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A CONCEPTUAL MODEL FOR DECISION SUPPORT SYSTEMS USING ASPECT BASED SENTIMENT ANALYSIS

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Abstract. Sentiment analysis and opinion mining is the most explored area of research where an opinion has been analysed for better decision and recommendation. Currently this field has been supported by many decision support systems that not only depend on the preferences of a decision support system (DSS) designer but also affected by the public thoughts and opinions. Potential users along with their opinions also play a vital role in decision making process. Minion's exploration using sentiment analysis is the process of analysing facts, sentiments and opinions that are expressed on different social media forums in the form of tweets or reviews. In this research work, a decision process and sentiment analysis has been amalgamated to strengthen the functionality of traditional DSS for better decision-making process from reviews of open forums. The proposed system comprises of data extraction from social media reviews, pre-processing using natural language processing (NLP), aspects extraction using part of speech (POS) tagger and normalized Google distance (NGD). Aspect optimization using genetic algorithm (GA) and finally polarity estimation of each sentiment expressed in the review using SentiWordNet is computed. The experimental results conclude the supremacy of the proposed work by adding the sentiment and opinion information performed better decision-making process than the existing state-of-art techniques.

***Key words**:* decision support systems, sentiment analysis, machine learning, normalized Google distance.

1. INTRODUCTION

Due to the rapid use of the World Wide Web, online discussions on different forums have been increased. Due to this, the amount of data has increased and can be utilized for a better decision-making process. Customer reviews related to a particular product are considered the most important source of information. These reviews are extremely essential in terms of both social and economic significance, through which someone gets the right decision about the product they are purchasing. Different companies, restaurants, and shopping malls can use these reviews to learn about the positive and negative attributes of their products and try to improve the quality of their products [1]. As far as the extraction of these reviews is concerned, all such opinions are mostly extracted either by public request or any programming-based interface (API). These are further classified into certain polarity scales such as binary (positive, negative) or multi (angry, happy, etc.).

Sentiment classification is a subfield of natural language processing (NLP) that analyses reviews and opinions into some predefined classes such as positive, negative, and neutral [2]. In most research studies, sentiment analysis is usually performed at three different levels, including sentence level, document level, and aspect level [3]. Aspect level sentiment analysis is the latest level of sentiment analysis, which works on the concept that an opinion contains both a sentiment and a target of opinion. As a result, the target of the opinion is directly identified [4].

Due to the latest advancements in sentiment analysis and its integration with Decision Support Systems (DSS), the prediction process has become more reliable. Because of its importance, there exists a need to develop systems that integrate the extracted sentiments and opinions with decision support systems to perfectly analyse the user reviews. Decision support systems are information-based intelligent systems, which take decisions in any particular domain [5] to extract and construct knowledge-based models.

The decision problems [6] are concerned with judging, ranking, and mining of complex problems that are usually complicated by having different criteria. Past studies have shown that users always prefer to take many criteria before making a final decision. Moreover, in most cases, there is controversy about the selection of any relevant match among different criteria. In many cases, optimal choice does not usually occur. Decision making is a multidisciplinary field, which is extracted from operational research, for solving complex problems using mathematical approaches. Some real-time applications of DSS are medical diagnosis [6], loan verification [7], business management [8], weather forecast [9], etc. The DSS and analysis of sentiments at sentence level have been heavily studied in previous studies as, for example, [10]. However, there are few current studies aimed at the integration of aspect-level sentiment analysis with DSS. Most DSS with sentiment analysis techniques are syntax-based and mainly focused on the standard structure of linguistics. These approaches were not focused on the semantic meaning of aspects and opinions. In this research, the sentiments and opinions of users are integrated with decision support systems. Sentiments and opinions enhance the working of decision support systems and as a result, improve the efficiency of the decision support system.

The main contributions of this paper are:

1) an aspect identification and optimization technique for sentiment analysis that produces a high-quality decision due to novel similarity measures and models;

2) use the lexicon-based method to calculate the polarity of sentences/reviews;

3) integrate aspects with decision support systems in order to increase the decision power of DSS.

The rest of this article is structured as follows: Section 2 describes the past studies of sentiment analysis and decision support systems. Section 3 illustrates the proposed conceptual model of aspect-level sentiment analysis with a decision support system. Section 4 shows the experimental results, comparison with state of art techniques, and discussion. Conclusions are given in Section 5.

2. LITERATURE REVIEW

Aspect-based sentiment analysis is a field of study that predicts people's sentiments, emotions, and attitudes by identifying aspects towards entities. These entities may be events, topics, products, etc. [11]. Opinion mining is another term that is closely related to sentiment classification. Opinions are the expressions that represent people's emotions, sentiments, and feelings. The four factors generate opinions, i.e., topic, holder, claim, and sentiment [12]. The following section provides a review of various existing methodologies from previous research works.

Aspect-level sentiment analysis contains feature extraction at the aspect level and sentiment classification. Banjar et al. [13] proposed a model to calculate the polarity estimation of users' tweets. Part of Speech tagger was used for aspect extraction and aspect refining. Aspect Co-Occurrence with semantic similarity was calculated. Later, polarity is estimated using a novel match pattern approach. Three different datasets were used, tweets from Twitter, public reviews, and forum reviews. The proposed model achieved 85.7% accuracy for extraction of aspects and 86.5% accuracy for polarity calculation. The proposed model for aspect level sentiment analysis achieved many improvements as compared to state of art techniques for sentiment analysis. Janjua et al. (2021) [14] introduced a hybrid approach to determine aspect-level sentiments using deep learning instead of machine learning techniques. The hybrid approach consisted of rule mining for aspect detection, Information Gain and PCA for sentiment detection, and Neural network for classification. Experiments were performed on five different benchmark Twitter datasets. The results showed that the proposed technique improved the results in determining the implicit and explicit aspects of multi-level terms.

Mowlaei et al. (2020) [15] proposed two different lexicon generation methods for aspect-level problems: Aspect-Based Frequency-Based Sentiment Analysis and Adaptive Lexicon Learning using a Genetic Algorithm (ALGA). The results were compared with some baseline methods. The results showed that proposed models achieved far better results as compared with baseline methods. Mir and Mahmood

(2020) [16] applied BiLSTM-CRF and hybrid NERC techniques on movie reviews dataset. The paper mainly focused on “Named Entity Recognition” to find entity related aspects. The results were also compared with some past techniques such as CRF and LSTM-CRF. Proposed techniques showed improved results as compared to other techniques. Ishaq et al. (2020) [17] argued the model that identifies aspects related to a sentiment and entity on every aspect. Semantic features are mined using “Word2Vec” from the text. To extract opinions, a convolutional neural network (CNN) was employed, and CNN parameters were tuned using a multi-objective function and a Genetic Algorithm (GA). The proposed model runs on two different domains of data, which were collected from online review sites: hotel reviews and automobile reviews. Nandal el al. (2020) [18] targeted these bipolar words in aspect-based sentiment analysis. A classifier called “Support Vector Machine” (SVM) was used to determine the sentiments. The dataset was collected from Amazon using a Scrappy based web crawler. Experimental results were very promising as compared with old techniques.

Alamanda (2020) [19] presented an online search engine which was developed for checking sentiments from users’ reviews and tweets. Aspects were extracted using a POS tagger and then Naïve Bayes and support vector machines were applied with RNN-LSTM to find out the accuracy of aspects. The use of deep learning techniques with machine learning techniques enhanced its performance. Tran et al. (2019) [20] presented novel techniques which help hotel staff gain more precise, proper information and insights from their guests and services. It was done by aspect-based sentiment analysis. The authors developed the modified BiLSTM-CRF model for the extraction of aspects with their polarities. At the end, topics were modelled using LDA. 75,933 reviews of 405 hotels were collected from the TripAdvisor website. Nawaz et al. (2019) [21] proposed a sentiment analysis technique that improves the quality of items using public reviews. Part of the speech tagger with Visuwords is used for aspect extraction and aspect reduction. The relational classifier was used to classify the reviews and assign the class in the form of “recommend”, “not recommend” etc. The proposed model achieved 87.45% for car reviews, 91.56% for hotel reviews, and 90.85% for mobile phone reviews. Bidirectional encoder representation from transformers (BERT) weakly supervised classifier (non-linear approach [23, 24]) was introduced for Aspect based sentiment analysis [22]. The proposed method could successfully increase the accuracy of ABSA tasks while also reducing space time complexity.

From the above discussion, it has been concluded that traditional state-of-the-art techniques for aspect-based sentiment analysis are hectic and unable to handle opinions. Due to the lack of DSS, their results are not up to the mark. Moreover, due to the complex nature of reviews, only sentiment analysis-based models may fail to give better results. Therefore, there is a need to design a system that identifies sentiments from free text with better precision. The proposed work is an attempt to design the system with the desirable results. From experimental evaluation, it has been concluded that the performance of the proposed technique is better than the current state of the techniques available in the literature due to the integration of DSS into the standard sentiment analysis process.

3. PROPOSED METHODOLGY

This section provides the description of the key phases of the proposed model. In this research, social media reviews have been utilized for analysis by using hybrid computational algorithms, i.e. Machine Learning and Decision Systems. The key steps of the proposed model include problem formulation, data pre-processing, aspect extraction, optimization, polarity calculation, and recommender systems. The graphical representation of the proposed model is also illustrated in Fig. 1.

3.1. Problem formulation

A review ‘R’ contains a set of terms in which an opinion was expressed by a user. Each review contains multiple aspect terms, and each aspect term has three different sentiment polarities i.e., positive, neutral, and negative:

$$R = t_1, t_2, t_3, \ldots, t_n \tag{1}$$

where n is the total number of terms, and

$$R_{Sub} = f\left(R, \mathrm{SSR}\right) \tag{2}$$

where R_{Sub} are the reviews that are subjective and SSR is the subjectivity score of reviews. Aspects are extracted from subjective reviews:

$$A = a_1, a_2, a_3, \ldots, a_i . \tag{3}$$

In equation (3), a_i denotes the i^{th} aspect word in aspect vocabulary A, and A is a subsequence of review. Optimal aspects are selected from aspects set in terms of:

$$A_{Opt} = f\left(A, \mathrm{GA}\right)), \tag{4}$$

where

$$A_{Opt} = a_{1\_opt}, a_{2\_op}, a_{3\_op}, \ldots, a_{i\_op}$$

$$P_k = P_1, P_2, P_3, \ldots, P_j, \ldots, P_c . \tag{5}$$

P_k denotes the candidate sentiment polarities, where c denotes the number of categories of sentiment polarity and the P_j is the j^{th} sentiment polarity. The aspect-based sentiment analysis model aims to identify the most likely sentiment polarity of a particular aspect. It can be stated as follows:

$$\text{Input} \Rightarrow \; R = t_1, t_2, t_3, \ldots, t_n \;\&\; A = a_1, a_2, a_3, \ldots, a_i$$

$$\text{Output} \Rightarrow \; P_k = \phi\left(a_i, P_j \setminus R\right). \tag{6}$$

In equation (6), ϕ shows a function that quantifies the degree of matching between the sentiment polarity P_j and the aspect a_i in the review R. Polarity of reviews is calculated using function ϕ. Finally, the model illustrated in Fig. 1 outputs the sentiment polarity with the highest matching degree to be the classification result.

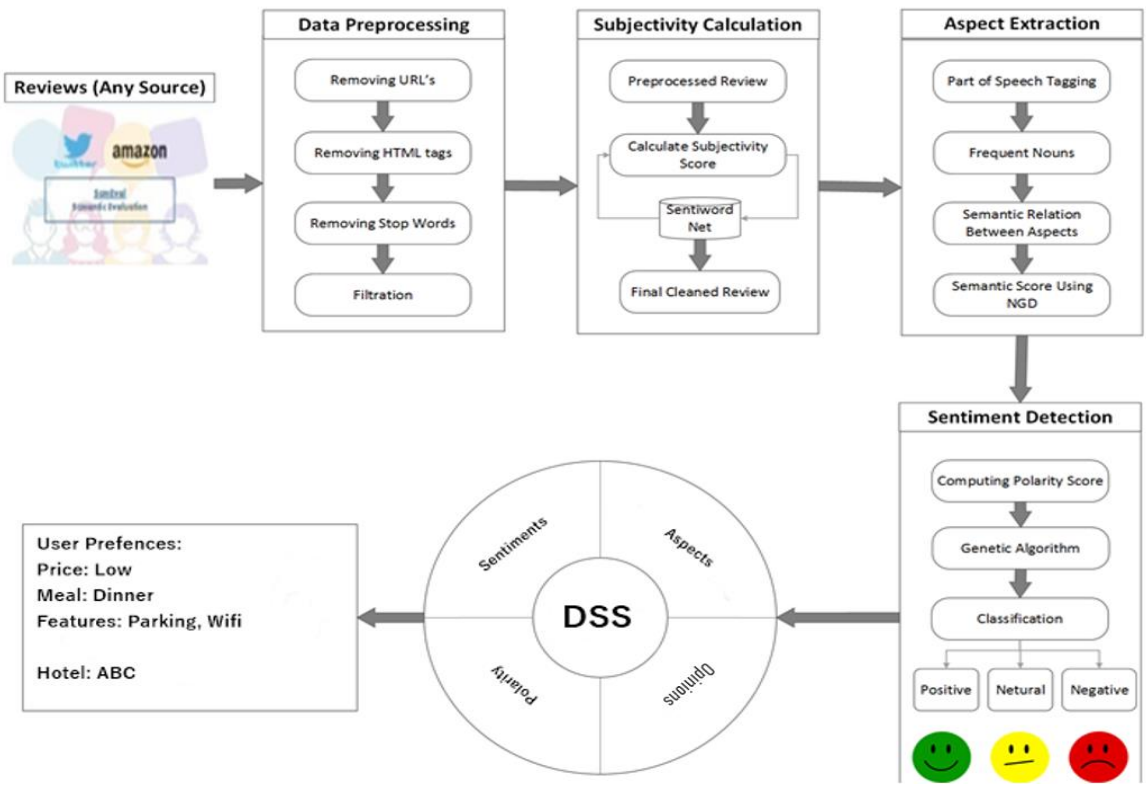

Fig. 1 – Proposed model.

3.2. Dataset

Three different types of datasets have been collected. The first benchmark dataset was about 515,000 customer reviews[1] [25] related to a particular hotel in Europe. In another dataset, almost 500 reviews[2] have been collected from the most usable hotel booking site, named as tripadvisor.com. The last dataset is composed of tweets that have been extracted from Twitter using the Twitter API (Application Program Interface). The key phrases used for extraction are hashtag such as #hotels, #restaurants, #outlet etc. Detail descriptions of these datasets are tabulated in Table 1.

Table 1

Dataset description

#	Dataset	Demographic Location	No. of reviews
1	Benchmark dataset	Europe	515,000
2	Hotel reviews	Asia	500
3	Twitter tweets	Miscellaneous	200

3.3. Data Preprocessing

Due to the noisy nature of reviews, there exists a need to clean and pre-process the data before further analysis. The core objective of this step is to prepare data in a format that can be efficiently utilized for further operations to derive meaningful results [6]. Numerous text processing algorithms and techniques such as HTML tags elimination, stemming, transformation and stop-word removal are applied. Initially, Porter stemmer [26] has been applied for stemming the text. Common words (i.e., is, am, be, are) that have no effect on the performance, has been eliminated. URLs and redundant terms are also filtered by using regular expression-based coding. Moreover, reviews having length less than three characters have also been eliminated. Whereas all the symbols and punctuation that create ambiguity are dropped out from the text.

3.4. Subjectivity Score Calculation

Almost all the reviews may contain two different types of sentences that are subjective and objective. The subjective sentences express positive and negative sentiments such as feelings, judgments, and opinions. While the objective sentences do not express any opinion at all, because some objective sentences are statements of facts [4]. For example, “I love the country” is a subjective sentence and “The world is massive” is an objective sentence. There is another example is movie review, “The movie A is the most watched movie all the time” is the objective sentence and “The movie A is the most influential movie of all time, or that it is the greatest movie of all time.” is the subjective sentence. In this research due to the importance of subjectivity, the following relationship is used for subjectivity score calculation:

$$\mathrm{SSR} = \frac{\sum_{i=0}^{n} w_i \left(S_{+ve} + S_{-ve} \right)}{n} \, . \tag{7}$$

Here, SSR is the Subjectivity Score of Review, W is the weight of word, S_{+ve} is positive score of word, S_{-ve} is negative score of words and n is total numbers of word in review.

3.5. Aspect Extraction

After the reduction of objective sentences, aspects are extracted from reviews and tweets using a Part-of-Speech tagger (POS) [27]. This process determines the key features that potentially participate in the analysis of the whole review. The POS tagger labels all the terms with parts of speech such as verbs, adjectives, adverbs, and nouns. Usually, improper nouns are considered as aspects [28].

Most of the aspects are multi conceptual in nature due to its semantic structure and appearance in the review. Therefore, it becomes necessary to consider the semantic relation of aspects with opinions. Due to this, the performance accuracy of the technique may degrade if such relations have not been considered. Most of the existing techniques do not consider the semantic relationship. In this research, semantic relationship between two words is computed by Normalized Google Distance (NGD) which is a semantic similarity measure. NGD works on the number of hits returned by the Google search engine for a given pair of words [29]. Whereas the words with the same meanings in NLP are considered to be "close" in units of NGD, while words with dissimilar meanings tend to be farther apart. The mathematical computation of number of hits against each aspect opinion pair is carried out as follows:

$$\mathrm{NGD}\left(w_1, w_2\right) = \frac{\max\left\{\log f(w_1), \log(w_2)\right\} - \log f(w_1, w_2)}{\log(N) - \min\left\{\log(f(w_1), \log(f(w_2)\right\}}. \tag{8}$$

Here

w_1 and w_2	First Word and Second Word
N	Pages present in Google. e.g., N: 25,270,000,000,000
$f(w_1)$ and $f(w_2)$	Number of pages contain word w_1 and w_2 (separate)
$f(w_1, w_2)$	Number of pages contain both words.

3.6. Sentiment Detection

Existing studies focused on using machine learning techniques to analyse opinions in text. However, one of the drawbacks is that execution time for these techniques increases due to the increased volume of aspect set of data. In addition, redundant and irrelevant aspects contribute to sentiment analysis [3], which reduces the technique's accuracy. The main purpose of this step is to optimize the aspects using a genetic algorithm (GA) and only consider the appropriate aspects.

A GA is a type of evolutionary algorithm (EA) that is purely based on the biological evolution theory [30]. Biological evolution is mainly composed of crossover, reproduction, and selection. In this research, GA is applied to extract the most optimal aspects from a large set of aspects. The genetic algorithm (GA) runs on the population in the form of chromosomes and the population size becomes fitter as iterations run in terms of fitness. During the iteration process, crossover and mutation are performed continuously to get better and better aspects from time to time [31]. Whereas, in each iteration two chromosomes are selected for crossover and one chromosome is selected for mutation. The crossover operation produces two new children, whereas the mutation produces one new child. After applying crossover and mutation, the chromosomes are compared by their fitness function. This process is repetitive and continues until certain convergence criteria on the fitness values are met or a fixed number of iterations is completed. At the end, the fitness value shows the optimal aspect. Each element of the chromosome represents the semantic relationship between two aspects.

Convergence can occur after a threshold of 230,000 iterations and after this, the population is not going to improve any more. In this way, the complete datasets after some specific number of iterations are converged and almost identical aspects are obtained. The aspects with the highest fitness value are the final aspects. The logical flow of the GA is shown in Algorithm 1.

Algorithm 1: Genetic Algorithm

```
// Initialization
for x = 1 to population_size
    for y = 1 to aspect_count
        Score ( x, y ) = SemRel ( x, y )
    end for
end for
for iterations = 1 to number of iterations
SelectParents (Parent1, Parent2) // Selection of parents
// Crossover
if Random(0, 1) < p c
        C1, C2 = Crossover (Parent1, Parent2)
else
        C1 = Parent1, C2 = Parent2
// Mutation
        Mutation (C1), Mutation (C2 )
```

```
        Calculate_Fitness (C1 ), Calculate_Fitness (C2)
    Select_For_Replacement ( R1, R2 )
     // Chromosomes with highest fitness values are selected
     Q1, Q2 = Bestof ( C1, C2, R1, R2 )
     R1 = Q1, R2 = Q2
     end for
```

After this process, the most optimal aspects are the inputs for the polarity calculation process, which is based on lexicon-based structure. There are many lexicons that are publicly available for the sentiment analysis process, and their performance is quite remarkable. However, because of the wide range of vocabulary and real-time process, the proposed technique uses "SentiWordNet 3.0" for this calculation [32]. By using a built-in lexicon, SentiWordNet provides the positive, negative, and neutral weight of aspects. Polarity is calculated by adding the weight of all aspects presented in the sentence along with the positive and negative scores obtained from SentiWordNet. SentiWordNet provides the synset's identification number (ID), part of speech (POS), sense number, and term lemma. During which the identification number (ID) uniquely identifies the synset and Lemma.

3.7. Decision Support System

The polarity obtained from the above steps is the potential component of the DSS. The traditional DSS system was based on a rating that was failed by considering all features. As there were several conflicting criterions for taking any decision that makes the decision problems complex [33–35]. The proposed modification to DSS will make the decision process more rational, clear, and efficient. The DSS module applies utility functions to modify the values of the domain attributes into numerical values that show the user's preferences such as like or dislike, positive or negative thinking about any item, product, or service. In this work, three different kinds of attributes that are categorical, numerical, and linguistic are considered along with aspects and polarity for decision. For numerical values, there is no need to transform the attributes to numerical values as they are already in numerical form. Categorical attributes are calculated using the utility function:

$$(U;F) = \frac{|U \cap F|}{|U|}. \tag{9}$$

Here, U is the user's preferred value and F shows the number of attributes for a specific object. The categorical attributes utility function calculates the percentage of preferred value intended by the specific object which the user wants to improve. For example, if the user preferences feature is 'food' and their $U=\{a,b,c,e,f\}$ and values provided as alternative are $F=\{x,a,b,e,z\}$. Then categorical criterion for feature 'food' are $= \frac{|\{a,b,e\}|}{\{a,b,c,e,f\}}$ = 0.6. Finally, the linguistic attributes are calculated using the utility function:

$$g\,(a;b) = |L| - \mathrm{abs}(\mathrm{post}(a) - \mathrm{post}(b)). \tag{10}$$

Here, a is a term preferred by the user and b is the term coming in alternative. The set of linguistic terms is L and the function post returns the position of specific value in set. Like in the example of the food feature if L = {Chinese, Italian, Continental, Thai} are the linguistic values. Let's assume that the user wants to eat Italian food and alternatively, continental food. Then post (Italian) is 2 and post (Continental) is 3:

$$g\,(\text{Continental; Italian}) = 4 - \mathrm{abs}(4-3) = 4 - 1 = 3.$$

4. RESULTS

Three different evaluation measures: precision, recall, and accuracy have been applied to validate the performance of the proposed technique for aspect extraction. Whereas K-Fold cross validation has been applied for the evaluation of sentiment classification. Initially, the dataset is divided into K bins of equal sizes, in which one bin is considered for testing and the remaining (K–1) bins for training [36]. K iteration has been performed and the results are averaged for aggregate values. In these experiments, the value of k for evaluation is taken as 5. The obtained results are tabulated in Table 2.

Table 2

Experimental results

#	Dataset	Accuracy	Precision	Recall
1	Hotel dataset (Benchmark)	88.65	87.13	87.75
2	Hotel reviews (Trip advisor)	91.02	88.11	88.36
3	Twitter tweets (Twitter)	89.64	88.84	88.34

When the proposed approach has been compared with the existing models [14, 37, 38], it has been observed that the performance of the proposed technique in term of accuracy, precision and recall is higher. These existing models, namely BERT + CNN [37], Lexicon + GA [14] and Lexicon + RNN [38] of sentiment analysis are chosen for comparison based on similar algorithms and domain datasets. As shown in Table 3, the proposed technique produced better accuracy, precision, and recall. The reason of improved accuracy is the addition of Normalized Google Distance and Genetic Algorithm based feature optimization technique to the traditional sentiment analysis process that was based on lexicon.

Table 3

Comparison with state-of techniques

#	Technique	Precision (%)	Recall (%)	Accuracy (%)
1	BERT + CNN [37]	85.40	84.30	84.30
2	Lexicon + GA [14]	87.12	87.32	87.26
3	Lexicon + RNN [38]	83.12	83.45	85.00
4	**Lexicon + GA + NGD (P.T)**	**88.03**	**88.15**	**89.77**

As far as the application of extracted aspects from POS tagger, optimized by Normalized Google Distance and Genetic algorithm is concerned, it is successfully deployed in the DSS for hotel recommendation. The stability and robustness of the proposed aspect-based sentiment analysis technique, shows that it can be further applied in other domains as a base of DSS. Based on sentiment analysis results and aspects, the proposed DSS predicts the hotels for people more accurately. Some of the results are listed in Table 4, when it applied to hotel recommendation.

Table 4

Recommendation of hotels

#	Price	Cuisine	Meal	Distance	Features	Result
1	High	Seafood	Lunch	Near to city	Wifi, Car Parking	Hotel A
2	Low	BBQ	Dinner	Near to Park	Credit cards accepted	Hotel B
3	High	–	Breakfast	Near to office	Private dining	Hotel B
4	–	–	Brunch	Sports club	Private dining	Hotel C
5	–	Tea	Super & Dinner	Specific area	Car Parking	Hotel D
6	Normal	Italian	Lunch	–	Wifi	Hotel E
7	High	Chines	Dinner	Any area	Credit cards accepted, Wifi, TV	Hotel C
8	Low	Turkish	Dinner	Near to Park	–	Hotel B

For ease of understanding, a Wordcloud-based visualization has been proposed to show the most frequent recommendations of a particular hotel. These reviews and tweet are also visualized as shown in Fig. 2. The most prominent words in the Wordcloud represent positivity of hotel reviews. Some of the negative words such as expensive, noisy, and overpriced are also available, that need improvements. Hotel administration can improve the quality using the recommendation generated by the proposed model.

Fig. 2 – Wordcloud visualization of hotel reviews.

5. CONCLUSION

Due to the rapid growth of the Web, there exist multiple platforms for users to express their views and ideas about any products and services. Owing to which bulk of information data have been generated that can be used for successive decision making. Traditional sentiment analysis process may utilize this for polarity estimation and classification, although it is quite remarkable, but sometimes may fail due to domain-based dictionaries and lack of optimal DSS.

This research work is an attempt to present a novel technique that is integration of aspect-based sentiment analysis with DSS along with novel similarity measures like NGD. From the experimental evaluation, it is observed that the performance of the proposed technique in term of accuracy, precession and recall is far better than the existing benchmark techniques.

In future, the proposed work can further be enhanced by introducing other similarity measures in DSS model. Another research direction is the application of the proposed techniques to other domains like event identification.

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