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Deriving customer preferences for hotels based on aspect-level sentiment analysis of online reviews

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ABSTRACT

An increasing number of travelers like to share their experience and feelings about hotel stays through social media, generating a sheer volume of online hotel reviews. The user-generated comments contain their preferences for different aspects of hotels, which are helpful for hoteliers to improve hotels' services. The key of deriving customer preferences from online hotel reviews is to identify fine-grained sentiment towards hotel attributes. However, the existing fine-grained sentiment analysis approaches cannot address the implicit aspect-level terms extraction very well, which is necessary to deal with the common situation that some aspects are omitted in the online reviews. To better understand customer preferences, we propose an unsupervised approach for aspect-level sentiment analysis with the implicit hotel attributes into consideration by integrating word embedding, co-occurrence and dependency parsing. A method based on overall sentiment values of hotel attributes is used to measure the customer preferences to support the hotel services analysis. Finally, online hotel reviews crawled from Ctrip.com are used to verify the proposed approach, and the results show that the hybrid approach outperforms the individual included techniques with respect to the sentiment classification performance. The analysis of customer preference for Dalian Bayshore Hotel suggests that the hotel's facility should be upgraded urgently, and different types of customers pay different attention to hotel attributes, such as price, hygiene, and location.

1. Introduction

Customers are increasingly booking hotel rooms through hotel websites or related online platforms, such as Airbnb, Hotels.com, Booking.com, Tripadvisor, Ctrip.com and Qunar.com. An important feature of an online transaction is the existence of spatial separation between customers and the list products or services on the platforms (Hua et al., 2017; Sun et al., 2020; Yan et al., 2020). Thus, customers cannot experience and feel their desired hotel rooms when ordering online, and thereby face relatively high uncertainty about the room attributes such as fitness and service quality. In this case, online customer reviews (namely online reviews) play an important role in mitigating such uncertainty (Kwark et al., 2014). A recent report shows that 81% of travelers would usually read online reviews before booking a hotel room, and 79% of them will read six or even twelve reviews before making a purchase decision (Siteminder, 2021). The behind intuition is that, online reviews are generated by customers who have really experienced the rooms and services, and thus their commented information about hotels' services in terms of quality, prices and service levels are much more convincing for potential customers than hotels' advertisements (Gavilan et al., 2018). Thereby, online reviews will significantly influence customers' attitudes, purchase decisions and thus firms' performance (Park and Kim, 2008; Wang et al., 2021; Yan and Han, 2021; Zhao et al., 2015).

Due to the effect of electronic word-of-mouth (eWOM), it is important for the hoteliers to obtain customers' preferences from online reviews in order to satisfy their requirements. As for hotels, the key is to understand the customers' preferences towards different aspects from their related online reviews. In general, a substantial number of positive and negative opinions are embedded in these user-generated elements, which reflect customer preferences for products or services (Gao et al., 2018; Nikolay et al., 2011). Thus, it is possible for managers to derive customer preferences from online reviews, so as to increase customer satisfaction and improve firms' performance (Ahani et al., 2019). In

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hotel industry, hoteliers can create preference profiles of different types of customers according to the identified praise and criticism opinions, and then can utilize them not only to improve hotels' facilities and services in a targeted manner. Therefore, it is necessary to mine customers' preferences for the services of hotels from online reviews.

In practice, a comment often contains diverse sentiments towards different hotel features. For example, in the comment "The location of hotel is very good, the service staff are also very enthusiastic, but the price is a bit expensive", the customer gives different opinions on the location, service and price of the hotel, indicating a positive sentiment towards the location and the service staff, but a negative one towards the price. It is generally considered that the overall sentiment of the comment is positive, and is obviously in contradiction with the customer's sentiment towards the hotel's price. In this case, it is necessary to delve into the comment to identify the specific sentiments towards different aspects of the hotel from the review rather than the overall sentiment. Moreover, there exists the situation where the subject of short sentences in online reviews is usually omitted. For example, in the comment "The hotel's service is very good, but a bit timeworn", "facility" is supposed to be the subject of the second half of the sentence but is omitted. If the subject cannot be identified, it is likely to ignore or misunderstand the customer's preferences or expectations. In this case, it becomes critically important for hoteliers to correctly identify the aspect-level sentiment so as to gain a better understanding of customers' preferences.

In recent years, many emerging technologies, such as data analysis, machine learning, deep learning, Internet of Things (IoT), and blockchain, are introduced to E-commerce operations (Shen et al., 2021, 2020). As a data analysis technique, text mining have been widely used to help managers to understand customer preferences from online reviews to support their operations management (Dou et al., 2021; Sun et al., 2017). Sentiment analysis is a typical text mining technique aimed at the task of detecting, extracting, and classifying opinions, sentiments and attitudes expressed in texts towards different topics (Chang and Huo, 2018; Montoyo et al., 2012; Tang et al., 2019). In the hotel industry, a few studies have attempted to uncover the aspects of hotels that are deemed as important by various customers through aspect-level sentiment analysis of hotels' online reviews (Luo et al., 2021; Yadav and Roychoudhury, 2019). These studies, however, do not take into account the case of omitting the subject of some short sentences in online reviews.

In fact, considerable efforts have been made to improve the performance of aspect-level sentiment analysis by focusing on some of or all its basic tasks that include aspect extraction, sentiment identification, and classification (Feldman, 2013; Schouten and Frasincar, 2016). The first two tasks aim to identify all sentiment expressions and the aspects to which they refer, and the last task is most often a binary classification problem, distinguishing between positive and negative sentiments. No matter whether it is a method for a single task or a method for all tasks, to our best knowledge, missing subjects have never been considered in the existing studies. This motivates us to develop a new approach to accurately identify fine-grained sentiments towards aspects of hotels.

To identify different types of customers' emotional preferences for hotels' different attributes from online reviews, we develop an aspect-level sentiment analysis framework based on natural language processing techniques in this study. In the introduced approach, a triple expression consisting of evaluated attributes, sentiment phrases, and affective modifiers of sentiment phrases is proposed to represent the sentiment elements. A method combining word embedding, co-occurrence information and dependency parsing analysis is developed to identify sentiment triples containing implicit evaluated attributes. An empirical study with collected hotels' online reviews crawled from Ctrip.com in China is used to test the effectiveness of the proposed approach.

The empirical analysis yields the following important findings and insights. *First*, the adoption of dependency parsing significantly improves the accuracy of identifying missing aspects with a precision increase by 15% compared to the baseline model without this technique. *Second*, sanitation is the basic requirement across all the types of customers; convenient transportation location leads to relatively higher satisfaction; couple customers and friend customers are concerned about room price; business customers and solo customers have higher requirements for the hotel atmosphere. *Third*, most customers are dissatisfied with the hotels' facilities, which suggests urgent improvements on the hotel's facilities, such as water heater, sound insulation and toilet.

The main contributions of this study to the extant literature are summarized as follows. First, a method combining word embedding, co-occurrence information and dependency parsing analysis is developed to identify sentiment triples that are composed of evaluated attributes, associated sentiment phrases, and affective modifiers of sentiment phrases. Second, an approach for measuring attribute oriented preferences of different types of customers is proposed on the basis of sentiment intensity calculation. The remainder of this paper is organized as follows. Section 2 reviews the most relevant literature. In Section 3, we present the developed methodology, followed by an empirical study in Section 4. Conclusions appear in Section 5.

2. Literature review

Our work is closely related to sentiment analysis of hotels' online reviews and fine-grained sentiment analysis. We review the most relevant studies in this section.

2.1. Sentiment analysis of online hotel reviews

In the literature, substantial efforts have been made to explore the effect of online hotel reviews on the hospitality industry (Schuckert et al., 2015). Some research efforts paid attention to the impact of online hotel reviews on hotel operations through empirical study, such as purchase intentions (Zhao et al., 2015), response management (Xie et al., 2014; Xu, 2020a), and customer satisfaction (Gavilan et al., 2018). However, those studies didn't consider the influences of customers' sentiment implied by related online reviews.

In recent years, sentiment analysis of hotels' online reviews has received increasing and considerable attention in the literature due to the revival of machine learning and natural language processing. The related studies can be classified into two groups. The first group attempts to establish systematic approaches that leverage the existing methods or tools to finish sentiment analysis of online reviews for different review management purposes, such as review helpfulness prediction (Chatterjee, 2020; Lee et al., 2018), review summarization generation (Hu et al., 2017; Tsai et al., 2020), and review response strategy (Chang et al., 2020). In those studies, sentiment analysis is only one step of the systematic approaches, and is performed at the document or sentence level to recognize the overall sentiment of a review.

In contrast, the second group of research focuses on new methods for pure sentiment analysis to acquire the sentiment polarities of online hotel reviews. For example, Shi and Li (2011) proposed a supervised machine learning approach based on uni-gram feature with information on frequency and TF-IDF to perform polarity classification of reviews. Ray et al. (2021) developed an ensemble application of BERT (Bidirectional Encoder Representations from Transformers) to fulfill a 3-class prediction of sentiment polarities, including positive, negative, and neutral. Notably, those research works aimed to identify the sentiment polarity of each piece of review, namely sentiment classification at the document level. Moreover, to our knowledge, no efforts specific to online hotel reviews have been made to explore the sentiment intensity by calculating sentiment values, except for the research work of (Mankad et al., 2016). They simply calculated the positive/negative sentiment score of each review by counting the number of positive/negative words in the review.

Although two groups of research devoted to sentiment analysis of online hotel reviews, both sentiment classification and sentiment value calculation are performed at the document or sentence level, and do not deep into the level of specific attributes in the sentences. Our study is concern with customers' preference for hotel with respect to different attributes such as sanitation, transportation, services, and prices. It is necessary to figure out the sentiment values of those hotel attributes through fine-grained sentiment analysis.

2.2. Fine-grained sentiment analysis

Fine-grained sentiment analysis, also called aspect-based opinion mining, consists of two fundamental sub-tasks: opinion targets extraction and target-oriented sentiment polarity identification (Schouten and Frasincar, 2016; Tang et al., 2019). There is a rich body of studies on this issue, which distinguish themselves from each other through the different ways to deal with aspect extraction and polarity classification. This stream research can be broadly grouped into knowledge-based approaches and learning-based approaches. In general, knowledge-based approaches focus on the construction of knowledge bases, such as ontologies and lexica (Chang et al., 2021), to help extract the opinion target and identify their sentiment polarity. For example, Cambria et al. (2014) developed an extended semantic and affective resource (i.e., SenticNet 3) to provide semantics and sentics for 30,000 multi-word expressions for a deeper and more multi-faceted opinion analysis. Sun et al. (2019) developed a feature-based and context-sensitive fine-grained sentiment analysis method supervised by semantic knowledge to explore eWoM of products.

With respect to learning-based approaches, the extant studies usually employ statistical learning methods (e.g. support vector machine and latent Dirichlet allocation) (Schouten and Frasincar, 2016) and neural network models (e.g. long short term memory and convolutional neural networks) (Zhou et al., 2019) to complete the sentiment analysis. In recent years, attention-based deep models have gained great attention from scholars to deal with aspect-level sentiment analysis (Zhang et al., 2021). For example, Fu et al. (2019) proposed a Variational Autoencoder based semi-supervised approach for sentiment classification at the aspect level, which adopts attention mechanism to deal with different parts of a review and employs aspect-specific word embedding learning to express a word that is sensitive to the given aspect.

Depending on whether these two sub-tasks (i.e., opinion targets extraction and sentiment words extraction) are completed separately or integrally, the studies can be classified into two categories: separate approaches and integral approaches. Separate approaches, as the name suggests, are devoted to complete one of the two sub-tasks alone. For example, Wu et al. (2018) proposed a hybrid method combining rules and gated recurrent unit network model to perform aspect term extraction and opinion target extraction. Wu et al. (2020) proposed a novel model to obtain opinions knowledge contained in review sentiment classification dataset to facilitate the target-oriented opinion words extraction task with insufficient annotated datasets. In contrast, integral approaches aim to solve these two-sub-tasks integratedly. For example, Guo et al. (2020) proposed an improved multi-way matching deep neural network model to integrate these two tasks in one phrase so as to prevent error propagation problem caused by separately addressing these two tasks.

Notably, the above-mentioned studies focus on explicit opinion targets but do not consider the situation where opinion targets are omitted due to language habit. For example, in the comment "Great for a romantic evening, but overpriced", the opinion target does not appear in the text, but it can be inferred that the opinion target is "price". It is very common for opinion targets to be omitted in short reviews (Xu et al., 2015). In the literature, a number of studies have been conducted to examine implicit opinion targets extraction, which can be classified into three categories according to the extraction method used, namely, unsupervised, semi-supervised, and supervised. Among them, unsupervised methods are most frequently used because these methods do not require data annotation for implicit features or any sort of training (Tubishat et al., 2018). Moreover, a variety of techniques are used in the unsupervised methods, including dependency parsing, association rule mining, mutual or association, hierarchy, ontology, topic modeling, co-occurrence, rule-based, and clustering (Tubishat et al., 2018). Despite the presence of diverse techniques, none of them can dominate the others in terms of extraction performance. The mixture of multiple techniques is a possible future direction to achieve performance by taking advantage of each included technique.

In summary, sentiment analysis techniques have been widely used to facilitate the hospitality management by gaining insights from the online hotel reviews. However, the existing studies focus on document-level or sentence-level sentiment analysis that identifies the overall sentiment orientation instead of fine-grained sentiment towards different aspects of the hotels. A great deal of efforts have been exerted to address the identification of aspect-level sentiment orientation with the explicit or/and implicit opinion targets into consideration. With respect to online reviews, considering implicit opinion target is necessary and there is still great potential for improvement in the implicit aspect extraction techniques by mixing multiple techniques. Note that, our study presents a hybrid approach for aspect-level sentiment analysis, with implicit aspect terms into consideration by combining dependency parsing and co-occurrence, which contributes to get better understanding of customer preferences for all aspects of the hotels.

3. The proposed methodology

In this section, we aim to develop a fine-grained sentiment analysis methodology to identify customers' preferences for hotels' attributes from online reviews, such as condition of facilities, location and ancillary service, and staff performance.

Fig. 1 shows that the proposed framework consists of five steps: data collection, sentiment resource construction, sentiment element extraction, sentiment values calculation and the personalized preferences analysis. Data collection is responsible for crawling online reviews from Ctrip.com and preprocessing the review texts using segmentation tools, which results in words or phrases tagged with part-of-speech. Notably, the key steps among them are sentiment resource construction, identification of implicit evaluated attributes, extraction of sentiment triples, and calculation of sentiment values. We present the specific methods under key steps as follows. Note that, although the constructed sentiment dictionary is specific to the hotel industry, it is easy to construct such a dictionary for another industry. The other key steps are domain-independent, and thus the proposed framework is suitable for the other industries with tailored sentiment dictionary.

3.1. Sentiment resource construction

As mentioned in the previous studies on sentence-level sentiment analysis, sentiment intensity is measured by sentiment words, negation words and degree adverbs together (Taboada et al., 2008; Zhang et al., 2012). Specifically, sentiment words express positive, neutral or negative opinion, negation words can convert the sentiment to the opposite orientation, and degree adverbs that modify the sentiment words can enhance or weaken the emotion. Therefore, we constructed three types of dictionaries to help identify the words related to sentiment intensity, i.e., sentiment dictionary, degree adverb dictionary and negative adverb dictionary, which are provided in details below.

(1) Sentiment dictionary

There already exist many publicly available sentiment dictionaries for Chinese text, e.g., "Terms for Sentiment Analysis" from HowNet[1],

[1] http://www.keenage.com/html/c_index.html

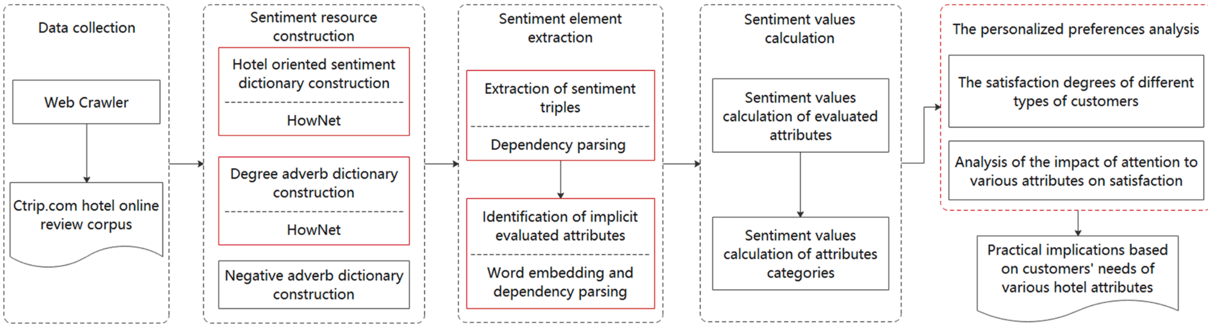


Fig. 1. Framework of the fine-grained sentiment analysis approach.

National Taiwan University Sentiment Dictionary (Ku and Chen, 2007). Based on these dictionaries, we create a sentiment dictionary by incorporating some other words that express customers' feelings about hotels' attributes, such as convenience, warmth, luxury, and expensive. To further expand the dictionary, we use the function of similarity of word embedding model to search synonyms of existing sentiment words, and then add them as other possible sentiment words. Finally, 9,947 sentiment words are contained in our dictionary. Some examples are shown in Table 1. Note that, since neutral sentiment words do not contain biased emotions that convey customers' preferences, they are not included in the sentiment dictionary.

(2) Degree adverb dictionary and Negative adverb dictionary

Based on "Terms for Sentiment Analysis" released by HowNet, which contains 220 words, we create our degree adverb dictionary. In the existing studies, amplifiers (e.g., very) which increase the semantic intensity of a neighboring lexical item and downtoners (e.g., slightly) which decrease it are most often mentioned (Quirk, 2010; Taboada et al., 2008). In contrast, since neutral degree adverbs have no or trivial impacts on the strength of sentiment words, there is no need to weight them.

According to the strengthening or weakening effect, each degree adverb in the dictionary is assigned with a certain modification weight. Specifically, if the degree adverb, such as "very", "too much", "extremely", can strengthen the sentiment intensity of sentiment words, its modification weight is assigned to 1.5. By contrast, if it weakens the sentiment intensity of a sentiment word, such as "slightly", "a little", "a bit", the modification weight is set to 0.5. In general, negative adverbs (e.g., "no", "not", "never" and "seldom") can reverse the sentiment orientation of the sentiment word modified by these adverbs, but have no impact on the sentiment intensity. Therefore, their modification weights are set to -1.

3.2. Identification of implicit evaluated attributes based on word embedding

Due to the casual and nonstandard expression of customers' comments, it's common to observe that some hotels' attributes of hotel are omitted. For example, in the comment "The hotel's service is very good, but a bit timeworn", the sentiment word "timeworn" is used to evaluate the attribute "facilities" of the hotel, which is omitted in the review text.

Table 1
Examples of sentiment words.

Sentiment orientations	Partial emotion words
Positive	Thoughtful, tidy, clean, close, elegant, quiet, convenient, meticulous, cost-effective, courteous, etc.
Negative	Secluded, messy, incomplete, old, crude, bad, smelly, terrible, etc.

If the omitted attributes are not recognized, it is likely to ignore or misunderstand customers' preferences or needs. Thus, it is necessary to correctly identify the omitted evaluated aspects. To this end, we propose an identification method based on word embedding to recall the omitted evaluated attributes.

As an unsupervised learning method, word embedding is devoted to transform words in natural language into dense vector through language model. In other words, it is capable of capturing semantic information about words in vector form without any prior knowledge. Based on the commonly used word embedding model word2vec (Mikolov et al., 2013), an identification method composed of two parts is presented to recognize the omitted attributes.

Part I: Constructing dictionary of the evaluated attributes. First, Jieba, a word segmentation tool, is used to segment and annotate the Part-Of-Speech (POS) of words in online reviews, and then the frequency of words is counted. In general, the more times an attribute is mentioned in online reviews, the more customers care about it. According to the extant research (Xu, 2020b), the evaluated attributes with high frequency can be clustered into six categories: sanitation, ancillary service, facilities, price, transportation and hotel atmosphere offered by hotels. Second, to recall more attributes when constructing attributes dictionary, the top 10 evaluated attributes selected based on occurrence frequency in each category are used as seeds of the corresponding category. In terms of word embedding, all the words with similar meaning to the seeds are added into the same category. Finally, since it is observed that some words are quite similar to the seed words in terms of the cosine of word embedding but are semantically quite different from the seed words. These words are called noisy words. For example, words "season", "environment", and "atmosphere" with high similarity to the seed word "price" in terms of word embedding are regarded as noisy words. To avoid the negative impacts of noisy words, we remove them manually to obtain a more perfect attributes dictionary.

Part II: Collecting sentiment words of omitted attributes. First, according to the sentiment triples of all online reviews, the co-occurrence relation (Dagan et al., 1995; Schütze and Pedersen, 1997) between evaluated attributes and sentiment words can be determined. Specifically, if a sentiment word occurs with multiple evaluated attributes in the sentiment triples, the evaluated attribute with the highest occurrence will be selected as the default evaluated attribute corresponding to the sentiment word. Then, it is possible to derive the omitted evaluated attribute from the sentiment words, and further to determine the attribute category according to the constructed attributes dictionary. As a result, a dictionary consisting of implicit evaluated attributes is obtained. Note that the mentioned sentiment triple is defined in the following subsection, and an algorithm that recognize sentiment triples from review text is also proposed.

3.3. Recognition of sentiment triples based on dependency parsing

Sentiment triple is composed of three elements: evaluated attributes, sentiment word and its modifiers. In practice, there may be more than one triple in a review comment, and some sentiment words may be related to multiple attributes. In this case, how to effectively identify the sentiment elements in a review comment and generate correct sentiment triples is an essential and challenging task in the fine-grained sentiment analysis. For this purpose, we propose a method based on dependency parsing to automatically recognize sentiment triples in the online reviews.

3.3.1. Dependency parsing

Dependency parsing (DP) reveals the syntactic structure of a sentence by identifying the grammatical components, including subject, predicate, object, modifier, adverbial, complement and head, and analyzes the dependency relationship between the related components (Chen and Manning, 2014). This approach can help us to effectively find out the evaluated attributes corresponding with specific sentiment words and related modifiers.

To our knowledge, the dependency parsing tool on the language technology platform (LTP)[2] developed by Harbin Institute of Technology can provide reliable technical support for the recognition of sentiment triples, and thus we use this tool in our analysis. The dependency parsing tool of LTP includes 14 types of dependency relations (Che et al., 2010), and the following seven types are used in our study. The details are shown in Table 2.

3.3.2. Extraction method of sentiment triples based on DP

In hotels' online reviews, evaluated attributes and sentiment words usually do not correspond one to one. To illustrate this, we take the review comment "The service, transportation and sanitation of this hotel are very poor" as an example. If we use the method based on the distance between words, only one triple < sanitation, poor, very > will be extracted, while missing the other two triples: <service, poor, very > and < transportation, poor, very > . To solve this problem, DP is applied to parse the relation between the sentiment elements in a review comment. Then, the parallel relationship of "service", "transportation" and "sanitation", i.e. *COO* relationship, can be identified, and following this approach, all the three triples in the review comment can be effectively extracted.

Based on the illustration above, the steps to identify sentiment triples via dependency parsing are summarized as follows. *First*, sentiment two-tuples of the form < evaluated attribute, sentiment word > are extracted from the online reviews according to dependency relations SBV, VOB, ATT, COO, and FOB. *Second*, the modifiers of sentiment word are recognized according to dependency relations ADV and CMP. *Finally*, the identified modifiers are incorporated into the sentiment two-tuples to constitute a sentiment triple. The detailed rules for extracting two-tuples and sentiment triples are introduced as follows, respectively, and also illustrated in Fig. 2. Note that in the dependency structure, there is a directed arc between words, in which the arrow starts from the dominant word (also called core word) and points to the subordinate word (also called modifier).

Table 2
Required relations in dependency parsing.

Relation types	Relation description	Examples
SBV	Subject-verb relation	The price is very cheap (price < –cheap)
VOB	Verb-object relation	No air conditioner (no –> air conditioner)
FOB	fronting-object relation	Bed sheets are not tidied up (sheets <– tidied up)
ATT	Attribute relation	Relatively cheap price (cheap < –price)
COO	Coordinate relation	Facilities and environment are good (Facilities –> environment)
ADV	Adverbial relation	Bed sheets are not tidied up (not <– tidied up)
CMP	Complement relation	The room is well cleaned (cleaned –> well)

(1) Extraction rules for two-tuples < evaluated attribute, sentiment word>

Note that dependency relations SBV, VOB, ATT, COO, and FOB are used to extracted the desired two-tuples. In this study, we develop five rules to fulfil the extraction process. The details are described as follows.

1) SBV Rule

If the following three conditions simultaneously hold, i.e., the evaluated attribute is the subject in a review comment, and the sentiment word is the predicate, and the relation between them satisfies the SBV relationship, the evaluated attribute and the sentiment word will be extracted as a sentiment two-tuple. For instance, as shown in Fig. 2(a), in the review comment "The price is very cheap", "The price", as the evaluated attribute, is the subject, and "cheap", as the sentiment word, is the predicate, and simultaneously the relation between "The price" and "cheap" satisfies the SBV relationship. According to this rule, we will obtain the sentiment two-tuple < The price, cheap > .

2) VOB Rule

This rule corresponds to the situation where the evaluated attribute is the object in a review comment, and the sentiment word is the predicate, and simultaneously they satisfy the VOB relationship. In this case, the evaluated attribute and the sentiment word will be extracted as a sentiment tuple. For instance, as shown in Fig. 2-(b), in the review comment "no air conditioner", "air conditioner", as the evaluated attribute, is an object, and "no", as the sentiment word, is the predicate in the Chinese context. Meanwhile, the relation between "air conditioner" and "no" satisfies the VOB relationship. Thus, the tuple < air conditioner, no > will be extracted as a sentiment two-tuple.

3) ATT Rule

If the sentiment word is the attributive in a review comment, and its modified object is the evaluated attribute, the evaluated attribute and the sentiment word form a sentiment tuple. For instance, as shown in Fig. 2-(c), the review comment "relatively cheap price" contains an attributive "cheap" that modifies the evaluated attribute "price". Thereby, the tuple < price, cheap > can be regarded as a sentiment two-tuple.

4) FOB Rule

If the evaluated attribute is the object in a review comment, and the sentiment word is the predicate related to the object meeting the FOB relationship, the object and the predicate form a sentiment two-tuple. As shown in Fig. 2-(d), the review comment "bed sheets are not tidied up" is composed of the object "bed sheets" and the predicate "are tidied up", their syntactic relationship is FOB. Thus, the tuple < bed sheets, are tidied up > is a sentiment two-tuple.

5) COO Rule

When more than one evaluated attribute appears side by side in a review comment, and syntactically conforms to the COO relationship

[2] The open source code library provided by LTP platform can realize dependency parsing relationships. In addition, the official website of LTP provides the online generation of dependency graph, from which we can intuitively and visually observe the sentence structures (http://ltp.ai/).

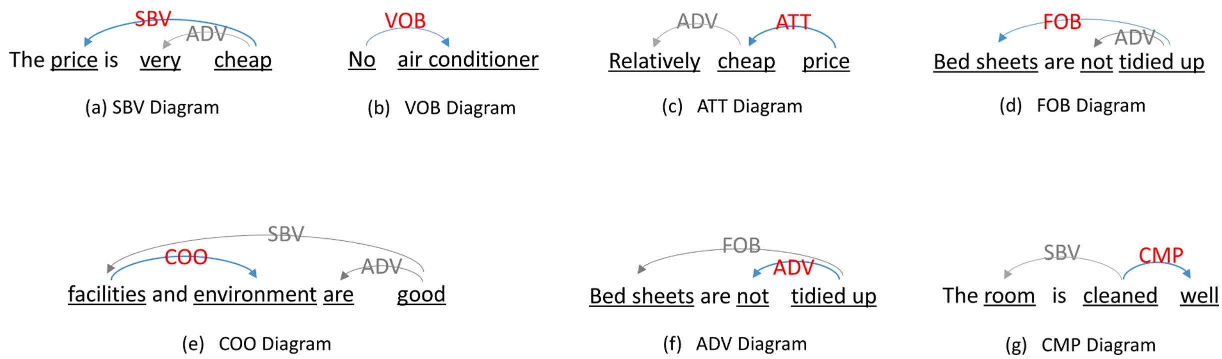


Fig. 2. Dependency parsing diagram.

with the sentiment word, each evaluated attribute and the sentiment word form a sentiment two-tuple. As shown in Fig. 2-(e), in the review comment “facilities and environment are good”, “facilities” and “environment” are juxtaposed subjects, and “facilities” has an obvious SBV relationship with the sentiment word. Then, it is considered that “environment” also has the SBV relationship with the sentiment word “good”. Thus, we will obtain two sentiment two-tuples, i.e., <facilities, good > and < environment, good > .

(2) Extraction rules for sentiment triples

Generally speaking, negative words, degree adverbs and other modifiers of sentiment words in online reviews have important influences on the sentiment polarity (positive and negative) as well as the sentiment intensity. Without modifiers of sentiment words, it is hard to accurately quantify customers’ sentiment orientations towards the evaluated attributes, hindering the identification of customer preferences. Therefore, it is far from enough to understand customer preferences based on the extracted sentiment two-tuples. To address this issue, two extraction rules based on dependency relations (i.e., ADV and CMP) are devised to identify the modifiers of sentiment words, which can be incorporated into the sentiment two-tuples containing the relevant

Algorithm 1: Sentiment Triples Extraction from Online Reviews
Input: Word segmentation set $W=[w_1,w_2,...,w_n]$; relation set $R=[r_1,r_2,...,r_n]$; attribute word dictionary T; sentiment word dictionary Q; modifier dictionary X; implicit evaluated attribute dictionary C.
Output: Set of sentiment triples $L=[d_1,d_2,...,d_n]$

FOR w_i in W:
(Step 1: To extract explicit sentiment triples)
    IF ($w_i \in T$) AND ($r_i \in \{SBV, VOB, FOB\}$ }) AND ($w_i \in Q$)
        Extract sentiment tuple $<w_i, w_j>$
        IF there exists w_i depending on w_j with ADV or CMP relation
            Extract sentiment triple $<w_i, w_j, w_k>$, and add it to L
    ELSE IF ($w_i \in Q$) AND ($r_i \in \{ATT, CMP\}$) AND ($w_i \in T$)
        Extract tuple $<w_j, w_i>$
        IF there exists w_k depending on w_i with ADV or CMP relation
            Extract sentiment triple $<w_j, w_i, w_k>$, and add it to L

(Step 2: To extract those triples identified by coordinated relation)
    ELSE IF ($w_i \in T$) AND (r_i is COO)
        Identify evaluated attribute w_{ii} which depends on w_i with COO relation
        Add sentiment triple $<w_{ii}, w_j, w_k>$ to L
    ELSE IF ($w_i \in Q$) AND (r_i is COO)
        Identify sentiment word w_{ii} which depends on w_i with COO relation
        Add sentiment triple $<w_j, w_{ii}, w_k>$ to L

(Step 3: To extract implicit sentiment triples based on the implicit evaluated attribute dictionary C.)
FOR w_i in W:
    IF sentiment word w_i has not been extracted
        Obtain the implicit evaluated attribute w_j based on C, and extract sentiment tuple $<w_j, w_i>$
        IF there exists w_k depending on w_i with ADV or CMP relation
            Add sentiment triple $<w_j, w_i, w_k>$ to L
RETURN L

Fig. 3. Algorithm of extracting sentiment triples.

sentiment words to form sentiment triples. The details are described below.

1) ADV Rule

When a modifier word exhibits an ADV relation with the sentiment word of an extracted sentiment two-tuple, the modifier and the sentiment two-tuple form a sentiment triple. As shown in Fig. 2-(f), the negative word "not" in the review comment "bed sheets are not tidied up" is the adverbial modifier of the sentiment word "are tidied up", and their syntactical relation is ADV. Thus, we can synthesize a sentiment triple < bed sheets, are tidied up, not > .

2) CMP Rule

If a modifier word exhibits a CMP relation with the sentiment word of an extracted sentiment two-tuple, a sentiment triple can be generated by synthesizing the modifier with the sentiment two-tuple. As shown in Fig. 2-(g), in the review comment "the room is well cleaned", the sentiment word "is cleaned" is a verb in Chinese, and the modifier "well" is a complement of the verb. Thus, these two words syntactically comply with the CMP relationship. Note that the evaluated attribute "the room" is the subject of the sentiment word, and exhibits a SBV relation with the sentiment word. Accordingly, the tuple < the room, is cleaned, well > is regarded as a sentiment triple.

Based on the above rules of dependency relation, the algorithm of extracting sentiment triples from the online reviews is shown in Fig. 3. The input of this algorithm includes the segmentation set W, which consists of the words in a review comment, and the relation set R, which consists of the dependency relations of each word in W, as well as the aforementioned lexical resources: attribute word dictionary T, sentiment word dictionary Q, modifier dictionary X, and implicit evaluated attribute dictionary C. The algorithm proceeds by accomplishing the following three steps in a serial way: extracting the explicit sentiment triples, identifying the sentiment triples by coordinated relation, and extracting sentiment triples implied by the implicit evaluated attributes.

3.4. Calculation of sentiment values

To precisely identify customers' preferences, it is necessary to examine the sentiment intensity on different hotels' attributes. Following the existing studies, e.g., Liang et al. (2019) and Taboada et al. (2008), the sentiment score is calculated by multiplying the intensity of modifiers by the sentiment value of the corresponding sentiment word. However, these studies consider by default that there is only a single degree adverb modifying the sentiment word. To consider the case that more than one degree adverbs modifying the sentiment word, for example, "very very very good", we introduce the parameter $\lambda(\lambda > 0)$ to calculate the overall weight of all degree adverbs in a sentiment triple. In this way, the following formula is defined to calculate the sentiment intensity on the attribute in a given sentiment triple. Note that, the value of λ only affects the intensity of sentiment values instead of the sentiment orientations, and its assignment would not change the analysis results of customer preferences that depend on whether the sentiment score is great or less than zero. The value of λ is empirically set to 0.2 based on the belief that most sentiment phrases are with no more than five degree adverbs modifying one sentiment word at the same time.

$$q_i = \begin{cases} 1*(-1)^c*(1+\lambda*\sum_{j=1}^{n} W_{da}^j), \text{ If the sentiment word in } d_i \text{ is positive} \\ -1*(-1)^c*(1+\lambda*\sum_{j=1}^{n} W_{da}^j), \text{ If the sentiment word in } d_i \text{ is negative} \end{cases} \quad (1)$$

In Eq. (1), d_i represents the i^{th} sentiment triple in a review comment, q_i is the sentiment value of d_i, and c denotes the number of negative adverbs in d_i. Note that W_{da}^j represents the weight of the j^{th} degree adverb in d_i and n represents the number of modifiers in d_i.

It should be noted that, there may be several sentiment triples belonging to the same attribute category in a review comment. In this case, we adapt a linear weighted sum of sentiment values of those evaluated attributes of the same category to represent the sentiment value of this type of attributes.

3.5. Measuring attribute oriented preferences of different types of customers

To accurately acquire customer preferences for hotels' attributes via the sentiment analysis of the online reviews, it is necessary to effectively match the sentiment values with preferences. In the literature, customer preferences have usually been measured based on conjoint analysis method since it was first introduced by Green and Rao (1971). On this basis, pros and cons extracted from online reviews are used to measure the customer preferences by most studies (Decker and Trusov, 2010; Li et al., 2014; Xiao et al., 2016). Following this line of studies, the ratio of the number of sentiment triples with positive emotions to the total number of sentiment triples that correspond to the same hotel attribute category is used to measure customer preferences for hotels' attribute categories. The calculation formula is defined as

$$P(u_j^i) = \frac{C_j^{i>0}}{C_j^i} \quad (2)$$

Note that $P(u_j^i)$ represents the preference of type j customers for the i^{th} evaluated attribute category; $C_j^{i>0}$is the number of sentiment triples that have positive emotions and correspond to the i^{th} evaluated attribute category mentioned by type j customers; C_j^i is the number of sentiment triples corresponding to the i^{th} evaluated attribute category mentioned by type j customers.

In addition, the existing studies pointed out that different types of travelers have different expectations of hotels' attributes (Li et al., 2015; Xu and Li, 2016), and thus it is necessary to measure the importance of different attribute categories for different types of customers. To depict customer preferences more comprehensively, attention degree is used to help measure the varying importance of different attribute categories. The following formula is defined to calculate the attention degree, i.e.,

$$A(u_j^i) = \frac{C_j^i}{C_j} \quad (3)$$

where $A(u_j^i)$ represents the attention degree of type j customers to the i^{th} evaluated attribute category; C_j^i is the number of sentiment triples of the i^{th} evaluated attribute mentioned by type j customers; and C_j is the total number of all sentiment triples mentioned by type j customers.

4. Experiment results and customer preferences analysis

In this section, we first adopt an experimental study to illustrate the rationality and advantages of the proposed approach. Specifically, we design two groups of experiments to examine the performance of evaluated attributes recognition and sentiment value calculation. Then, we attempt to identify customer preferences based on the collected data. Dataset, experimental results and customer preferences analysis are presented as follows.

4.1. Resource description

(1) Data collection

A total number of 57,734 Chinese hotels' online reviews were crawled from Ctrip.com for this experimental study. Each item is mainly composed of users' nickname, comment text, overall comment rating, customer types, comment time, and so forth. Some examples are shown in Table 3.

(2) Validation data set

In order to illustrate the recognition performance of the proposed approach, we randomly selected 1000 items from the 8939 online reviews of Dalian Bayshore Hotel to form the validation dataset. To evaluate the performance of our proposed approach, we adopt three metrics that are commonly used to assess machine learning algorithm for classification in the analysis, i.e., precision, recall and F-value (Musicant et al., 2003; Schütze et al., 2008). Precision represents the ratio of all correctly identified reviews with positive sentiment polarity to all identified reviews with positive sentiment polarity. The higher the Precision is, the better the approach performs. Recall refers to the proportion of correctly identified reviews with positive sentiment polarity in all reviews with positive sentiment polarity in the golden standard dataset. The greater the Recall is, the better the approach performs, as well. F1-value is the harmonic average value of Precision and Recall, which can comprehensively reflect the overall performance of the classification approach. The calculation equations are defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F_1\text{ - }value = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

where *TP* is the number of the correctly identified reviews with positive sentiments; *FP* is the number of the reviews with negative sentiments incorrectly classified as the reviews with positive sentiments; *FN* is the number of the reviews with positive sentiments incorrectly classified as the reviews with negative sentiments.

Note that sentiment triples contained in the validation data set were manually labeled, some of which are shown in Table 4.

The descriptive statistics of the validation data set are displayed in Table 5 and Fig. 4. As shown in Fig. 4-(a), most of online reviews contain

Table 3
Examples of hotels' online reviews.

User's nickname	User type	Comment time	Score	Comment text
Do**mon	Solo	2019–10-17	5.0	This hotel is very close to Xinghai Square. Traffic is convenient and there is a convenient store downstairs. The night view is also pretty. All in all, it deserves a good rating.
Hey**he	Couple	2018–07-08	3.8	The calcimine over the bed peels off badly, and spills over the quilt and pillow, making it fell unhygienic! The light switches are separately placed on the two sides of the bed, which is very inconvenient to control.
Horse**horse	Friend	2019–10-06	5.0	The five of us booked two rooms. The bed is big enough for three people. Since we only stayed for one night, there were not too many needs, and a clean room was enough. There is a Rosen downstairs, which is very convenient.

Table 4
Examples of validation dataset.

Comment text	Triples	Sentiment values
It is a fantastic hotel. It is quite suitable for business and family travelers. The room is pretty tidy and the equipment is very complete. There is also a refrigerator. It provides membership rights for LeTV, and thus we can watch movies. The front desk is also super enthusiastic.	< hotel, fantastic, []> <room, tidy, [pretty]> < equipment, complete, [very]> < front desk, enthusiastic, [also, super]>	Sanitation: 1 Service: 1 Facilities: 1 Price: 0 Transportation: 0 Hotel atmosphere: 1
Both the service attitude and environment are good. But the facilities in this room are a little bit unsatisfying, and the flushing function is completely broken. In winter, the heating does not seem to work well, and the air conditioner does not work well. Fortunately, there are two quilts.	< service attitude, good, [both]> < environment, good, [both]> < facilities, unsatisfying, [a little bit]> < heating, work well, [seem, not]> < air conditioner, work well, [not]>	Sanitation: 1 Service: 1 Facilities: −1 Price: 0 Transportation: 0 Hotel atmosphere: 0
Overall situation is good. The location is good, and the Xinghai Park is just across the road. It is convenient to go to Shengya Ocean World. The front desk is very enthusiastic, but the price is a bit expensive during tourist season.	< overall situation, good> < location, good> < front desk, enthusiastic, [very]> < price, expensive, [a bit]>	Sanitation: 0 Service: 1 Facilities: 0 Price: −1 Transportation: 1 Hotel atmosphere: 1

Table 5
Descriptive statistics.

	Min	Max	Mean	Median	Mode	Standard deviation
Comment text	4	349	27.26	16	11	29.99
Sentiment triples	0	16	2.49	2	2	1.60
Overall ratings	0.0	5.0	4.58	4.5	4.5	1.18
Comment time	2017-04-02	2020-03-29		2018-07-06	2017-12-03	

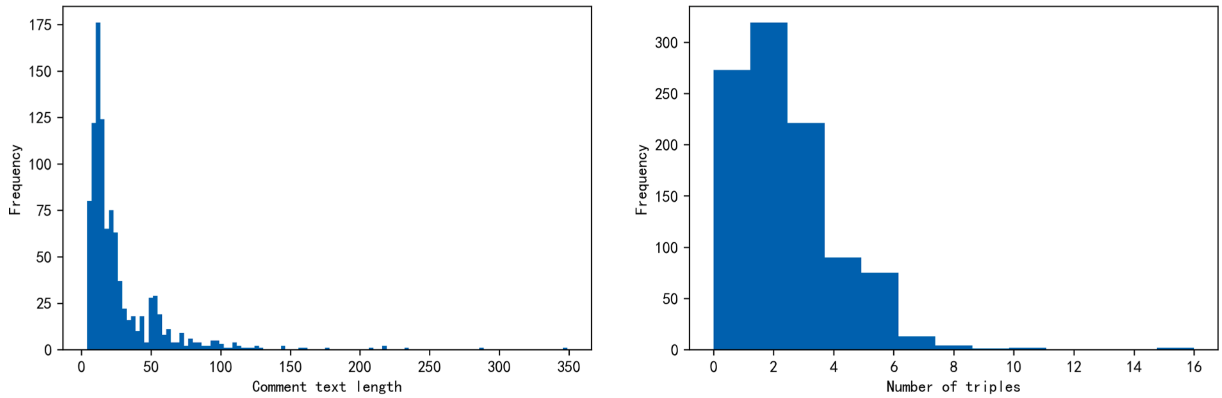
less than 50 words; few reviews have more than 150 words; the longest review contains 349 words; and the average length of all reviews is 27.26. Most of online reviews contain less than 6 sentiment triples; the largest number of triples contained in a review comment is 16, and the average number of triples contained in each review item is 2.5. Most of the overall ratings are larger than 4. Note that the earliest comment time is April 2, 2017, and the latest time is March 29, 2020.

4.2. Experiment results and discussion

(1) Results of evaluated attributes recognition

According to the proposed method for attribute identification in Section 3.2, six categories of attributes were identified from 8939 online reviews, including service, price, facilities, transportation, sanitation, and Hotel atmosphere. Some examples of each attribute category are shown in Table 6. The association relationships between attribute categories and sentiment words were also recognized, some examples are shown in Table 7.

To assess the performance of the proposed recognition method for implicit evaluated attributes, a set of experiments is used to compare the proposed method with a baseline model and its several extensions in terms of precision, recall and F-value. The baseline model extracts the attribute words according to part-of-speech (POS) rules, and its



(a) Statistics histogram of comment text length
(b) Statistics histogram of the number of triples

Fig. 4. Histogram of descriptive statistics.

Table 6
Examples of recognized evaluated attributes.

Attribute category	Examples of related words
Service	Service, attitude, customer service, staff, manager, front desk, proprietor, quality, cleaning, reception, sweeping, make up, waiter, service quality, work efficiency
Price	Price, fee, room rate, room price, cost-performance
Facilities	Facilities, configuration, home appliances, equipment, article, furniture, supplies, utensils, decoration, air conditioner, infrastructure
Transportation	Traffic, transportation, location, place, site, surrounding, vicinity, travel, bus, subway, bus stop, business district, city center
Sanitation	Environment, sanitation, decoration, sound insulation, ventilation, natural lighting, vision, landscape, scenery, sea view, view
Hotel atmosphere	Overall, entirety, in short, hotel, apartment

Table 7
Examples of relationship between attributes and sentiment word.

Attribute category	Examples of related sentiment words
Service	Passionate, caring, patiently, friendly, indifferent, considerate, thoughtful, kind, observant, meticulous, cordial
Price	Expensive, cheap, cost-effective, discount, not expensive, concessional, price increase, worthy
Facilities	New, old, complete, antiquated, shabby
Transportation	Convenient, quick, well-suited
Sanitation	Wet, dark, dirty, sanitary, clean, tidy, leaky, warm, dusky, bright, moldy, fusty, foul smelly, neat

extensions include the integration with word embedding, denoted by Baseline_WE, and the integration with both word embedding and dependency parsing, denoted by Baseline_WE_DP. The comparison results are shown in Table 8.

Table 8 shows that there are significant discrepancies between the precision, recall and F-value of the recognition results obtained by various recognition methods. Specifically, Baseline (second row in Table 8) has the lowest precision and F-value, but the second highest recall. The reason may be that Baseline regards all nouns as attribute words according to POS, leading to a mass of noises. When the word embedding model is integrated into the Baseline model (third row in Table 8), both the precision and the recall obviously increase, whereas the recall is still unsatisfying. This is because word embedding is used to identify the synonyms of attribute words, and some words that do not belong to the evaluated attribute are eliminated. Furthermore, integrating dependency parsing technique into the Baseline model significantly improves the performance precision, recall, and F-value, with the F-value being the highest (forth row in Table 8). The possible reason is that the use of dependency parsing can identify the sentiment elements in the reviews more effectively, and thus we can recall more sentiment triples. In terms of the recognition of implicit evaluated attributes alone, the recall rate even attains 87.63%, which indicates that the proposed method works effectively with respect to the omission of evaluated attributes.

Table 8
Results of evaluated attributes recognition.

Recognition methods	Precision	Recall	F-value
Baseline	50.94%	76.41%	61.13%
Baseline_WE	72.54%	59.94%	65.64%
Baseline_WE_DP	86.52%	72.90%	79.13%
Implicit attributes recognition	–	87.63%	–

(2) Results of sentiment value calculation

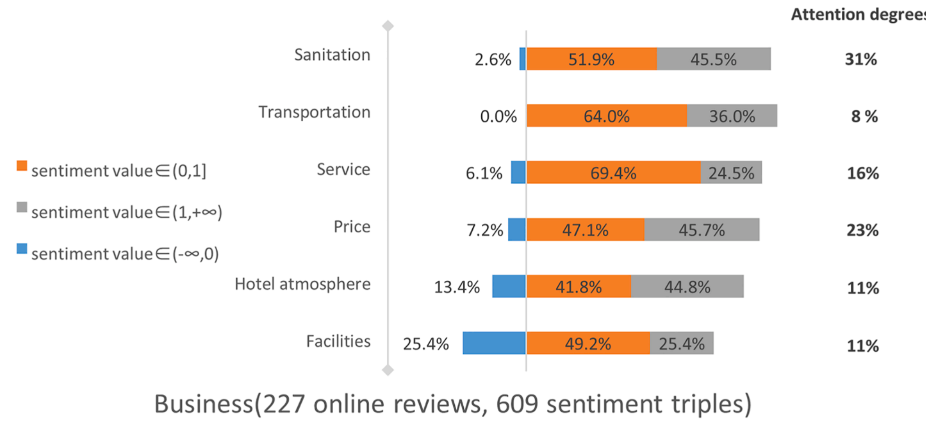
To further examine the performance of the proposed method regarding sentiment triple extraction, sentiment words and their modifiers should be considered, which can be used to help compare the performance of sentiment value calculation. To our knowledge, however, there is no standard metrics for such comparison. Since the sentiment value is calculated based on the results of sentiment classification, the performance of sentiment classification with respect to precision, recall and F-value The results are shown in Table 9.

Table 9 shows that with the incorporation of word embedding and dependency parsing, the precision, recall rate, and F-value are gradually increasing. To be specific, the Baseline model (second row in Table 9) extracts nouns, adjectives, and adverbs from segmented sentences as sentiment triples based on POS, leading to precision, low recall, and low F-value. This is because the POS-based rule for extracting sentiment triples introduces a mass of noises. When the word embedding model is integrated into the Baseline model (third row in Table 9), the precision, recall and F-value obviously increase. The main reason is that by incorporating word embedding, some incorrectly recognized triples are eliminated. Furthermore, the Baseline_WE_DP model (forth row in Table 9) incorporating the dependency parsing technique significantly

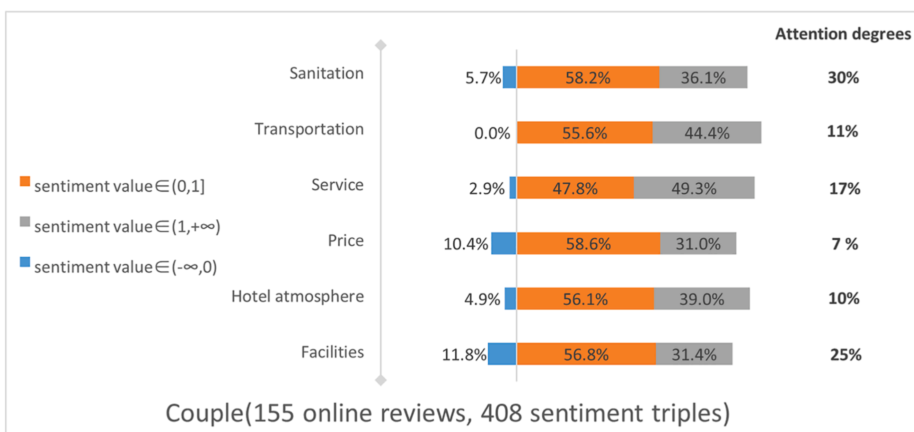
Table 9
Comparison on sentiment orientation classification.

Recognition methods	Precision	Recall	F-value
Baseline	17.87%	26.70%	21.41%
Baseline_WE	61.86%	51.12%	55.98%
Baseline_WE_DP	78.18%	68.74%	73.16%

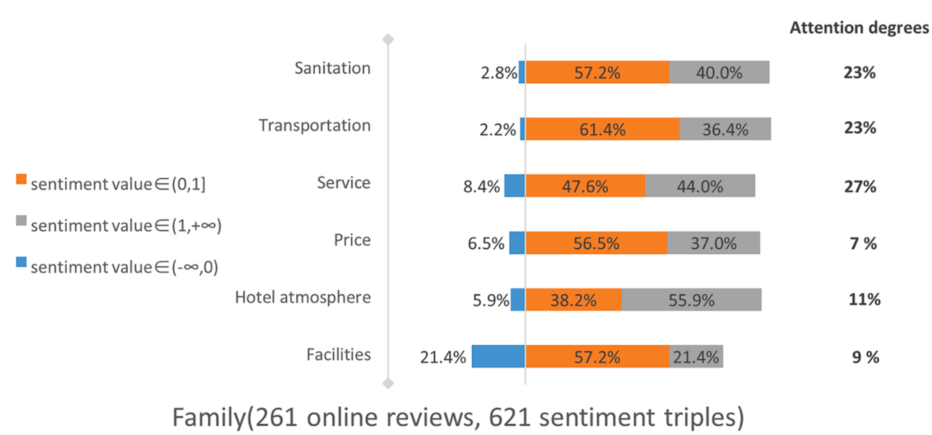
improves that precision, recall, and F-value, with the F-value being the highest. The possible reason is that the use of dependency parsing can effectively and correctly identify the relation between sentiment elements in online reviews. Based on these identified relationship, sentiment triples are extracted from online reviews and sentiment values of hotels' attributes are computed, so as to further identify the preferences of different types of customers regarding various hotel attributes, including service, facilities, transportation, sanitation, price, and hotel



(a) Business customers

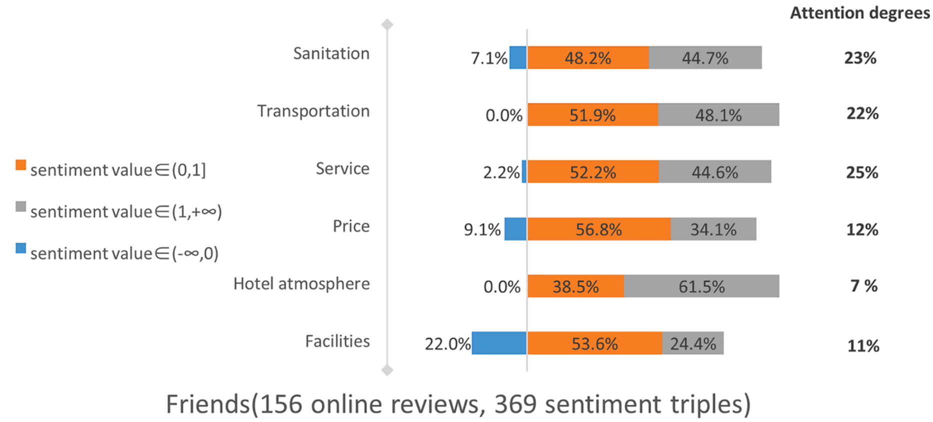


(b) Couple customers

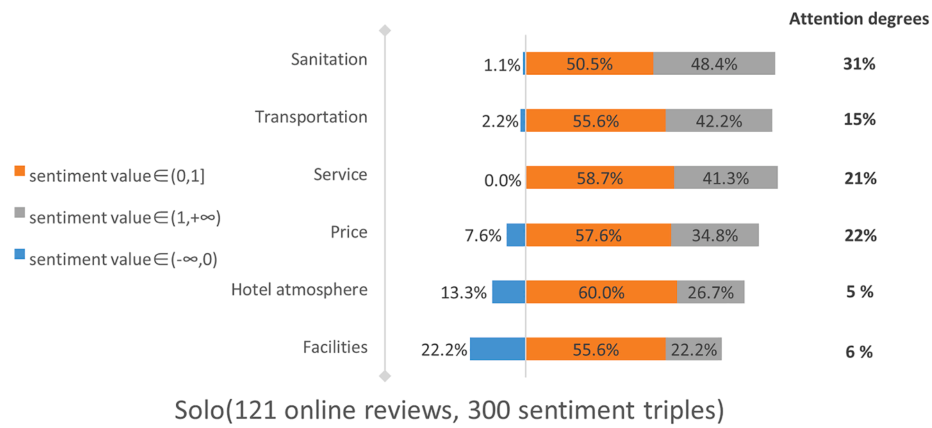


(c) Family customers

Fig. 5. Preferences and Attention degrees of different types of customers on each attribute category.



(d) Friends customers



(e) Solo customers

Fig. 5. (*continued*).

atmosphere, which are presented in the following subsection.

4.3. Customer preferences analysis

Generally speaking, customers may exhibit different preferences for hotels' attributes across customer types, even for the same attribute. Based on the data crawled from Ctrip.com, customers can be classified into five groups: solo, family, business, couple and friends, according to their travel types. Without loss of generality, we take Dalian Bayshore Hotel as an example to illustrate how to derive customer preferences from sentiment analysis of online reviews. We first apply the proposed sentiment analysis method identify the sentiment triples related to the hotels' attributes from online reviews, and then characterize customer preferences for the hotels' attributes following the calculation of customers' sentiment values for sentiment triples.

Based on Eqs. (2) and (3), the preferences and attention degrees of different types of customers for each attribute category are calculated. The results are shown in Fig. 5. Note that, the sentiment values of sentiment triples fall into three intervals, namely, $(-\infty, 0)$, $(0, 1]$ and $(1, +\infty)$. Specifically, sentiment triples with negative values indicate that the customers writing this reviews are dissatisfied with the mentioned hotel attributes contained in the sentiment triples. In contrast, sentiment triples with positive sentiment values mean that the customers are satisfied with the mentioned hotel attributes, and sentiment values greater than 1 indicates that the customers have higher satisfaction than that of sentiment values between 0 and 1.

As shown in Table 10, for all types of customers, the attention degrees on sanitation exceed 20%, which have the highest or second highest rank. This indicates that sanitation has the most important impact on the satisfaction for most types of customers. With regard to the other attribute categories, different types of customers show different attention degrees. Specifically, business customers tend to pay more attention to sanitation and price, rather than transportation convenience. Family customers care more about service, sanitation and transportation, while couple customers are more likely to care about sanitation and facilities. The concerned attributes of solo customers are sanitation, price, and service, and customers being friends pay more attention to service, sanitation and transportation.

With respect to the preference for each attribute category, *first*, sanitation gains relatively greater attention from all types of customers, as well as higher satisfaction. This indicates that sanitation is the basic requirement across the customers and Dalian Bayshore Hotel provides a good sanitary condition. This finding is consistent with that of (Gu and Ryan, 2008; Xu and Li, 2016), which reports that the cleanliness of the bedroom and bathroom are very important and can enhance customer satisfaction. *Second*, all types of customers are satisfied with the transportation convenience of Dalian Bayshore Hotel. It is found that the hotel is close to the world's largest city square, Xinghai Square, which has a convenient transportation location. *Third*, family customers pay the greatest attention to the hotel's service, but they gain the lowest satisfaction. The possible reason might be that family customers usually travel together with elderly people and children, who need more

Table 10
Preferences and attention degrees of all types of customers.

Customer type	Sanitation		Transportation		Service		Price		Atmosphere		Facilities	
	AD	Pref	AD	Pref	AD	Pref	AD	Pref	AD	Pref	AD	Pref
Business	0.31	0.974	0.08	1.0	0.16	0.939	0.23	0.928	0.11	0.866	0.11	0.746
Couple	0.3	0.943	0.11	1.0	0.17	0.971	0.07	0.896	0.10	0.951	0.25	0.882
Family	0.23	0.972	0.23	0.978	0.27	0.916	0.07	0.935	0.11	0.941	0.09	0.786
Friend	0.23	0.929	0.22	1.0	0.25	0.978	0.12	0.909	0.07	1.0	0.11	0.78
Solo	0.31	0.989	0.15	0.978	0.21	1.0	0.22	0.924	0.05	0.867	0.06	0.778

*AD-attention degree, Pref-preference.

stringent requirements on the hotel's service. *Fourth*, family customers pay less attention to the room price, but their satisfaction are the highest. In contrast, couple customers and friend customers have relatively lower satisfaction with the room price. *Fifth*, business customers and solo customers pay different attention to the hotel atmosphere, but they are the least satisfied with this aspect. This in turn shows that these two types of customers have higher requirements for the hotel atmosphere. *Sixth*, although different types of customers have different degrees of attention to facilities, they generally show lower satisfaction, which means there is still a lot of potentials for improvement in facilities. This is consistent with the observation that a few customers complained on the hotel facilities in the reviews, such as "facilities are old", "hard towels in bathroom", "poor air condition", "water heater cannot provide sufficient hot water!", "unstable Wi-Fi signal and slow Internet speed", and so on. This finding supports the existing studies. For example, Xu and Li (2016) show that the facility including old furniture, dirty bathrooms, noisy swimming pools, and so forth is the determinant of customer dissatisfaction. Gu and Ryan (2008) believe that some attributes to hotel facility are necessary for customers, which are not sufficient in themselves to create a high level of satisfaction but their absence may cause customers' dissatisfaction. It can be concluded from the above analysis that most customers are relatively satisfied with Dalian Bayshore Hotel in all attributes except the facilities. The following suggestions is helpful for the hoteliers to increase the hotel's attraction to different types of customers. *First*, family customers who can accept high prices, high-end comfortable rooms can be recommended, as well as extra services, such as high-quality meals. *Second*, friends and couples who are more likely to accept cost-effective rooms, affordable discounts can be offered in priority. *Third*, the hotel's facilities are the most conspicuous bottleneck among all attributes, and should be upgraded and improved as soon as possible. In the hotel's reviews, sound insulation and toilet facilities are most complained of, therefore, the facility upgrade can start from these two aspects, following by other complained aspects related to the hotel's facility.

5. Conclusion

Online reviews, as customers generated comments on products and services, have gained increasingly and considerable concerns in recent years. This study focuses on how to effectively identify the fine-grained customer preferences for hotels. To this end, we define a sentiment triple to represent the sentiment elements contained in the online reviews, and employ the dependency parsing technique to identify the dependency relationship between the sentiment elements, which effectively improves the performance of identifying evaluated attributes and their sentiment values. To recognize the evaluated attributes hidden in the online reviews, a method combining word embedding with co-occurrence information and dependency parsing is presented, which can help obtain the semantic information and dependencies of words in an unsupervised manner, and can effectively recall the hidden attributes. The proposed approach is illustrated with an example of Dalian Bayshore Hotel. Our empirical results show that all types of customers are satisfied with the hotel's sanitation, but they generally show relative lower satisfaction on the hotel's facilities, which suggests an urgent improvement on the facilities.

This study proposes a fine-grained sentiment analysis approach to identify customers' preferences for hotels from online reviews, which can help improve hotels' services. Nonetheless, there are some limitations that should be further improved. *First*, it is very difficult for us to directly use machine learning methods to perform fine-grained sentiment analysis on online reviews, due to the lack of well-labeled training corpus. To ensure the accuracy of the identification, part of the learning data is constructed manually and need manual correction, which cannot be fully automated. In future research, semi-supervised learning method can be used to construct more well-labeled corpus for fine-grained sentiment analysis, and provide sufficient training corpus for subsequent neural network models to achieve more accurate recognition of sentiment elements and more efficient analysis of sentiment values. *Second*, preference extraction can be used not only to improve hotels' services, but also to further predict future demands. This encourages future efforts to explore demand forecasting for hotels' rooms based on the sentiment analysis of online reviews.

CRediT authorship contribution statement

Jing Zhang: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Xingchen Lu:** Software, Investigation, Data curation, Visualization. **Dian Liu:** Validation, Writing – original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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