extracted words, sentences, and document levels of features in the text. They further proposed a convolution neural network based on syntax dependency trees to deal with fact-implicit sentiment classification tasks. Kauter et al. [8] noticed both explicit and implicit expressions in sentences and used a fine-grained representation to express the sentiment of a specific topic. Li et al. [17] introduced large-scale external knowledge to study aspect-based implicit sentiment. Based on event-centered text representations, Zhou et al. [39] inferred sentiment polarities of implicit sentiment sentences. Li et al. [14] adopted explicit and implicit information to capture explicit and implicit context information. Consequently, the ACOS quadruples have yet to use in implicit sentiment analysis of sentences.

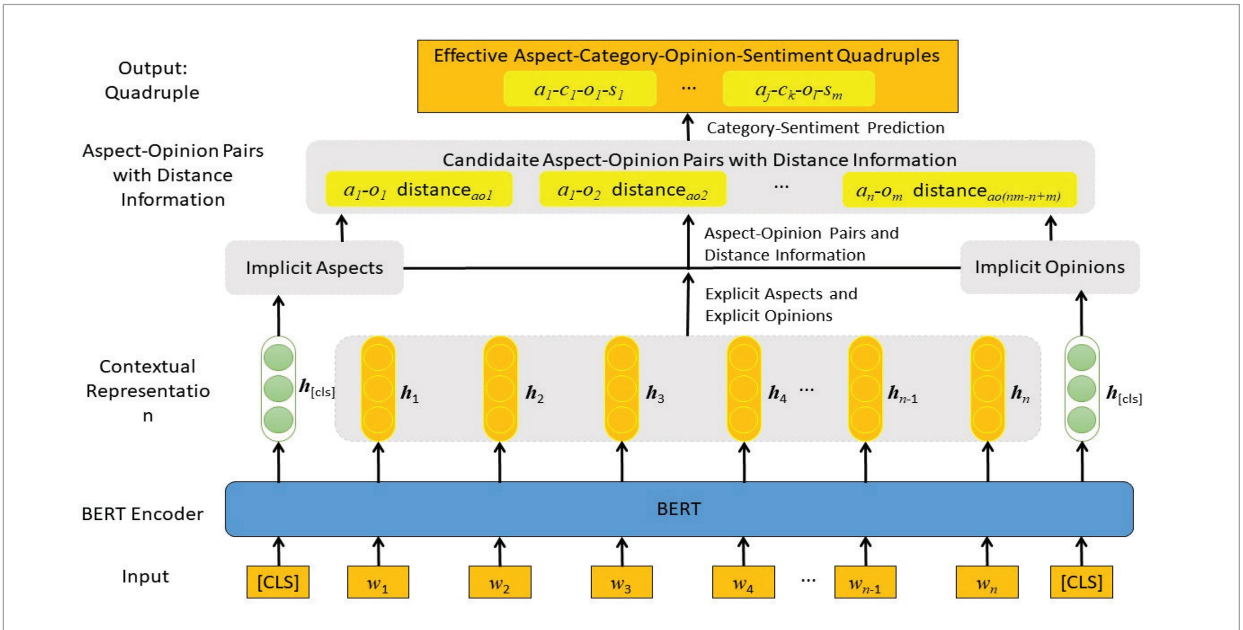
3. Distance-Extract-Classify-ACOS Quadruple Extraction Method with Distance Information

Based on the distances of aspects and opinions in sentences, we propose the Distance-Extract-Classify-ACOS quadruple extraction method with distance information, as shown in Figure 1. This method divides into two steps: aspect-opinion co-extraction and aspect-category-opinion-sentiment quadruple extraction. The aspect-opinion pairs are first extracted, and then the categories and sentiments are extracted. Finally, the aspect-category-opinion-sentiment quadruples are established.

Input. For a review sentence with n words, it can be expressed as $\boldsymbol{r} = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_n]$.

As shown in Figure 1, in the input part, two classification symbols ([CLS]) are added to the front and end

Figure 1
The framework of the Distance-Extract-Classify-ACOS quadruple extraction method with distance information



of each sentence. The front symbol is used to detect whether there is an implicit aspect. The end one is used to detect whether there is an implicit opinion. The formal representation of the input for ACOS extraction is I_{QE} = [[*CLS*], $\boldsymbol{w}$1, $\boldsymbol{w}$2, · · ·, $\boldsymbol{w}$n, [*CLS*]], where QE represents ACOS quadruple extraction.

BERT encoder. BERT [5] can generate deep bi-directional language representation. The BERT encoder represents words as the following formulas.

$$\boldsymbol{Q} = \boldsymbol{X}\boldsymbol{W}^{\boldsymbol{Q}}, \boldsymbol{K} = \boldsymbol{Q}\boldsymbol{W}^{\boldsymbol{K}}, \boldsymbol{V} = \boldsymbol{K}\boldsymbol{W}^{\boldsymbol{V}}, \tag{1}$$

$$Attention(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = softmax(\frac{\boldsymbol{Q}\cdot\boldsymbol{K}^T}{\sqrt{d_k}})\boldsymbol{V}, \tag{2}$$

where $\boldsymbol{Q}$, $\boldsymbol{K}$, and $\boldsymbol{V}$ are the query, key, and value vectors; $\boldsymbol{X}$ is the input word embeddings; and $\frac{1}{\sqrt{d_k}}$ is the scaled factor. Specifically, each query vector $\boldsymbol{Q}$ focuses on different aspects. The query vector gets the corresponding key and value vectors, i.e., $\boldsymbol{K}$ and $\boldsymbol{V}$, representing aspects and opinions, while the value vector $\boldsymbol{V}$ describes the sentimental polarity corresponding to aspects and opinions.

Contextual representation. When the sentence is fed into the BERT model, it outputs a hidden layer vector, i.e., context representation, denoted by $\boldsymbol{H}_{\text{context}}$, can be expressed as follows.

$$\boldsymbol{H}_{context} = [\boldsymbol{h}_{[CLS]}, \boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_n, \boldsymbol{h}_{[CLS]}], \tag{3}$$

where $h_{[CLS]}$ at the beginning and end respectively represent implicit aspect and opinion; and $\boldsymbol{h}_1$, $\boldsymbol{h}_2$, · · ·, $\boldsymbol{h}_n$ are explicit aspects and opinions for a sentence.

Aspect-Opinion Pairs with Distance Information. By feeding $\boldsymbol{H}_{\text{context}}$ to a conditional random field (CRF) [13] layer, aspect and opinion terms can be obtained as follows:

$$\boldsymbol{R}^{ao} = [\boldsymbol{r}_1^{ao}, \boldsymbol{r}_2^{ao}, \cdots, \boldsymbol{r}_n^{ao}] = CRF(\boldsymbol{h}_1, \boldsymbol{h}_2, \cdots, \boldsymbol{h}_n). \tag{4}$$

The distance between two words is defined as the number of words between the two words. If the distance between an aspect word and an opinion word is very close, then the aspect-opinion pair is likely effective. On the contrary, it may be ineffective. Thus, it is necessary to consider the distance factor in the quadruple extraction task. The positions of aspect and opinion terms (aspect-opinion pair) are marked by $\boldsymbol{P}^{ao}$ = {*SA, EA, SO, EO*}, where *SA* and *EA* stand for the start and end positions of an aspect term, respectively; similarly, *SO* and *EO* represent the start and end positions of opinion terms, respectively. Then the distances between the aspect and opinion terms, denoted by Dis_{ao}, can be represented as follows.

$$Dis_{ao} = \min(abs(SA\text{-}AO), abs(SA\text{-}EO), abs(EA\text{-}SO), abs(EA\text{-}EO)), \tag{5}$$

where *abs()* is the absolute value function. For the aspect and opinion terms with location information, the *SA*, *EA*, *SO*, and *EO* symbols of implicit aspects express as –1.

Inspired by TAS-BERT [28], we can get two output parameters by using two classification symbols to predict whether there are implicit aspects or opinions in the sentence. Then, we can get sets of candidate aspects and opinions, denoted by C_a and C_o. By the Cartesian product of C_a and C_o, the final aspect-opinion pairs are as follows.

$$C_{ao} = a_1o_1, a_1o_2, \cdots, a_no_m, \tag{6}$$

where a_j and o_l (j = 1, 2, · · ·, n; l = 1, 2, · · ·, m) represent the aspects and opinions in the sentence $\boldsymbol{r}$. For each aspect category $c_k \in C$, we combine the average vectors of all aspect-opinion-distance triplets, i.e., $\boldsymbol{avg}_a$-$\boldsymbol{avg}_o$-$\boldsymbol{avg}_d$. For each aspect-opinion-distance triplet, if there are implicit aspects or opinions in the triplets, then the distance is set to a small value to ensure that implicit aspects and opinions can play a role in the triplet. The closer the distance between the aspect and the opinion is, the more likely it is to be effective for the aspect-opinion pair in the sentence. Then we input it into a fully-connected layer with the *softmax* function, and each aspect-category-opinion triplet can obtain a sentiment polarity as follows.

$$s_m = softmax(\boldsymbol{W}_{aodc}^T[\boldsymbol{avg}_a; \boldsymbol{avg}_o; \boldsymbol{avg}_d] + \boldsymbol{b}_{aodc}), \tag{7}$$

where $s_m \in$ {*positive, negative, neutral, ineffective*} indicates the sentiment of the aspect-opinion-category triplet, or the current quadruple is ineffective.

Output. For each review sentence $\boldsymbol{r}$, all ACOS quadruples can be obtained as follows.

$$\boldsymbol{D}_{ACOS} = \{a_1\text{-}c_1\text{-}o_1\text{-}s_1, \cdots, a_j\text{-}c_k\text{-}o_l\text{-}s_m, \cdots\}, \tag{8}$$

where a_j-c_k-o_l-s_m is an ACOS quadruple; and a_j, c_k, o_l and s_m represent the aspect term, aspect category, inion term and sentiment polarity of the quadruple, respectively.

4. Experiments

4.1. Datasets

Restaurant-ACOS and Laptop-ACOS datasets [16] are selected as our experimental datasets. The former comprises SemEval 2016 task 5: aspect-based sentiment analysis [34] and its extended datasets [6, 26]. This dataset has more than 2000 sentences. The average word of each sentence is close to 20, and there are about 1.6 quadruples in each sentence. The latter is crawled from some shopping websites. It covers ten types of laptops under six brands such as Samsung, MSI, MBP, Lenovo, ASUS, and Acer. It contains more than 4000 sentences. Its sentence lengths are shorter than the first dataset, and its quadruples are more than the former one. Its quadruples' proportion in sentences is fewer than the former dataset. The two datasets are the largest datasets in the field of quadruple extraction. The specific indicators of the two datasets are shown in Table 1.

Table 1

Indicators of Restaurant-ACOS and Laptop-ACOS datasets

Indicator	Restaurant-ACOS	Laptop-ACOS
Categories	13	121
Sentences	2286	4076
Average words per review	19.49	9.14
Quadruples	3658	5758
Quadruples' proportion in sentences	1.60	1.42

Table 2

The distribution of sentiment polarity in the two datasets

dataset	Positive		Negative		Neutral		Total	
	Train	Test	Train	Test	Train	Test	Train	Test
Restaurant-ACOS	1117	406	529	152	57	25	1703	583
Laptop-ACOS	1832	459	1212	302	216	55	3260	816

Based on the labeled quadruples, we add a sentiment polarity label to each sentence. To ensure the accuracy of sentiment polarity labels of sentences, we first let two professionals label independently for each sentence. If their labels are the same, then their labels are the final sentiment polarity of the sentence. If their labels are different, let the third expert label the sentiment polarity and compare their labels to get the final sentiment polarity of the sentence. Table 2 shows the distribution of sentiment polarities in two datasets. It shows that positive and negative sentiment polarities account for a large proportion.

4.2. Evaluation Index

In the ACOS quadruple extraction task, if all elements in a quadruple are the same as those marked, the quadruple is correctly extracted. Conversely, the quadruple is wrongly extracted. To evaluate the effectiveness of the quadruple extraction, we use the general evaluation indexes of binary classification tasks: precision (P), recall (R), and F1 scores. For implicit sentiment analysis with/without the quadruples, we use the accuracy (Acc) and macro-F1 scores as evaluation indexes. We also repeat the experiment five times for each validation experiment and use their average value as the final experimental result. The maximum and minimum values of each result are less than 0.5%.

4.3. Performance Comparisons of ACOS Quadruple Extraction Methods

The most popular quadruple extraction models, including Double-propagation-ACOS, JET-BERT-ACOS, TAS-BERT-ACOS, and Extract-Classify-ACOS are selected to compare with the proposed Distance-Extract-Classify-ACOS quadruple extraction method. At the same experimental conditions, all comparative experiments are rerun and all parameters are optimized.

Double-Propagation-ACOS. Double propagation [26] is a rule-based extraction method. It cannot extract aspect categories in the quadruple task. Cai et al. [4] first extracted the original aspect-opinion-sentiment (AOS) triplets to predict aspect categories from sentences. Based on the AOS triples, they further extracted the quadruples.

JET-BERT-ACOS[1]. JET [38] uses an end-to-end framework, and its tasks remain the same as double propagation. It introduces BRET for the pre-training layer. It extracts AOS triples to predict aspect categories. Then, the ACOS quadruples are obtained. In this model, the Adam optimizer and cross-entropy loss function are adopted. The training parameters of BERT are as follows. The maximum sequence length is 128; the dropout is 0.1; the batch size is 8; the learning rate is 0.00005; the transformer layer is 12; the hidden layer is 768; and the heads are 12.

TAS-BERT-ACOS[2]. TAS-BERT [28] combined sentiment analysis and aspect extraction into one model. It also added aspect category and sentiment polarity to the end of the original sentence. It further inputs them into BERT to obtain aspect representation. Then it extracts aspect-category-sentiment (ACS) triplets. To achieve the task of quadruple extraction, the baseline model jointly extracts aspect opinions and sentiments by the BERT method. It makes a Cartesian product of each aspect and opinion. The ACOS triplets are established by combing aspect categories, sentiments, aspects, and opinions. The BERT parameters are the same as JET-BERT-ACOS.

1 https://github.com/xuuuluuu/Position-Aware-Tagging-for-ASTE.

2 https://github.com/sysulic/TAS-BERT.

Extract-Classify-ACOS[3]. This model first extracts aspect-opinion pairs from a sentence. Then it predicts aspect category and sentiment by the BERT method. It also makes Cartesian products of aspects and opinions. Combing with aspects, opinions, aspect categories, and sentiments, it obtains effective ACOS quadruples. The learning rate of aspect and opinion extraction is set as 0.00002. The category-sentiment prediction is 0.00003. Other parameters are the same as those mentioned above.

The performance comparisons of ACOS quadruple extraction methods are shown in Table 3. Double-Propagation-ACOS obtains higher precision than TAS-BERT-ACOS on the Restaurant-ACOS dataset, but the recall rate is inferior. It concludes that the rule-based method is unsuitable for implicit aspect-opinion extraction. At the same time, the F1 scores of all models on the restaurant-ACOS dataset are higher than their F1 scores on the laptop-ACOS dataset. The reason is that the restaurant-ACOS dataset is smaller than the laptop-ACOS dataset.

The Extract-Classify-ACOS method's recall and F1 scores are superior to those of the TAS-BERT-ACOS method on Restaurant-ACOS and laptop-ACOS datasets. Because the rule for judging the extraction success is stringent, the F1 scores of all models are generally low. The proposed Distance-Extract-Classify-ACOS model achieves the best recall and F1 scores on Restaurant-ACOS and laptop-ACOS datasets, respectively. Compared with the Extract-Classify-ACOS method, the recall scores of the Distance-Ex-

3 https://github.com/NUSTM/ACOS.

Table 3

Performance comparisons of ACOS quadruple extraction methods (%)

Method	Restaurant-ACOS			Laptop-ACOS		
	P	R	F1	P	R	F1
Double-Propagation-ACOS	35.89	18.72	24.61	14.58	0.63	1.21
JET-BERT-ACOS	58.91	29.46	39.28	45.87	15.68	23.37
TAS-BERT-ACOS	28.36	48.42	35.77	46.28	20.15	28.08
Extract-Classify-ACOS	38.68	52.45	44.52	45.36	29.14	35.48
Distance-Extract-Classify-ACOS (Ours)	39.77	**54.53**	**45.99**	**44.93**	**32.78**	**37.91**

tract-Classify-ACOS model increase by 2.08% and 3.64% on Restaurant-ACOS and laptop-ACOS datasets, and the F1 scores of the Distance-Extract-Classify-ACOS model increase by 1.47% and 2.43% on Restaurant-ACOS and Laptop-ACOS datasets, respectively. It implies that the distances of aspects and opinions in sentences are considered to be effective in the proposed Distance-Extract-Classify-ACOS model.

Compared with Double-Propagation-ACOS, JET-BERT-ACOS, and Extract-Classify-ACOS models, the recall and F1 scores of the Distance-Extract-Classify-ACOS model are increased by 2.08%-35.81% and 1.47%-21.38% on the Restaurant-ACOS dataset, respectively; and the recall and F1 scores of the Distance-Extract-Classify-ACOS model are increased by 3.64%-32.15% and 2.43%-36.7% on the Laptop-ACOS dataset, respectively. It implies that the aspect-opinion distances in the Distance-Extract-Classify-ACOS model improve the effectiveness of quadruple extraction.

In short, the performance of the proposed Distance-Extract-Classify-ACOS model has a small improvement compared with the best baseline model, i.e., Extract-Classify-ACOS on Restaurant-ACOS and laptop-ACOS datasets. However, the proposed Distance-Extract-Classify-ACOS model achieves significant improvement over the other three baseline models on the two datasets. Therefore, the proposed Distance-Extract-Classify-ACOS model can effectively extract ACOS quadruples.

4.4. Applications of the Distance-Extract-Classify-ACOS Quadruples for Implicit Sentiment Analysis

To confirm the effect of the Distance-Extract-Classify-ACOS quadruples on implicit sentiment analysis models, we put the quadruples in the LSTM, GRU, TextCNN, and BERT models. At the same experimental conditions, we conduct all experiments and optimize all parameters for these implicit analysis models.

LSTM and GRU. They are extensively adopted in sentiment analysis tasks. The embedding dimension is 64; the sequence length is 100; the number of hidden layers is 2; the number of hidden layer neurons is 128; the dropout is 0.8; and the learning rate of the Adam optimizer is 0.001.

TextCNN[4]. It is widely used to achieve natural language processing tasks. The dimension of embedding is set as 64; the sequence length is 100; the number of filters is 256; the size of the convolution kernel is 5; the number of hidden layer neurons is 128; the dropout is 0.5; the batch size is set as 64, and the learning rate of the Adam optimizer is 0.001.

BERT[5]. It has made great achievements in natural language processing tasks. The batch size is 8, and the learning rate is 0.00002.

The original sentences, aspects-opinions (AO) pairs, and aspects-categories-opinions (ACO) triples and ACOS quadruples obtained by the Distance-Extract-Classify-ACOS quadruple extraction model are input into the LSTM, GRU, TextCNN, and BERT models to confirm the effectiveness of the quadruples on implicit sentiment classification. From Table 4, when the inputs are original sentences, the performance of BERT is the best on Restaurant-ACOS and Laptop-ACOS datasets. The accuracy and Macro-F1 scores of BERT on the Restaurant-ACOS dataset are larger than those of BERT on the Laptop-ACOS dataset. The main reasons are that the sentences' lengths on the Laptop-ACOS dataset are shorter than those on the Restaurant-ACOS dataset. More semantic information about the context is needed in sentences.

For the LSTM model, original sentences, AO pairs, and ACO triples are input into the model, and its performance increases on Restaurant-ACOS and Laptop-ACOS datasets. For the GRU model, when the original sentences, AO pairs, and ACO triples are respectively as the model's inputs, its performance is almost the same on the Restaurant-ACOS dataset, and its accuracy and macro-F1 scores rise to 76.47% and 67.05% on the Laptop-ACOS dataset. For the TextCNN model, when AO pairs and ACO triples are respectively as the model's inputs, the model with ACO triples obtains better performance than the model with AO pair on the Restaurant-ACOS dataset, and the model performs the same accuracy and macro-F1, i.e., 77.70% and 53.92%, on the Laptop-ACOS dataset. On the two datasets, the performance of the model with ACO triples is the best compared with the model with the original sentences, AO pairs, and ACO triples. For

4 https://github.com/gaussic/text-classification-cnn-rnn.

5 https://github.com/google-research/bert.

Table 4
Comparisons of the accuracy and macro-F1 scores of LSTM, GRU, TextCNN, and BERT models with the original sentences, AO pairs, ACO triples, and ACOS quadruples obtained by Distance-Extract-Classify-ACOS on Restaurant-ACOS and Laptop-ACOS datasets

Method	Restaurant-ACOS		Laptop-ACOS	
	Acc.	Macro-F1	Acc.	Macro-F1
LSTM(original sentences)	69.64	27.37	60.05	39.85
LSTM(AO pairs)	69.81	39.89	71.69	49.51
LSTM(ACO triples)	70.50	40.22	74.76	52.07
LSTM(ACOS quadruples)	93.48	62.64	97.92	97.16
GRU(original sentences)	70.33	38.29	57.35	41.61
GRU(AO pairs)	69.81	39.80	73.41	58.85
GRU(ACO triples)	68.44	39.17	76.47	67.05
GRU(ACOS quadruples)	93.31	62.54	97.67	95.01
TextCNN(original sentences)	74.44	44.81	73.41	49.85
TextCNN(AO pairs)	72.56	46.65	77.70	53.92
TextCNN(ACO triples)	74.96	49.12	77.70	53.92
TextCNN(ACOS quadruples)	93.14	62.03	97.18	95.91
BERT(original sentences)	88.89	77.16	87.12	69.35
BERT(AO pairs)	80.70	52.27	81.29	55.78
BERT(ACO triples)	86.55	55.79	81.90	56.73
BERT(ACOS quadruples)	95.91	83.51	98.47	98.88

the BERT model, the accuracy and macro-F1 scores of the model with AO pairs, ACO triples, and original sentences increase in turn on Restaurant-ACOS and Laptop-ACOS datasets.

For the LSTM, GRU, TextCNN, and BERT models, the accuracy and Macro-F1 scores of the model with ACOS quadruples extracted by Distance-Extract-Classify-ACOS method are superior to the model with original sentences, AO pairs, and ACOS triples. In these models with ACOS quadruples, the accuracy and Macro-F1 scores of BERT are the highest, i.e., 95.91% and 83.51% on the Restaurant-ACOS dataset (resp. 98.47% and 98.88% on the Laptop-ACOS dataset), respectively. From the four experimental results using the original sentence as input, BERT achieves the best results, with macro-F1 values of 77.16% and 69.35% on the Restaurant-ACOS and Laptop-ACOS datasets, respectively. Compared with other deep learning models, BERT only uses the attention mechanism, which can be called a "violent" model, thus achieving good results. Meanwhile, all models perform better on the Laptop-ACOS dataset than the Restaurant-ACOS dataset. The main reasons are as follows. (1) The number of ACOS quadruples on the Laptop-ACOS dataset is fewer than that on the Restaurant dataset. (2) The ACOS quadruples replace the original sentence as input, thus reducing the influence of irrelevant words in original sentences.

In brief, the performance of the LSTM, GRU, TextCNN, and BERT models using the quadruples obtained by the Distance-Extract-Classify-ACOS model has significant improvement. Though the proposed Distance-Extract-Classify-ACOS quadruple extraction model has a small improvement compared with the existing best quadruple extraction method, i.e., Extract-Classify-ACOS, the proposed Distance-Extract-Classify-ACOS quadruple extraction method is beneficial for implicit sentiment analysis models, including LSTM, GRU, TextCNN, and BERT. Therefore, the ACOS quadruples achieved by the Distance-Extract-Classify-ACOS method are relatively effective in enhancing the performance of implicit sentiment classification models on Restaurant-ACOS and Laptop-ACOS datasets.

5. Conclusion

This paper proposed a Distance-Extract Classify-aspect-category-opinion-sentiment (Distance-Extract-Classify-ACOS) quadruple extraction method with distance information for implicit sentiment analysis. Compared with other ACOS quadruple methods, including the Double-Propagation-ACOS, JET-BERTACOS, TAS-BERT-ACOS, and Extract-Classify-ACOS quadruple extraction models, the proposed Distance-Extract-Classify-ACOS quadruple extraction method showed the best performance. Using the quadruples extracted by the Distance-Extract-Classify-ACOS quadruple extraction method, the implicit sentiment classification models, including GRU, LSTM, TextCNN, and BERT, performed better than those models with original sentences, aspects-opinions pairs, and aspects-categories-opinions triplets. Since the sentiment polarities in the Restaurant-ACOS dataset are imbalanced, we will enrich the dataset by expanding the dataset or use some dataset augmentation methods to replenish the dataset in the future work. Meanwhile, we can find other enhancement information to establish a new ACOS quadruple extraction method and apply the extracted quadruples to improve the abilities of implicit sentiment analysis models.

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