

# A Mutually Enhanced Bidirectional Approach for Jointly Mining User Demand and Sentiment (Student Abstract)

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## Abstract

User demand mining aims to identify the implicit demand from the e-commerce reviews, which are always irregular, vague and diverse. Existing sentiment analysis research mainly focuses on aspect-opinion-sentiment triplet extraction, while the deeper user demands remain unexplored. In this paper, we formulate a novel research question of jointly mining aspect-opinion-sentiment-demand, and propose a Mutually Enhanced Bidirectional Extraction (MEMB) framework for capturing the dynamic interaction among different types of information. Finally, experiments on Chinese e-commerce data demonstrate the efficacy of the proposed model.

## Introduction

With the rapid development of social media, massive reviews contain users' sentiment and implicit demand towards products, mining such information can help merchants obtain feedback quickly and make strategic adjustments in a more timely manner. The following example is from an online e-commerce platform, where a user discussed his/her use experience of washing machine "A nice appearance, but sound is very loud, which is comparable to that of tractor". Existing fine-grained sentiment analysis approach mainly focuses on aspect-opinion-sentiment triplet extraction such as *sound-loud-negative*, *sound-comparable to that of tractor-negative* by jointly performing "aspect extraction", "opinion extraction" and "aspect-based sentiment classification". The mined results implied that the user had a negative sentiment with the sound. If we can further mine the demand of "improve product quality" simultaneously, it will be beneficial for customer service chatbot to contact the technical department to solve relevant problem as soon as possible and improve users' satisfaction (Yao et al. 2020). To mine the user demand and sentiment, there are several challenges need to be addressed. First, the expressions of aspect/opinion are complex, as users not only use adjectives but also phrases to express their viewpoint, which is difficult to identify the entities and distinguish their boundaries. Second, the implicit demand usually has hidden dependencies on the aspect-opinion-sentiment, the dissatisfaction ex-

pressed by opinions can further trigger the mining of demand, hence, how to capture the dynamic semantic interaction among different types of information is important for identifying the demand.

Therefore, we formulate a novel research question of jointly mining aspect-opinion-sentiment-demand, and propose a mutually enhanced bidirectional extraction framework. Specifically, the model leverages the advantages of query construction in Machine Reading Comprehension (MRC) to fuse extracted elements as priori knowledge, which can better transfer and guide information among different tasks. In addition, the mutually enhanced bidirectional mechanism for aspect-opinion pairs mining from two directions can further capture the dynamic interaction, where aspects and opinions can be naturally characterized as inspiration in query and highlight in input text respectively.

## Proposed Model

Given a product review  $X$ , the goal is to identify quadruple  $Q = \{(a_i, o_i, s_i, d_i)\}_{i=1}^{|Q|}$ , where  $a_i$  and  $o_i$  are aspect and opinion,  $s_i$  is the corresponding sentiment (positive or negative), and  $d_i$  is implicit demand (predefined in  $D = \{d_k\}_{k=1}^{|D|}$ ,  $d_k$  can be praise, product quality improvement and product service improvement, etc). Among them,  $|*|$  represents the number of  $*$ . We propose a mutually enhanced bidirectional method, which mainly includes two modules, namely, the query construction module based on enhanced mechanism and the semantic interaction module based on pre-trained language model, to collaboratively realize the deep mining of the four elements.

**Enhanced Mechanism for Query Construction.** During the query construction, we adopt multi-step progressive enhancement based on BMRC (Chen et al. 2021) for element extraction, and further introduce mutually bidirectional enhancement between aspect-opinion. In Step1,  $Q_1^{A2O}$  and  $Q_1^{O2A}$  are constructed to extract all aspects  $A = \{a_i\}_{i=1}^{|A|}$  and opinions  $O = \{o_i\}_{i=1}^{|O|}$  in  $X$ . To reduce the impact of vague entities boundary and better explore the relationship between  $A$  and  $O$ , we construct  $Q_2^{A2O} = \{ \text{'What opinions of } a_i?'\}_{i=1}^{|A|}$  and  $Q_2^{O2A} = \{ \text{'What aspects of } o_i?'\}_{i=1}^{|O|}$  in step2. The mutually bidirectional enhancement mechanism is implemented by con-

structuring query and input  $X$  with extracted results, which are obtained in step1 from two directions respectively, i.e. in A2O, aspects extracted in A2O are fused in query  $Q_2^{A2O}$ , opinions extracted in O2A are highlighted by special separation token in  $X$  ( $\dots [SEP]o_i[SEP], \dots, o_i \in O$ ).

$$X' = \begin{cases} x_i, & x_i \notin O \\ [SEP]x_i[SEP], & x_i \in O \end{cases}$$

The bidirectional extraction results are further fused and subsumed to obtain the aspect-opinion pair  $P = \{(a_i-o_{ij})\}_{i=1}^{|A|}$  ( $o_{ij}$  can be Null). Further, the sentiment is classified by introducing each extracted  $(a_i-o_{ij})$  into  $Q_3$ . Finally, implicit demands based on fine-grained sentiments are mined. The semantic information in predefined demand categories is helpful for demand mining, so we construct  $Q_4 = \{What\ is\ implicit\ demand\ of\ (a_i-o_{ij}-s_i)? + d_k'\}_{k=1}^{|D|}$ .

**Semantic Interaction Mining between Query and Text.** With the constructed queries, to effectively capture the semantic association between the query and the text,  $I = [[CLS], q_1, q_2, \dots, q_m, [SEP], x_1, x_2, \dots, x_n]$  is input into the pre-trained language model BERT. The input  $I$  is constructed by different queries and text in each step, and the parameters of BERT are shared to obtain the representation vector  $h_i$  of each token.

$$H = \text{BERT}(I)$$

The aspect-opinion-sentiment-demand extraction is jointly trained by four linear classifiers, which mine the start and end of aspects or opinions, sentiment and demand simultaneously. The overall training loss  $L$  is given as follows, where  $L_{CE}$  represents the cross-entropy loss function.

$$\begin{aligned} p(y_i) &= \text{softmax}(\text{linear}(h_i)) \\ L &= L_{CE}(p(y_{CLS}^s), y_{CLS}^s) + L_{CE}(p(y_{CLS}^d), y_{CLS}^d) \\ &+ \sum_i L_{CE}(p(y_i^{start}), y_i^{start}) + \sum_i L_{CE}(p(y_i^{end}), y_i^{end}) \end{aligned}$$

## Experiments and Results

**Dataset.** To verify the effectiveness of the proposed model, we constructed a review dataset from November 1, 2021 to March 1, 2022 on a famous e-commerce website in China. We selected electrical products reviews such as refrigerator, electric oven, washing machine, etc. Two people are invited to annotate the extraction and classification labels, the Fleiss' kappa coefficient of the final annotation result is 0.77. The annotated dataset obtained 1944 labeled reviews, including 4849 aspect-opinion-sentiment-demand quadruples. The training set, test set and validation set are randomly split 5 times according to 7:2:1, and the experimental results are the average on the runs with different splittings.

**Baseline Methods.** The proposed model is compared with three baseline methods: (1) TSF (Peng et al. 2020) is a pipeline model inspired by the two-stage idea, which includes the extraction of aspect-opinion respectively and further pairing up the extraction results into quadruples. (2)

		TSF	RACL+	BMRC	MEBE
Aspect-Opinion Extraction	P	59.33	63.78	65.92	67.97
	R	63.40	61.72	67.99	67.46
	F1	61.30	62.73	66.94	<b>67.71</b>
Sentiment Judgment	P	57.91	61.77	64.54	66.87
	R	61.88	59.87	66.56	66.36
	F1	59.83	60.81	65.53	<b>66.61</b>
Demand Detection	P	55.59	59.13	62.29	64.56
	R	59.42	57.26	64.23	64.08
	F1	57.44	58.18	63.25	<b>64.32</b>

Table 1: The Experimental Results.

RACL+ (Chen and Qian 2020) takes the relationship between tasks into account by coding the cooperation signals between different tasks to make them promote each other. (3) BMRC (Chen et al. 2021) draws on the MRC framework to complete the extraction of elements by asking questions step by step.

**Results.** It can be seen from Table 1 that the proposed model MEBE achieves the best performance in three tasks with F1 of 67.71, 66.61 and 64.32, respectively. Compared with the other baseline methods, BMRC performs better in terms of F1, take demand detection task as an example, F1 varies from 57.44 to 63.25, which indicates that machine reading comprehension framework can generate a more effective representation of dependencies among elements. By introducing the mutually enhanced mechanism, the proposed MEBE model improves the performance, F1 ranges from 63.25 to 64.32 for demand detection, these results show that capturing the dynamic information interaction between tasks may help identify the ambiguous boundaries of extracted entities in Chinese reviews, thus mine the relationship between aspects and opinions.

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