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A HYBRID METHOD OF ASPECT-BASED SENTIMENT ANALYSIS FOR HOTEL REVIEWS

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Abstract. *The purpose of this study was to introduce a hybrid method of aspect-based sentiment analysis for hotel reviews. Hotel staff attentiveness, hotel cleanliness, value for money, and hotel location are all highly regarded hotel aspects. The proposed method is made up of two major components. BM25 is used in the first component to group the review sentences into the most relevant hotel aspect cluster. Word2Vec's skip-gram was utilized to generate the keywords relevant to each hotel aspect, which were then used as queries to organize review sentences into suitable hotel aspect cluster. Finally, hotel review sentences in each cluster are assigned a sentiment polarity as positive or negative using the sentiment polarity analyzer, which is an ensemble model comprised of five predictive models developed by C4.5 decision tree, Multinomial Naïve Bayes (MNB), Support Vector Machines (SVM) with linear kernel, SVM with RBF kernel, and Logistic Regression (LR). After evaluating the proposed hybrid method via recall, precision, F1, and accuracy, our proposed method yielded satisfactory outcomes at 0.820, 0.805, 0.810, and 0.815, respectively. Furthermore, we also compared our hybrid method to a baseline utilizing the same training and test sets. The recall and precision scores of our proposed method were marginally higher than the baseline, with enhanced recall and precision scores at 4.76% and 4.88%, respectively.*
Keywords: Aspect-based sentiment analysis, Hotel review, Hybrid method, BM25, Ensemble method

1. **Introduction.** Customer reviews are a valuable resource for assisting products and services owners in recognizing critical customer suggestions regarding their products and services. Furthermore, these data also enable business owners to comprehend the reasons why their customers "*dislike*" or "*like*" their products and services [1-3]. Many e-commerce and social media platforms now include a channel that customers can use to review or comment on purchased products or services. This results in a significant increase in consumer review data. Analyzing a large number of customer reviews manually is time-consuming and it also has the potential to introduce bias [4,5]. A research area called "*sentiment analysis*" has been proposed to handle this problem. Sentiment analysis involves examining and recognizing customer sentiments expressed in customer reviews

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using text mining, computational linguistics, and natural language processing (NLP) techniques [6-8]. Determining the polarity of the customer review is the main mission of sentiment analysis. To determine the polarity level in a textual review, text classification technique has been applied [8-13]. Although sentiment analysis based on a text classification approach helps to reduce analysis time, it only provides positive, neutral, or negative sentiments of customers. Unfortunately, the analysis results do not explain why consumers "*dislike*" or "*like*" particular products and services. Consequently, this information may not be adequate for enhancing products and services or retaining customers. In order to identify the reasons why the customers "*dislike*" or "*like*" these products and services, feature/aspect-based sentiment analysis has been applied to addressing this issue [14-17]. This task is known as "*aspect/feature-based sentiment analysis*". It is a very fine-grained application of sentiment analysis [15-17]. It aims to identify distinct features/aspects of a product or service and define the sentiment associated with each feature/aspect. Simply speaking, this task entails analyzing customer feedback data by correlating sentiments to various product or service aspects. Aspects or features in this context relate to the factors, attributes, characteristics, or components of a product or service that might affect the customer's perception (e.g., the cleanliness of a hotel, the delivery time of a service, or the customer's perspective of staff hotel attentiveness). These aspects or features may differ from a product or service characteristic. Aspect/feature-based sentiment analysis is essential because it allows businesses to examine enormous volumes of data in great detail and generate valuable insights automatically. Finally, the business can enhance the quality of its products and services to better fulfill customer demands [17].

As the issue mentioned above, this becomes the main challenge in this study. The purpose of this work is to provide a hybrid method that combines two approaches (i.e., unsupervised learning and supervised learning approaches). Hotel reviews were used as our dataset in this study. Those hotel reviews were first broken up into sentences, after which the similarity analysis approach was used to identify the specific aspect (such as staff hotel attentiveness, hotel cleanliness, value for money, and hotel location) buried in those sentences. After assembling each sentence into a specific aspect cluster, each sentence in that specific aspect cluster was assigned to either positive or negative to demonstrate its polarities using an ensemble model.

The are 6 sections in this paper where Section 1 introduces the research problem. Section 2 describes our datasets, while Section 3 provides preliminaries. The proposed method is described in Section 4. The results and discussion are then presented in Section 5. Finally, the conclusions are discussed in Section 6.

2. **Dataset.** The dataset relevant to hotel reviews was used in this study. These hotel reviews were written in English and gathered from the TripAdvisor website. The label class for each document is initially determined by using the review's rating. We describe a hotel review as "*Positive* (*POS*)" if the original rating score was 4 or 5, while we define it as "*Negative* (*NEG*)" if the original rating score was 1 or 2. Three linguists then assist in determining which specific hotel aspect (i.e., staff hotel attentiveness, hotel cleanliness, value for money, and hotel location) is featured in those sentences and assist in determining the sentiment polarity of those sentences. In our dataset, there are various numbers of sentences in each hotel review. Some hotel reviews contain numerous sentences, while others contain only a few sentences. However, the average number of hotel review sentences is six and the summary of our dataset can be described in Table 1.

3. **Preliminaries.** Two tasks should be done at the preliminary stage. They are the processes of utilizing Word2Vec to generate keywords for each hotel aspect and developing a sentiment polarity analyzer based on text classification.

Table 1. Summarization of the dataset

<table>
<tr><th rowspan="2">Total of hotel reviews</th><th colspan="2">Sentiment polarity of hotel reviews</th><th colspan="2">Number of sentences related to staff hotel attentiveness</th><th colspan="2">Number of sentences relaed to hotel cleanliness</th><th colspan="2">Number of sentences related to value for money</th><th colspan="2">Number of sentences related to hotel location</th></tr>
<tr><th>POS</th><th>NEG</th><th>POS</th><th>NEG</th><th>POS</th><th>NEG</th><th>POS</th><th>NEG</th><th>POS</th><th>NEG</th></tr>
<tr><td>3,000</td><td>1,500</td><td>1,500</td><td>1,678</td><td>1,089</td><td>1,908</td><td>1,060</td><td>1,340</td><td>1,121</td><td>1,408</td><td>1,089</td></tr>
</table>

3.1. **Generating the keywords related to each hotel aspect using Word2Vec.** The Python NLTK was employed to perform sentence pre-processing. The steps of pre-processing that are commenced are tokenizing text, eliminating punctuations, word correction, expanding contractions, removing digits and special characters, and converting the text data to lowercase, respectively. Also, the POS tagging library was performed to extract bigram words (i.e., verb phrase, adjective phrase, and noun phrase). In this study, unigram and bigram of words were utilized simultaneously. Later, stop-words were removed. Finally, stemming was conducted to reduce inflected words to their '*word stem*' using the Python NLTK's snowball algorithm. In addition, the pre-processed sentences were also used in Section 3.2. Finally, these sentences were provided in the form of a vector format known as vector space model. Later, Word2Vec was performed to generate keywords relevant to each hotel aspect.

Word2Vec [18-20] is a common tool for creating word embeddings. This is done by utilizing the continuous bag of words (CBOW) and skip-gram training algorithms. CBOW is used to predict the word in the window's middle, whereas skip-gram predicts surrounding words based on the context of the window. This research employed Word2Vec's skip-gram to correlate relevant words with each hotel aspect, called Keywords-for-Aspect. The Python's gensim module was utilized to learn and extract the significant words relevant to each hotel aspect for each hotel aspect (see Table 2). The number of dimensions of the embeddings in this investigation was 100, and the default window was 5. The minimum number of words to consider is 5, and the maximum number of partitions is 3. Finally, *information gain* (*IG*) was performed to identify the most relevant keywords of each hotel aspect.

Table 2. Keywords for each hotel aspect

Hotel aspect	Examples of keyword	The number of words
Staff hotel attentiveness	friend, quick, help, nice, very nice	78 words
Hotel cleanliness	dirty, clean, good, hygien, very clean	80 words
Value of price	expensive, low, price, value, cheap price	54 words
Convenience of hotel location	close, near, shop, center, airport, city center, shop center	60 words

3.2. **Developing a sentiment polarity analyzer.** This stage involves developing the sentiment polarity analyzer, which will be used to determine the sentiment polarity of each sentence in each hotel aspect cluster. In this study, the proposed sentiment polarity analyzer is driven on the voting ensemble method that employs multiple predictive models to achieve a higher predictive performance, than using a single prediction model. The prediction process of the voting ensemble in classification involves summing the votes for distinct class labels from various models and predicts the class with the majority's vote.

The proposed voting ensemble model is made up of five predictive models created via C4.5 decision tree, Multinomial Naïve Bayes (MNB), Support Vector Machines (SVM) with linear kernel function, SVM with RBF kernel function, and Logistic Regression (LR), respectively. On our dataset, 10-fold cross validation is applied to minimizing bias analysis and preventing overfitting [21]. By employing 10-fold cross validation, for the sentiment polarity analyzer, an ensemble approach model is applied with the best model of each machine algorithm.

Firstly, these customer reviews are pre-processed using the mentioned processes outlined in Section 3.1. Afterwards, they are represented as a vector, which is known as the vector space model. The weight of each word is determined using *term frequency – inverse gravity moment* (*tf-igm*) [22]. This term weighting scheme is adopted because it is a supervised term weighting (STW) scheme that can provide class distinguishing power by determining the significance of a word in a document of a particular class. The *tf-igm* formula can be written as Equation (1) and Equation (2), respectively.

$$tf\text{-}igm(w_i, s_j) = tf(w_i, d_j) \times (1 + \lambda \times igm(w_i)) \tag{1}$$

$$igm(w_i) = \frac{freq_{i1}}{\sum_{r=1}^{M} freq_{ir} \times r} \tag{2}$$

where $tf(w_i, d_j)$ is the frequency of a specific word appearing in sentence s. In *igm*, the total number of sentences in the r-th class that contain the word w_i is shown by the expression $freq_{ir}$ $(r = 1, 2, \ldots, M)$. These sentences have been arranged in descending order. Consequently, $freq_{i1}$ represents the frequency of w_i in the class in which it appears the most frequently, whereas the adjustable coefficient, denoted as λ, is used to maintain the relative balance of a word's weight between the global weight *igm* and the local weight *tf*. In general, the default value of λ is 7.0. However, λ can be modified to a number between 5.0 and 9.0. In this study, the coefficient value is set to 7.0.

After assigning weight scores to each word and representing review sentences as vector space models, this vector is used to develop the sentiment polarity analyzer. The machine learning algorithms that are employed to create the ensemble predictive model are discussed below.

***C4.5*:** It is a modification over the ID3 algorithm that generates a decision tree. C4.5 employs the gain ratio impurity approach to determine the splitting feature [23], unlike ID3 which used the information gain. It chooses one data feature at each node of the tree that divides its set of instances most efficiently into subsets enhanced in one class or the other. The normalized information gain calculated from the selection of a feature is used as a criterion for data partitioning.

***Multinomial Naïve Bayes (MNB)*:** This algorithm is a probabilistic learning method that is primarily employed for text classification. MNB predicts the class of a text using the Bayes theorem [24]. Basic Naïve Bayes employs the maximum likelihood to estimate the class probability, denoted as $P(c_j)$, and the probability of feature w_i appearing in class c_j, denoted as $P(w_i, c_j)$. The formula used to calculate the class probability can be written as the following.

$$P(c_j) = \frac{count(documents\_in\_c_j)}{Total\_documents\_in\_corpus} \tag{3}$$

To estimate $P(w_i, c_j)$, the formula can be

$$P(w_i, c_j) = \frac{count(w_i, c_j) + 1}{\sum_{w \in V} count(w, c_j) + |V|} \tag{4}$$

In Equation (4), the Laplace smoothing is applied to preventing the problem of zero probability, and $|V|$ is the total number of words in the vector.

Finally, to predict the class label of an instance, the following formula is employed.

$$C_{MAP} = \arg\max_{c} P(c) \prod_{j} P(w_i|c) \tag{5}$$

The MNB algorithm is easy to implement. Also, it is very scalable and can handle large datasets with ease.

***Support Vector Machines (SVM)*:** Basically, SVM is developed for binary classification tasks [25]. In the context of text classification, let $D = \{x_1, x_2, x_3, \ldots, x_i\}$ be training examples belonging to one class X, where X is a compact subset of R^N. The formula for a binary classification according to the SMV is as follows.

$$\min \frac{1}{2}\|w\|^2 + \frac{1}{\nu l}\sum_{i=1}^{l} \xi_i - \rho \tag{6}$$

$$\text{Subject to } \ (w \cdot \phi(x_i)) \geq \rho - \xi_i \text{ where } i = 1, 2, \ldots, l \text{ and } \xi \geq 0 \tag{7}$$

where ξ_i is the slack variable, whereas w is the slope of the hyperplane used to separate the data. If w and ρ solve this problem, the following formula is the decision function:

$$f(x) = sign((w \cdot \phi(x)) - \rho) \tag{8}$$

In general, the SVM algorithm uses a kernel function to enable linear separation in a feature space for a large number of linear inseparable data. Simply speaking, it is used to map a lower dimensional data into a higher dimensional data. Since most text classification issues may be resolved linearly, the linear kernel is utilized in this study to classify the textual sentiment. However, several studies on text categorization have used the RBF kernel functions and yield satisfactory results. As a result, SVM employed both kernel functions in this study.

***Logistic Regression (LR)*:** In general, this algorithm is utilized for binary classification. A sigmoid function is applied to the weighted combination of the input features in LR classifiers [26]. If P_1 denotes the probability of an instance belonging to positive class, and P_0 denotes the probability of an instance belonging to negative class. The LR model has the following form.

$$z_i = \log\left(\frac{P_{i1}}{P_{i0}}\right) = b_0 + b_1 x_{i1} + b_2 x_{i2} + \cdots + b_k x_{ik} \tag{9}$$

where P_{i1}/P_{i0} referred to the odds ratio, b_j is the value of the j-th coefficient, $j = 1, \ldots, k$, and x_{ij} is the value of the i-th instances of the j-th predictor. The parameters $(b_0, \ldots, b_k)$ of the logistic model can be estimated by using the maximum likelihood method. The LR model can be used to estimate the likelihood of an event occurring and the formula is written as follows.

$$P(Y_i = 1|X_i) = \frac{e^{b^T X_i}}{1 + \left(e^{b^T X_i}\right)} = \frac{1}{1 + \left(e^{b^T X_i}\right)} \tag{10}$$

where $e^{b^T X_i}$ is the linear predictor of the LR function, while Y_i is the event under study, often known as the dependent variable. If the probability cutoff is 0.5, an instance can be labeled as positive if $P_1 > 0.5$; however, an instance can be labeled as negative if $P_1 < 0.5$. To estimate the parameters of the LR model, the maximum likelihood approach maximizes the coefficients of the log likelihood function.

4. **A Hybrid Method for Aspect-Based Sentiment Analysis.** This section described the proposed method for aspect-based sentiment analysis. This stage makes use of any remaining data that was not used to develop the predictive model of the sentiment polarity analyzer. Our proposed method incorporates two main approaches.

4.1. **Assembling sentences into specific clusters.** Firstly, each hotel review is split down into sentences, and then these customer reviews are pre-processed using the processes outlined in Section 3.1. Later, word count is performed to count the number of each word in a sentence. Finally, those review sentences are assembled into a specific cluster (i.e., staff hotel attentiveness, cleanliness, value for money, and location) using the BM25 [27], which is a similarity analysis approach. Then, the keywords-for-aspect is used as the *query* (Q) for comparing the similarity with the vector of review sentences (s). The BM25's formula can be defined as follows.

$$BM25(Q,s) = \sum_{i=1}^{|Q|} idf(q_i) \times \left(\frac{tf\ (q_i, s) \times (k_1 + 1)}{f(q_i, s) + k_1 + \left(1 - b + b \times \frac{|s|}{sl_{avg}}\right)} \right) \tag{11}$$

$$idf(q_i) = \log \left(\frac{N - df(q_i) + 0.5}{df(q_i) + 0.5} \right) \tag{12}$$

where $tf(q_i, s)$ refers to the term frequency used to determine the frequency of query terms q-th occurs in the set of obtained sentences, while $|s|$ is the number of words in the obtained sentence s, and sl_{avg} defines the average length of the sentences in the corpus. $tf(q_i, s)$ is normalized using the parameter b, and its value should be between 0.5 and 0.8. The free parameter k_1 is employed to control the value calculated by $(1-b+b\times(|s|/sl_{avg}))$. If the value of k_1 is 0, this only determines whether a term is present in a sentence, whereas greater values of k_1 indicate that the weight of the terms increases with the number of times a term t appears in a sentence s. The typical values for b and k_1 in this study were 0.8 and 2.0, respectively. For the $idf(q_i)$ component, N is the whole number of obtained sentences in the corpus and $df(q_i)$ is the number of obtained sentences containing the term q-th of Q. If a sentence contains '*term-words*' that are representative of different clusters, it can then be grouped into many clusters.

4.2. **Identifying sentence's sentiment using the sentiment polarity analyzer.** After grouping customer review sentences into specific hotel aspect clusters, *tf-igm* is used to re-weight the customer review sentences corresponding to the specific aspect vector. Later, the sentiment polarity analyzer examines the sentences in each vector to determine the sentiment polarity (i.e., positive and negative). Finally, each aspect cluster's sentences are divided into two sentiment classes: positive and negative. The information contained in each category explains why consumers "dislike" or "like" each hotel aspect.

5. **Results.** The results of the proposed method are provided in this section.

5.1. **Evaluations of sentiment classification models.** This section presented the results of each sentiment classification model developed by different machine learning algorithms. Experimental results of these sentiment classifiers measured by recall, precision, F1, accuracy, and AUC are presented in Table 3.

TABLE 3. The results of each sentiment classification model developed by different machine learning algorithms

Algorithms	Average of recall	Average of precision	Average of F1	Average of accuracy	AUC
C4.5	0.78	0.77	0.77	0.77	0.789
MNB	0.81	0.80	0.80	0.80	0.812
SVM with linear kernel function	0.83	0.82	0.82	0.82	0.832
SVM with RBF kernel function	0.81	0.79	0.80	0.80	0.810
LR	0.82	0.81	0.81	0.81	0.821
Proposed ensemble method	0.84	0.83	0.83	0.83	0.838

5.2. **Comparison of the proposed sentiment polarity analyzer and the baseline.** In addition, we compared the proposed sentiment polarity analyzer model to the baseline model proposed by Iqbal et al. [28] because the objective of this method is similar to our work. However, the algorithms utilized to develop sentiment are different. The main algorithm used in Iqbal et al. [28] is the LSTM algorithm. The dataset used for the comparison is the same dataset used in this study. After evaluating these methods via recall, precision, F1, and accuracy, the results of these measurement metrics are presented in Table 4.

TABLE 4. The results of comparison between the proposed sentiment polarity analyzer model and the baseline

Method	Recall	Precision	F1	Accuracy
The proposed model of sentiment polarity analyzer	0.84	0.83	0.83	0.83
The baseline proposed by Iqbal et al. [28]	0.79	0.78	0.78	0.79

When compared to the baseline method, the results show that our method increases recall, precision, F1 and accuracy scores by 6.33%, 6.41%, 6.41% and 5.06%, respectively. Our proposed model outperforms the baseline since it is based on the ensemble method, which is always less noisy. Furthermore, the ensemble method is more stable and can reduce model bias/variance, which can result in underfitting/overfitting. Another reason why our proposed model outperforms the baseline approach is that our dataset is small. As a result, it may have an impact on the performance of the LSTM algorithm, which is the primary algorithm utilized to generate the predictive model in the baseline method.

5.3. **Evaluations of the proposed hybrid method for aspect-based sentiment analysis.** However, after evaluating our hybrid method for aspect-based sentiment analysis via recall, precision, F1, and accuracy, the results of these measurement metrics are presented in Table 5.

TABLE 5. The results of the proposed hybrid method for aspect-based sentiment analysis

Processing steps in the proposed method	Average of recall	Average of precision	Average of F1	Average of accuracy
Assembling sentences into specific hotel aspect clusters	0.80	0.78	0.79	0.80
Identifying sentence's sentiment using the sentiment polarity analyzer	0.84	0.83	0.83	0.83
Average scores	0.820	0.805	0.810	0.815

By utilizing BM25 for sentence clustering into specific hotel aspect clusters, this algorithm helps to achieve great performance and efficiency when composing relevant sentences for each hotel aspect. This is due to the fact that this algorithm employs heuristic techniques for document length normalization in order to satisfy the concavity constraint of the term frequency. In addition, BM25 represented the relative relevance and weight of terms in sentences. This means BM25 more precisely assesses the importance of a sentence by extracting detailed information from words, sentences, and sentence collections rather than depending just on term appearance. Meanwhile, since the sentiment polarity analyzer is developed using the ensemble method, it was able to perform better than any single contributing model and generate superior predictions. As a result, the proposed sentiment polarity analyzer produces satisfactory results. However, if the method of assembling sentences into specific hotel aspect clusters produced unsatisfactory results, it could have an impact on the next stage, which is using a sentiment polarity analyzer to determine each sentence's sentiment.

In addition, we compare our hybrid method to a baseline method proposed by Namee et al. [29] using the identical training and test sets. Our proposed method improved recall and precision scores by 4.76% and 4.88%, respectively. Greater recall and precision indicate that our hybrid method produces more relevant results than irrelevant ones and performs effectively.

6. **Conclusions.** This study's primary objective was to present a hybrid method for aspect-based sentiment analysis of hotel reviews. Considered hotel aspects include hotel attentiveness, hotel cleanliness, value for money and convenience of hotel location. The proposed method was comprised of two primary components. The first component applied the BM25 algorithm to assembling the review sentences corresponding to each specific hotel aspect into a particular cluster. In this stage, the Skip-gram component of Word2Vec was employed to generate keywords relevant to each hotel aspect, which were subsequently used as queries to assemble sentences into a cluster corresponding to each hotel aspect. Finally, the sentiment (positive or negative) of each hotel review sentence in each cluster is then determined using the sentiment polarity analyzer, an ensemble model made up of five prediction models created using the C4.5 decision tree, MNB, SVM with linear kernel, SVM with RBF kernel, and LR. In addition, we compared the proposed sentiment polarity analyzer model with the baseline model presented by Iqbal et al. [28]. When compared to the baseline method, the results show that our method increases recall, precision, F1 and accuracy scores by 6.33%, 6.41%, 6.41% and 5.06%, respectively. Finally, our proposed hybrid method yielded satisfactory results with recall, precision, F1, and accuracy scores of 0.820, 0.805, 0.810, and 0.815, respectively. Furthermore, we also compared our hybrid method to a baseline with the same training and test sets. The recall and precision scores of our proposed method were slightly better than the baseline, with improved recall and precision scores at 4.76% and 4.88%, respectively.

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