



## SEMANTIC ANALYSIS FOR ONLINE TRAVEL ACCOMMODATION REVIEWS

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### ABSTRACT

Currently, most tourists use the Internet to retrieve information for supporting their decision in selecting the tourist places that conform to their preferences. The most common method is the decision based on reviews of experienced tourists. However, tourists must read enormous reviews in order to select their preferred tourist places. This article presents an analysis module for online travel accommodation reviews. The analysis module combines several techniques, such as ontology, natural language processing, and fuzzy logic. However, this article focuses on applying the natural language processing for semantic analysis to solve the accommodation feature extraction problems. The experimental results of the feature extraction process are achieved in 79.22% of overall accuracy, 100% of overall precision, and 76.05% of overall recall.

**Keywords:** feature extraction, online reviews, semantic analysis.

### INTRODUCTION

In recent, travel-related organizations have transformed their own organizations into e-tourism for encouraging tourists to spend money for their products or services. Although there are many e-tourism websites that collect opinions about tourist destinations from experienced tourists, those opinions have rarely been used by other tourists because they have never been processed or extracted the valued information. If tourists want to know about these destinations in details, they must read enormous reviews. It is due to the fact that the existing websites provided only an overall rating of each destination from these reviews. Moreover, most tourism websites are static which tourists could not search for information according to their individual needs [1].

There are several research focused on information extraction from online customer reviews. Zhang, Narayanan and Choudhary [2] mined online customer reviews for product feature-based ranking by identifying subjective and comparative sentences in reviews and using a directed graph to determine the relative quality of products. Ramkumar, Rajasekar and Swamynathan [3] scored products from online reviews using fuzzy logic to calculate the spam level scores of each review and the scores for each feature of a product. Jakob and Gurevych [4] extended an opinion mining algorithm with rule-based anaphora resolution algorithm, called CogNIAC, to improve feature identification in movie reviews. However, this algorithm does not yield high precision when resolving impersonal and demonstrative pronouns. Hu and Liu [5] mined and summarized online product reviews based on data mining and natural language processing methods including various techniques such as Part-of-Speech tagging, frequent feature identification, opinion words extraction and predicting the orientations of opinion sentences. It revealed a total number of positive and negative reviews for each product feature to users.

As described above, most of them are applied with product reviews. They present the product rating

based on their features in the form of binary scores, such as “positive/negative”, “recommend/ don’t recommend” or “yes/no”. Typically, users are interested in knowing the strength of opinion about a travel accommodation; therefore just a “positive/negative” binary score seems insufficient. It would be vastly preferable if we could give the accommodation a numeric score or at least grade it from a list of qualitative ratings (i.e., 5 means excellent, 4 means good, 3 means average, 2 means poor, and 1 means terrible) [6]. According to the findings of online consumers or shoppers’ requirements, the details and relevant product information and explanations are needed for decision making by consumers in order to select products or services [7]. Tourists also want to know about the travel accommodation in details (e.g. How about bed or air condition in the room? or How about services or cleanliness of the accommodation?) and use both rating score and accommodation information for selecting their preferred travel accommodations promptly and efficiently. Hence, this article presents an analysis module for online travel accommodation reviews. The proposed module focuses on a design of semantic analysis approach (as the part of “feature extraction process”) for natural language understanding of the online reviews. In addition, this article proposes a method for calculating a tourists’ satisfaction level on each extracted feature and on the entire review in the numeric score (5-rating scale) and visualizes the accommodation feature relationships in hierarchy as knowledge representation of the accommodation.

### MODULE FRAMEWORK

An analysis module for online travel accommodation reviews focuses on the semantic analysis of accommodation reviews in the English language by extracting accommodation information from reviews as accommodation features and calculating tourists’ satisfaction levels on each accommodation feature and on the entire reviews. The extracted accommodation features



and their satisfaction levels are stored in a knowledge base which will be retrieved later by other tourists. The module framework is depicted in Figure-1.

This proposed module is an Internet-based application that is implemented with PHP, JavaScript, HTML, and other related web technologies. It consists of four components as follows: user interface, knowledge inference engine, knowledge base, and knowledge explanation engine.

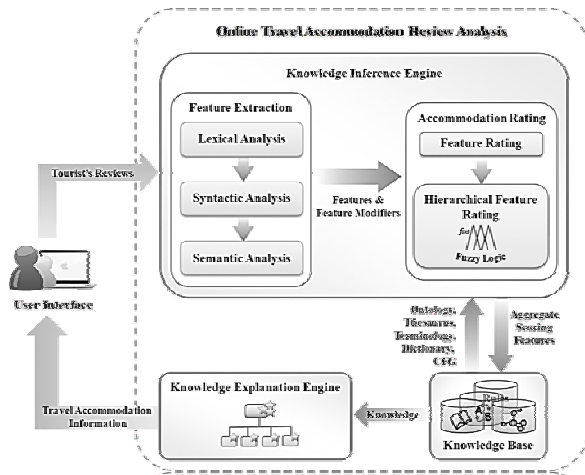


Figure-1. Module framework.

### User Interface

The user interface of a review analysis module is designed as a user-friendly graphic user interface (GUI). Tourists can access this module via the user interface to write a review about a travel accommodation, which is used as input data for the module. Moreover, tourists can interact with the module through web browsers (e.g. searching for accommodation information), and examine an output of reviews summarization in a tree structure as shown in Figure-2.



Figure-2. A graphic user interface of an analysis module for online travel accommodation reviews.

### Knowledge Base

The knowledge base is used to store extracted knowledge including necessary information for automatic

information extraction. There are four components as follows:

### Tourism Ontology

The tourism ontology was revised from a class hierarchy of the E-tourism ontology version 8 [8] by analyzing accommodation features from 400 accommodation reviews using Rocchio's *TF-IDF* weighting approach [9]. In addition, the synonym words which have the same or very similar meanings, such as the "fridge" and "cooler" are also added to the SKOS ontology [10], which is a part of the tourism ontology. For each synonym set, there is a designated word representing all synonym words. All the selected features are added to the tourism ontology. The revised ontology consists of 10 classes and 95 key properties including their relationships. The knowledge in the tourism ontology will be applied for the feature extraction process and the accommodation rating process in the knowledge inference engine of the review analysis module described later.

### Terminology

The terminology is a word collection assigned a satisfaction level in 5-rating scale for each word which was confirmed by a language expert, where "rating = 1" implies terrible, "rating = 2" implies poor, "rating = 3" implies average, "rating = 4" implies good and "rating = 5" implies excellent. There are five types of words stored in the terminology as described below.

- Adjective, each one is assigned a fixed satisfaction level such as "Excellent" = 5, "Effective" = 4, "Moderate" = 3 and "Unfriendly" = 2, and "Awful" = 1.
- Special verb, each one is assigned a fixed satisfaction level as same as an adjective, such as "Deteriorate" = 2 and "Work" = 4. Typically, verbs are not associated to any criticisms. However, some verbs can criticize an accommodation feature.
- Special word, each one is assigned a feature to which it implies and a fixed satisfaction level as same as an adjective. The special word can be noun, verb, adjective, or phrase and can be calculated without the feature word because it identifies the feature by itself. For instance, "Dirty" = Satisfaction level 2 and implies to the Cleanliness feature, "Walking distance" = Satisfaction level 4 and implies to the Location feature, etc.
- Adverb, each one is assigned an adjustable rating such as "Very" =  $\pm 1$ , "So" =  $\pm 1$ , "Extremely" =  $\pm 1$ , "Most" =  $\pm 2$ , and so on. When this word type is calculated, a feature rating will obtain the same rating of adjective, that is, if tourists review in positive, the feature rating will increase.
- Negation adverb, each one is assigned an adjustable rating as same as an adverb. However, when this word type is calculated, the feature rating will contrast with a rating of adjective, i.e., if the tourist reviews is positive, the feature rating will decrease such as "Not"



=  $\pm 2$ , “Almost” =  $\pm 1$ , “Never” =  $\pm 2$ , etc. Also, the satisfaction level of all word types are used in the accommodation rating process described later.

### Dictionary

The proposed module uses a dictionary for lexical and syntactic analysis. The module applies LEXiTRON version 3.0 beta which is an online dictionary developed by the Human Language Technology Laboratory of Thailand's National Electronics and Computer Technology (NECTEC), Thailand since 2003 [11]. The LEXiTRON dictionary was originally constructed from a corpus which consists of frequently-used vocabularies in many topics from trusted publications. Currently, the database has more than 79, 000 entries of English [12].

### Context Free Grammar Rules

A context free grammar (CFG) is a set of rewrite rules that express the ways that symbols of the language can be grouped and ordered together [13]. They are used for syntactic analysis and semantic analysis in the feature extraction process.

### Knowledge Inference Engine

The knowledge inference engine performs two processes: the natural language parsing (named feature extraction process); and the tourists' satisfaction calculation (named accommodation rating process), as described below:

### Feature Extraction

The feature extraction is a process of digesting and selecting the significant keywords or features (noun), feature modifiers (adjective, special verb, special word, adverb, and negation adverb), and relationships among these features from review contents. These extracted features, feature modifiers, and feature relationships are used for calculating a tourists' satisfaction or accommodation rating described later. The feature extraction process is divided into three steps as follows:

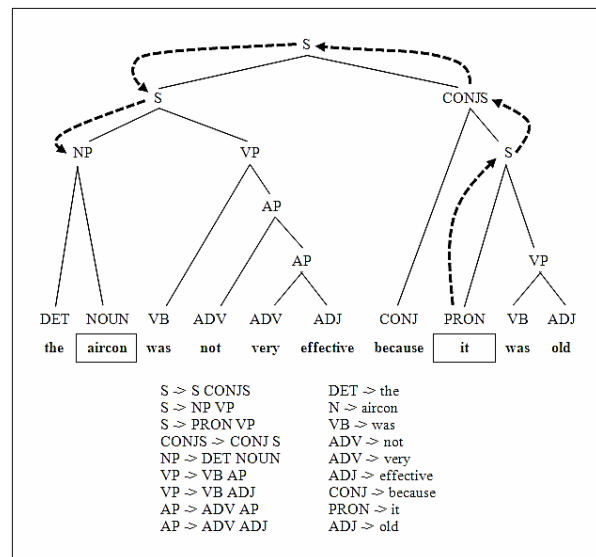
- **Lexical Analysis:** The lexical analysis performs word segmentation and transforms synonym words into the designated words of synonym sets in the SKOS ontology.
- **Syntactic Analysis:** The syntactic analysis performs relationship analysis between the words in a sentence (or part-of-speech) according to a context-free-grammar (CFG) parsing approach.
- **Semantic Analysis:** The semantic analysis is a process for interpreting the meaning of reviews derived from the syntactic analysis. Its input is a parse tree of a criticism sentence with specified grammar (according to the context free grammar rules). The algorithm of the semantic analysis consists of 8 steps as follows:

**Step 1:** Searching for an antecedent noun phrase in the parse tree according to the pronominal anaphora

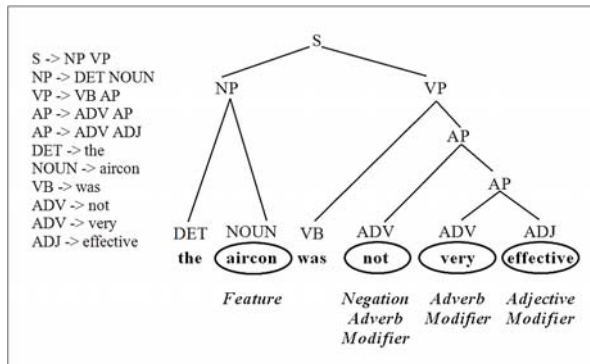
resolution adapted from Hobbs (1978)'s algorithm [14] in cases of pronoun word “He”, “She”, “It”, and “They”. Figure-3 illustrates an example of pronominal anaphora resolution. For the example, the pronoun word “it” refers to the noun phrase “aircon” according to the pronominal anaphora resolution adapted from Hobbs's algorithm.

**Step 2:** Searching for a pair of feature and feature modifier (adjective, adverb, and negation adverb) within the parse tree of the criticism sentence as shown in Figure-4. First, an adjective “effective” will be identified as an adjective modifier of a feature “aircon”, if it and the feature are in the same sentence with the nearest distance comparing with other nouns in the sentence, and there is no a preposition phrase node (PP) between them. Second, an adverb “very” and a negation adverb “not” will be identified as an adverb modifier of the feature “aircon”, if it modifies an adjective “effective” that is the adjective modifier of the same feature.

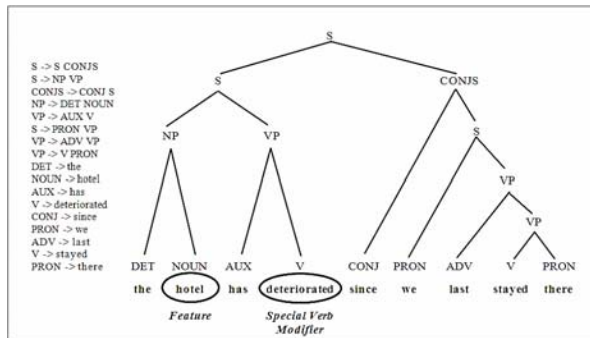
**Step 3:** Searching for a pair of feature and special verb within the parse tree of the criticism sentence as depicted in Figure-5. The special verb word “deteriorated” will be identified as a verb modifier of a feature, if it and the feature “hotel” are in the same sentence with the nearest distance comparing with other nouns in the sentence, and there is no a preposition phrase node (PP) between them.



**Figure-3.** An example of the pronominal anaphora resolution.



**Figure-4.** An example of searching for pairs of feature and feature modifier.



**Figure-5.** An example of searching for pairs of feature and special verb modifier.

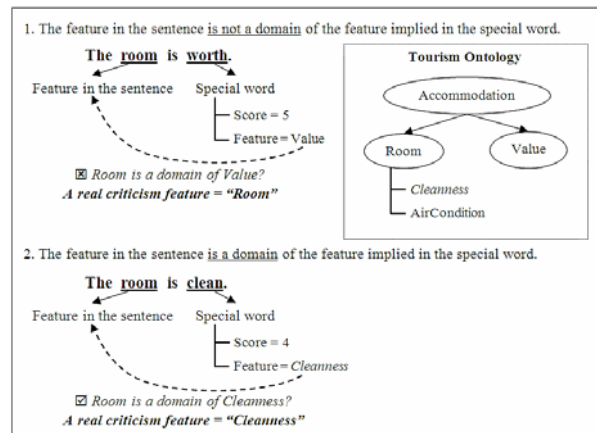
**Step 4:** Searching for a special word that can be criticized an accommodation feature without the feature word in the criticism sentence.

**Step 5:** Searching for vague domains of a feature implied in the special word. Note that some features implied in a special word can be criticized in various domains of accommodation property. For example, the feature “cleanness” implied in the special word “dirty” belongs to room, bathroom, and accommodation domains.

This vague domain case is solved by finding surrounding words of feature which indicates the domain or accommodation properties that the feature belongs to. If no surrounding words are found, the vague feature is proposed that it is criticized in aspects of overall accommodation.

**Step 6:** Searching for a real criticism of vague features in case of a special word that is matched with one feature in a criticism sentence, e.g. “The room is worth.” There are two features extracted in the sentence, i.e. the feature “room” found in the sentence and the feature “value” implied in the special word “worth”.

As illustrated in Figure-6, there are two cases of identifying an appropriate feature of a criticism as follows.



**Figure-6.** An example of searching for a real criticism of vague features in case of a special word that is matched with one feature in a criticism sentence.

First, if the feature “room” found in the criticism sentence is not a domain of the feature “value” implied in the special word “worth” as presented in the tourism ontology, the feature “room” found in the sentence is identified by the special word “worth” because it is directly criticized by a reviewer. Therefore, the feature “room” found in the sentence is identified as a real criticism feature and the special word “worth” is considered as its feature modifier.

Second, if the feature “room” found in the criticism sentence is the domain of the feature “cleanness” implied in the special word “clean”, the feature “cleanness” implied in the special word “clean” is a real criticism feature because the feature “room” found in the sentence is less specific than the feature “cleanness” implied in the special word as illustrated in the ontology.

**Step 7:** Considering other commentary words or phrases, except feature modifiers. This step will be performed, if a feature is not matched with any feature modifiers and a commentary word or phrase such as “Need” and “In need of” are found after a feature word. As a result, the satisfaction level of a criticism will be decided as 2 points because the feature is regarded as a negative criticism.

**Step 8:** Considering other commentary words or phrases, except feature modifiers. This step will be performed, if a feature is not matched with any feature modifiers and a commentary word or phrase such as “Have”, “Has”, “There is”, “There are”, “There was”, “There were”, “With”, and “No” are found and it precedes a feature word. As a result, the satisfaction level of criticism will be decided as 2 or 4 points in case of negative and positive criticism, respectively.

After all the mentioned steps, the results of the knowledge inference engine, e.g. features with their relationships and feature modifiers, commentary words and special words, etc. are extracted and stored in the



knowledge base in order to apply to accommodation rating in the next process.

### Accommodation Rating

This process performs the computation of a tourists' satisfaction level on each accommodation feature and an overall accommodation rating. The computation method is divided in two steps as follows.

- **Feature Rating:** The feature rating is the computation of tourists' satisfaction level on each extracted accommodation feature. First, the features are indicated by the nouns or significant keywords appeared in each sentence. Second, the feature rating will be assigned by the scores of adjective and adjusted by a rating of adverb and negation adverb words from the terminology. Finally, the calculated score is stored in tourism ontology divided by features. An example of room rating from the sentence "The room is dirty but the air conditioning was almost very effective", is shown in Figure-7. Kindly note that, each simple sentence is parsed and then a feature and feature score are extracted, i.e., RoomProperties feature with rating score = 2 is extracted from the first simple sentence "the room is dirty" and the AirConditioning feature with rating score = 4 is extracted from the second simple sentence "the air conditioning was almost very effective".

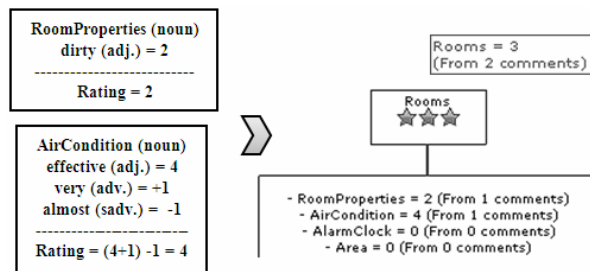


Figure-7. An example of feature rating.

- **Hierarchical Feature Rating:** In order to calculate the hierarchical feature rating or an overall score of tourists' satisfaction, the scoring features (from the feature rating steps) will be used as input data in a fuzzy inference system with bottom-up hierarchy of accommodation information as reported in our previous work [15], i.e., each feature score of the higher layer is calculated from the feature scores of the lower layer. For instance, hotel rating is calculated from the room and location scores while the room score is calculated from air condition and bed scores, as shown in Figure-8.

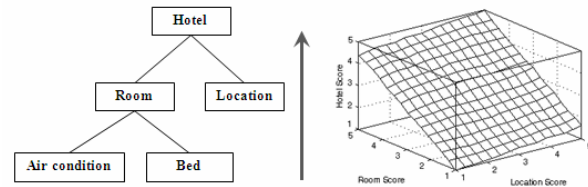


Figure-8. An example of hierarchical feature rating.

### Knowledge Explanation

After all the mentioned steps, the information in the knowledge base will be retrieved by tourists via the user interface. The knowledge explanation engine performs clear and easy understanding reviews with star rating and visualizing them into a tree structure according to the classes and properties of the tourism ontology.

Figure-9 illustrated the knowledge representation of accommodation categories, which details are derived from the research study in tourist's satisfaction [16-18] such as location, room, and service. In this tree structure, the overall rating is presented as stars.

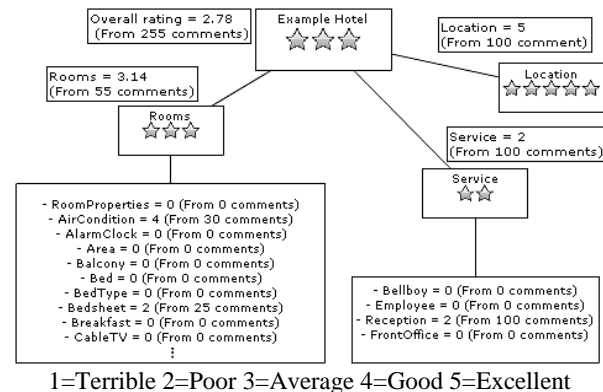


Figure-9. An example of the knowledge representation

### MODULE EVALUATION

#### Testing Environment

This experiment uses a new dataset of 200 reviews from TripAdvisor.com randomly selected from several accommodations. It covers all 5 satisfaction levels (40 reviews in each level) consisting of 1,382 criticisms, 211 non-criticisms, and 97 criticisms with errors (such as typographical, grammatical, spelling, and vocabulary errors). These 97 criticisms with errors are pruned because they are out of scope in this research.

A criticism means an opinion that judges the qualities of the accommodations, which may be clearly expressed as the word of feature (including feature relationship) and feature modifier. These criticisms and non-criticisms are classified by a language expert.

To evaluate the accuracy of the feature extraction process, only criticisms given in the review dataset are concentrated. The results of feature extraction evaluation are defined in four terms.



- TP (True Positive): the number of criticisms that can be correctly extracted.
- FP (False Positive): the number of non-criticisms that is extracted.
- FN (False Negative): the number of criticisms that cannot be extracted.
- TN (True Negative): the number of non-criticisms that is not extracted.

Using these terms, the performance of the feature extraction process should be evaluated by Accuracy, Precision, and Recall measure as (1)-(3) [19].

$$\text{Accuracy} = \frac{TP + TN}{(TP + FP + FN + TN)} \times 100\% \quad (1)$$

$$\text{Precision} = \frac{TP}{(TP + FP)} \times 100\% \quad (2)$$

$$\text{Recall} = \frac{TP}{(TP + FN)} \times 100\% \quad (3)$$

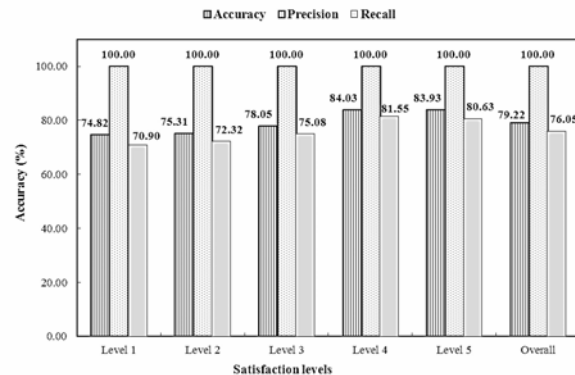
## EXPERIMENTAL RESULTS AND DISCUSSIONS

This section discusses the experimental results based on testing environment as stated above. The proposed module is evaluated in terms of Accuracy, Precision, and Recall measures which are calculated from the terms of criticism classification as illustrated in Table-1.

**Table-1.** The confusion matrix of the terms of criticism classification.

	Data Extracted (+)	Data Not Extracted (-)
Criticism (+)	TP=1,051	FN=331
Non-Criticism (-)	FP=0	TN=211

The experimental results are achieved in 79.22% of overall accuracy, 100% of overall precision, and 76.05% of overall recall as shown in Figure-10. All of the satisfaction levels are achieved in 100% of precision because all non-criticisms in every level cannot be extracted ( $FP=0$ ) owing to the accommodation feature absence.



**Figure-10.** The Accuracy, Precision, and Recall of the feature extraction process.

By the way, the extraction process works incorrectly in some levels, particularly in level 1 and 2 which is obtained the minimum of Recall (only 70.90% and 72.32%) because the tourist reviews in both levels always criticize with long explanations. There are many significant keywords that are useful for semantic analysis and appear in this long explanation criticism. These keywords are separated in many sentences and omitted in some cases. Thus, the designed semantic analysis approach does not support the long explanation criticism. Furthermore, many commentary words or phrases are in need of connotative meaning interpretation or pragmatic analysis that is out of scope of this research.

## CONCLUSIONS AND FUTURE WORK

This article presents an analysis module for online travel accommodation reviews. The proposed module focuses on a design of semantic analysis approach for language understanding and proposes the approach for calculating a tourists' satisfaction level with accommodation services and facilities. Moreover, this module performs a clear and easy understandable review summarized by visualizing the results in a tree structure. The tourists can use these results by exploring an accommodation in details to select an accommodation that conforms to their preferences. The experimental results of the feature extraction process are achieved in 79.22% of overall accuracy, 100% of overall precision, and 76.05% of overall recall.

There are some improvements that could be performed in the near future, e.g. updating the knowledge base in order to provide higher accuracy of results, such as collecting more related words in terminology and synonyms in SKOS ontology, increasing accommodation features in the tourism ontology, improving the set of context free grammar rules in order to analyze complex sentences that partly omit constituents of a clause. In addition, improving the semantic analysis process on aspects of word sense ambiguity could be performed. Considering some adjective words with a neutral connotation, that are used to criticize in either positive or



negative senses, together with the feature word could be identified an appropriate rating score.

The proposed module could be useful in tourism business. The tourism business entrepreneurs can use this module to analyze customers' opinions that affect their business and apply the extracted knowledge for developing their accommodation services and facilities in order to meet more customers' need and gain more advantages over the competitors. In addition, users or tourists can apply the extracted knowledge for supporting their decisions on selecting travel accommodations easily and quickly.

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