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ASPECT-BASED SENTIMENT CLASSIFICATION FOR CUSTOMER HOTEL REVIEWS

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Abstract. *Using only ratings to gauge public opinion about products and services is insufficient to improve product quality or understand the reasons for consumer preferences. This problem was addressed by employing feature/aspect-based sentiment analysis to examine the polarity of customer evaluations. An aspect-based sentiment analysis method was designed for hotel evaluations, taking account of staff attentiveness, room cleanliness, hotel facilities, value for money and location convenience. A collection of keywords for each hotel aspect was learned using Word2Vec as one of the three fundamental solution mechanics. This corpus was then utilized to select hotel features during developing an aspect-based multiclassification model to categorize sentences containing customer evaluations into their specific aspect classes. A binary-based sentiment classifier was also developed to assign the sentiment polarity of each sentence in each aspect class. Term frequency-inverse gravity moment (tf-igm) was employed as a term weighting scheme, while the SVM algorithm was used to construct text classification models. Our proposed method gave superior results to the baseline with improved average recall, precision, F1 and accuracy scores of 3.45%, 2.38%, 2.35% and 2.35%, respectively, compared to the baseline.*
Keywords: Aspect-based sentiment analysis, Hotel aspect, Sentiment polarity, Customer hotel review, Word2Vec, tf-igm, Support vector machines

1. **Introduction.** Personal assessments of goods and services are often presented as ratings. These ratings indicate levels of customer satisfaction but do not reveal the reasons why customers like or dislike particular products or services. Thus, considering the rating alone does not provide sufficient information to improve product and service qualities. Consequently, customer reviews become an important information source that assists owners of products and services to understand the real reasons for customer satisfaction. Reviews provide feedback regarding what customers truly want since they are written by consumers who have purchased and used the products or services [1-3].

Previous sentiment analysis studies often used customer reviews as summary results (i.e., positive, neutral or negative). Consider an example of customer review, "*This product has a good price and it has a good design. Unlucky, I still don't have enough money*".

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This example identifies positive customer sentiment. Recognizing only summary information does not comprehensively elucidate how customers feel about products because details concerning specific aspects of a product are missing. Therefore, other customers or product owners may not understand the exact reasons for product '*like*' or '*dislike*', with insufficient information for decision-making to purchase that good or service. From the point of view of the owners, summary results are insufficient for the detailed improvement of a product or service [4]. Customer reviews can also express different sentiments covering diverse aspects, while some sentiments may not be relevant (e.g., "*Unlucky, I still don't have enough money.*"). Thus, retrieving the correct sentiment relevant to each specific aspect can be difficult. To cope with this challenge, many studies during the past decade have addressed aspect-based sentiment analysis to identify and predict the sentiment expressed toward each aspect in a sentence [4-17]. Several researchers have paid attention to this domain study until now [4-17].

Aspect-based sentiment analysis (ABSA) [4-7] (known as target-based, feature-based and entity-based) identifies and assigns sentiment aspects by examining the opinion itself rather than linguistic constructs (i.e., document [18] and sentence levels [19]). The output of ABSA provides a more granular and detailed level of information; especially in cases where the same customer review has different aspects that have diverse sentiments [4-17]. Simply speaking, aspect-level sentiment analysis identifies the sentiment expressed in a review sentence toward an opinion aspect target.

Early research in ABSA was found in [8,9]. They initiated studies on aspect identification in product reviews using opinion lexicon and an association rule-based system. In 2006, Zhuang et al. [10] presented automatic review mining and summarization to extract the features by which movie reviewers expressed their opinions and determine whether the sentiments were positive or negative. Later, Jakob and Gurevych [11] used conditional random fields to identify aspect terms and phrases. They showed a significant improvement in the F1 score compared to [10]. Copious research still attempts to solve this problem. Kiritchenko et al. [12] presented a state-of-the-art performance of review classification using interesting linguistic and lexical features. Zhang et al. [13] used a graph convolutional network (GCN) aspect-specific sentiment classification method, while Hoang et al. [14] used contextual word representations from the pre-trained language model BERT, together with a fine-tuning method using additional generated text to solve out-of-domain aspect-level sentiment classification. Alqaryouti et al. [15] proposed a hybrid method of aspect-based sentiment analysis that integrated domains of lexicons and rules to identify entities and the relevant aspects from the reviews, and then classified the corresponding sentiments using natural language processing (NLP) techniques. Janjua et al. [16] proposed a hybrid method for multi-level aspect-based sentiment classification based on a multi-layer perceptron (MLP) using Twitter data to perform finer-grained sentiment analysis by considering both explicit and implicit aspects, while Iriani et al. [17] combined Word2Vec with a restricted Boltzmann machine and back-propagation network to build a framework to classify hate, extremism and radicalism in Indonesian social media posts.

Sentiment analysis has been studied for a long time and continues to attract attention. When changing the domain of study, the problems encountered become different, and the process of automatically recognizing aspects and related sentiments is complicated because linguistic phenomena are hard to analyze, interpret and understand. Identifying the correct aspects is often the most difficult analytical subtask because customers express their opinions using wide-ranging aspects. A dataset of multilingual hotel reviews is difficult to understand using an automatic analysis, and a slight change in meaning can cause multiple errors in the sentiment analysis. Reviews sometimes contain complex statements with sarcasm used to complain about the hotel. Consequently, hotel reviews have attracted research interest as datasets for sentiment analysis studies. Here, the study challenge was taken up to present a method of aspect-based sentiment classification for customer hotel reviews. The proposed method commenced by assigning each sentence into a specific aspect class (i.e., staff service, cleanliness, hotel facilities, value for money and convenience of location). Sentences in each aspect class were then classified into two categories as positive or negative. This revealed the reasons why previous customers liked or disliked particular services and allowed hotel owners or other customers detailed access to levels of information for each hotel aspect.

This paper is organized as the following. Datasets were presented in Section 2 and Section 3 detailed preliminaries and the proposed method. Section 4 presented the experimental results. It also included the results of comparing the proposed framework to a baseline. Finally, this study is concluded in Section 5.

2. **Datasets.** Our datasets were downloaded from the Booking.com website. Each hotel review was based on a 10-star rating scale. Customer reviews with 8-10 rating scores were assigned as the positive class, while customer reviews with 1-4 rating scores were assigned as the negative class. We ignored 5-7 rating scores because these scores might represent neutral feeling. Here, three linguistic experts were recruited to help with two tasks. First, they identified the main aspects that customers use when deciding which hotel to select as staff attentiveness, room cleanliness, hotel facilities, value for money, and convenience of location. Second, they developed three datasets for our experiment by manually gathering relevant sentences of each hotel aspect class, and then each sentence in each hotel aspect class was also labelled its suitable feeling (or sentiment). The annotation structure of the third dataset used as the experiment dataset can be illustrated as Figure 1. All datasets are summarized in Table 1.

```
<dataset>
  <hotel_review ID = "00001">
      <sentences>
         <sentenceID = "1">
            <text> The staff is friendly. <\text>
            <aspect> staff service <\aspect>
            <polarity> pos <\polarity>
         <\sentenceID>
         <sentenceID = "2">
            <text> The room is very clean and comfortable. <\text>
            <aspect> cleanliness <\aspect>
            <polarity> pos <\polarity>
         <\sentenceID>
         ....
         ....
      <\sentences>
  <\hotel_review>
<\dataset>
```

FIGURE 1. An example of the dataset used for the experiment stage

3. **Preliminaries and Proposed Method.** This section describes for preliminary stage, and experimental setting. The details can be explained as follows.

3.1. **Preliminaries.** There are two tasks in our preliminaries. Each task can be described in more detail below.

1) Generating relevant keywords of each hotel aspect

This section details the method of generating keywords that are relevant to each hotel aspect from the first dataset. To generate relevant keywords of each hotel aspect, it

Table 1. Datasets

Dataset	Objective of dataset usage	Number of training sets	Number of test sets	Total number of sentences
#1	Developing of word corpus of each hotel aspect and aspect-based multiclassification model	400 sentences per hotel aspect	100	2,500
#2	Developing of binary-based sentiment classifier modeling	Each hotel aspect contained 400 sentences per class (positive and negative)	Each hotel aspect contained 100 sentences per class (positive and negative)	3,600
#3	Experiment	–	200 documents	100 sentences per aspect (100 positive and 100 negative)

Table 2. Examples of keyword for each hotel aspect

Hotel aspects	Examples of keyword	Number of obtained words
Staff service	friendly, very friendly, quickly	112 words
Cleanliness	dirty, clean, good hygiene, hygiene	98 words
Hotel facilities	restaurants, lounge, swimming pool, wifi, fitness center	116 words
Value price	expensive, low, price, good value	97 words
Convenience of location	close to, near, shopping center	94 words

commences with tokenization, and then performs stop-word removal, word correction, lemmatization, and lowercase conversion, respectively. Finally, those sentences are represented in a vector format. However, the domain experts provided 10 keyword examples per hotel aspect. Keywords of each aspect were then used as the main initial learning keywords of Word2Vec to generate and associate all keywords relevant to each hotel aspect from the first dataset. Word2Vec consists of two main training algorithms, i.e., the continuous bag of words (CBOW) and skip-gram [20]. CBOW is used to predict the central word based on the context words in a window, while skip-gram is an algorithm used for predicting the context word for a target word [20]. The gensim module in Python was utilized to perform Word2Vec and Word2Vec setting was described as the following. The number of dimensions of the embeddings was 100 and the default window was 5. The minimum count of words to consider when training a model is 5, while the number of partitions during training is 3. Similar words were assembled in the same group (or hotel aspect). This corpus is called, hotel aspect keywords (HAK) corpus. Some words relevant to each hotel aspect can be presented as Table 2.

2) Developing of text-based classification models

Two text-based classifiers were developed as an aspect-based multiclassification model and a binary-based sentiment classifier. Firstly, the aspect-based multiclassification model was built by using the first dataset and the obtained classifier model was used to automatically classify sentences in customer reviews into specific hotel aspect classes by applying a real-world experiment. Later, the binary-based sentiment classifier was built by using the second dataset and the obtained classifier model was used to determine the sentiment polarity of each sentence in each hotel aspect group. With using a small dataset for learning of text-based classification models, support vector machines (SVM) might be an appropriate algorithm for this study [21].

Text pre-processing was driven by tokenization, and then stop-word removal, word correction, lemmatization and lowercase conversion were performed. Later, these texts were represented as vector space model (VSM) format. The HAK corpus was also required to select customer reviews of hotel features and develop the aspect-based multiclassification model but when developing a binary-based sentiment classifier, the HAK corpus was not required. Each term feature was weighed using *term frequency-inverse gravity moment* (*tf-igm*) because this term weighting scheme can increase the distinguishing power of term classes [22,23]. Afterwards, the vector representing the review sentences was then used to model the multilabel aspect-based sentiment classifiers using the supervised SVM learning algorithm to solve both classification and regression problems. In classification problems, SVM determines a decision boundary (called a hyperplane) between classes that is as far away as possible from any point in the training data [24]. Some points are discounted as outliers. Fundamentally, SVM applies the structural risk minimization (SRM) principle to finding the best hyperplane on input space based on the hypothesis $h(x) = wx + b$, described by a weight vector w and a threshold b such that the lowest true error can be guaranteed, where the error of h is the probability that h will make an error on randomly selected examples. The best hyperplane can be calculated by maximizing the margin ($\delta = 1/\|\vec{w}\|$), formulated by Equation (1).

$$\textit{Minimize: } \min(w) = \frac{1}{2}\|\vec{w}\|^2 \tag{1}$$

$$\textit{Subject to: } \forall_{i=1}^{n} : y_i\left(\vec{x}_i\vec{w} + b\right) \geq 1 \tag{2}$$

$$\textit{Constraint: } L\left(\vec{w}, b, \alpha\right) = \frac{1}{2}\|\vec{w}\|^2 - \sum_{i=1}^{l} \alpha_i\left(y_i\left(\left(\vec{x}_i\vec{w} + b\right) - 1\right)\right) \tag{3}$$

The maximum margin can then be formulated using the constraint in Equation (1) subject to Equation (2) as the *quadratic programming* (*QP*) problem. The constraint in Equation (3) was applied to solving the problem by calculating its optimized value as gradient (L), where $L = 0$. Consequently, the constraint in Equation (3) was modified as follows.

$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{j=1}^{l} \alpha_i\alpha_j y_i y_j \vec{x}_i\vec{x}_j \tag{4}$$

$$\alpha_i \geq 0 \quad (i = 1, 2, \ldots, l) \quad \sum_{i=1}^{l} \alpha_i y_i = 0 \tag{5}$$

A linear and the Gaussian radial basis function (RBF) were used as kernel functions for SVM. The linear kernel function is mostly preferred for text classification problems that can be linearly separated, while RBF is used as kernel functions in SVM because it can make a proper separation with no previous knowledge of data. The RBF kernel function is usually chosen for non-linear data.

3.2. **Proposed method.** In this stage, the third dataset is used. The overview of the proposed method is presented as Figure 2.

The third dataset is pre-processed and it is commenced by splitting each customer review text into sentences. Afterwards, those sentences are performed by tokenization, and then perform stop-word removal, word correction, lemmatization, and lowercase conversion respectively, those texts are represented as the VSM format. Afterwards, each term

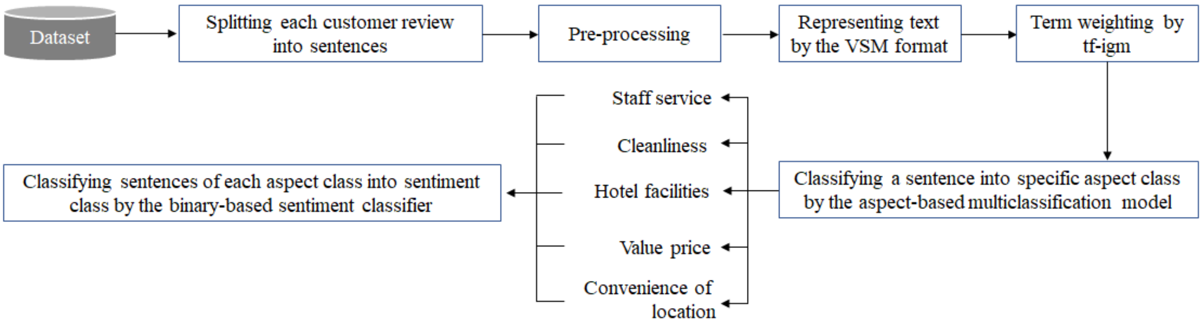

Figure 2. The overview of the proposed method

feature is weighed using *tf-igm*. Following text pre-processing, the aspect-based multiclassification model automatically classified sentences in customer reviews into their specific hotel aspect class. Binary-based sentiment classification was then performed to determine the sentiment polarity of each sentence in each hotel aspect class. Finally, the total numbers of positive and negative sentiments were established. By following this process, hotel owners will be able to recognize the reasons why customers like or dislike particular services.

4. **Experimental Results.** In this study, recall (R), precision (P), F1, and accuracy (Acc) were applied to measuring the performance of the aspect-based multiclassification model, the binary-based sentiment classifier, the proposed method of aspect-based sentiment analysis, and comparing the proposed method to the baseline.

4.1. **Results of the proposed methods.** After evaluating the aspect-based multiclassification model and the binary-based sentiment classifier, test sets from the first and second datasets are used to evaluate classification performance. The results are presented in Table 3. It can be seen that both models developed by SVM returned satisfactory results because SVM works relatively well when there is a clear margin of separation between classes. However, our dataset was small and the SVM algorithm is better suited to large datasets. Although our dataset was small, many features were obtained. It is well-known that SVM is also more effective in high-dimensional spaces because it scales relatively well to high-dimensional data. As a result, classification models developed by the SVM algorithm often return satisfactory results. However, when considering the kernel functions used for SVM in this study, the SVM with linear kernel gave more accurate results than the SVM with RBF kernel because most text classification problems are linearly separable. Text classification frequently works well with only a linear kernel, while training an SVM text classifier with a linear kernel is faster than using another kernel type.

Table 3. Results of the proposed methods

Proposed methods	Algorithm	R	P	F1	Acc
Aspect-based multiclassification model	SVM with linear	**0.89**	**0.88**	**0.88**	**0.89**
	SVM with RBF	0.87	0.86	0.86	0.87
Binary-based sentiment classifier	SVM with linear	**0.92**	**0.88**	**0.90**	**0.91**
	SVM with RBF	0.90	0.87	0.88	0.90

Finally, both models (aspect-based multiclassification model and binary-based sentiment classifier) developed by SVM with a linear kernel were selected for using in the proposed method. The results of those proposed methods (SVM with linear kernel function) that are evaluated by average recall, precision, F1, and accuracy through the use of the third dataset are 0.90, 0.88, 0.89, and 0.90 respectively. Finally, our proposed method was compared with the baseline proposed by Akhtar et al. [25].

4.2. **Method comparison.** The method of Akhtar et al. [25] was chosen as the baseline because their work was quite similar to our proposal, where both studies were driven using the same lexicon and corpus-based approach for aspect-based sentiment analysis. Both studies initially identified the aspect that was then classified into a polarity class. However, in the baseline, they provided a benchmark setup for aspect category detection and sentiment classification for Hindi using basic lexical features like n-grams, non-contiguous n-grams and character n-grams along with POS tag and semantic orientation (SO) scores as a measure of token association toward positive and negative sentiments. Here, we used only unigrams (or words) as features for our comparison. In addition, the algorithm used to model the classifiers for identifying aspect category and sentiment polarity was the SVM with linear kernel function. Then, the first dataset was used to model the aspect classifier, while the second dataset was used to model the sentiment polarity classifier. Finally, the third dataset was used for the comparative experiments. Comparison results for the proposed method and the baseline are presented in Table 4.

Table 4. Results of comparing the proposed method and the baseline

Methods	**R**	**P**	**F1**	**Acc**
The method proposed by Akhtar et al. [25]	0.84	0.82	0.83	0.83
Our proposed method	0.87	0.84	0.85	0.85

Table 4 showed that our method returned better results than the baseline. There are probably three reasons. First, using the HAK corpus obtained the most relevant features from customer hotel reviews and reduced data outliers. Consequently, this increased SVM text classification performance. Second, *tf-igm* as the term weighting scheme precisely calculated the distinguishing classes of a term, especially for multiclass problems. Third, using the SVM algorithm to model the text classifiers minimized the need for feature selection. SVMs can generalize well in high-dimensional feature spaces, making text classification easier to apply, with also the advantage of being more resilient than other approaches. Furthermore, when considering computational time, our proposed method was faster than baseline.

However, although our proposed method gave improved average scores of recall, precision, F1 and accuracy, it was not superior to the baseline from every viewpoint. Firstly, the classifiers in the bassline actually applied three machine learning algorithms, i.e. Naïve Bayes, decision tree, and sequential minimal optimization implementation of SVM (SMO). However, here, we used only SVM to build the classifiers. Second, with the use of our dataset, our proposed method was more efficient than the baseline method. Therefore, it might be possible that if we utilized the same dataset, features, and algorithms as the baseline method, this would impact the experimental results.

5. **Conclusions.** Using only rating scores to assess public opinion about goods and services is insufficient to enhance product quality or comprehend the root causes of consumer likes and dislikes. Owners of goods and services need to understand the reasons behind certain customer feelings. This issue was solved by analyzing the sentiment polarity of customer reviews using feature/aspect-based sentiment analysis. Here, a method of aspect-based sentiment classification was proposed to classify hotel reviews by considering staff attentiveness, room cleanliness, hotel facilities, value for money and location convenience. The three main mechanisms of our proposed method involved learning a set of keywords of each hotel aspect using Word2Vec. This corpus was then used to select hotel features by developing an aspect-based multiclassification model to classify sentences found in hotel

customer reviews into their specific aspect classes. Each sentence in each aspect class was then assigned sentiment polarity using the binary-based sentiment classifier. To develop classifier models, *tf-igm* is used as a term weighting scheme, while the SVM algorithm was used to develop the classifiers. The SVM with linear kernel returned better results than the SVM with RBF kernel. Compared to the baseline, our proposed method gave improved average scores of recall, precision, F1 and accuracy at 3.45%, 2.38%, 2.35% and 2.35%, respectively. In further studies, we will apply linguistic structural analysis to enhancing more complex sentence comprehension. Sarcastic sentences require accurate interpretation to increase sentiment analysis performance.

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