Machine Learning with Applications 6 (2021) 100114

Contents lists available at ScienceDirect

Machine Learning with Applications

journal homepage: www.elsevier.com/locate/mlwa

Restaurant recommender system based on sentiment analysis

Elham Asani [a], Hamed Vahdat-Nejad [a,*], Javad Sadri [b]

[a] Faculty of Electrical and Computer Engineering, University of Birjand, Birjand, Iran
[b] Computer Science and Software Engineering Department, Concordia University, Montreal, Quebec, Canada

ARTICLE INFO

Keywords:
Recommender system
Sentiment analysis
Context-awareness
Preference extraction
Semantic computing

ABSTRACT

Today, exploiting sentiment analysis has become popular in designing recommender systems in various fields, including the restaurant and food area. However, most of the sentiment analysis-based restaurant recommender systems only use static information such as food quality, price, and service quality. The analysis of users' opinions and the extraction of their food preferences lead to the provision of personalized recommendations, which is a research gap in literature; In this paper, a context-aware recommender system is proposed that extracts the food preferences of individuals from their comments and suggests restaurants in accordance with these preferences. For this purpose, the semantic approach is used to cluster the name of foods extracted from users' comments and analyze their sentiments about them. Finally, nearby open restaurants are recommended based on their similarity to user preferences. For evaluation, the TripAdvisor website has been used and comments from 100 different users have been collected during the first 9 months of 2018. The precision, recall and f-measure of the system are measured in three scenarios of top1, top3, and top5. The results indicate that the proposed system can provide recommendations with a precision of 92.8%, giving users a high degree of precision. Besides, the system outperforms the previous research in these criteria.

1. Introduction

Recommender systems help users make informed decisions by collecting information about their preferences in a variety of areas, including products and services (García-Sánchez, Colomo-Palacios, & Valencia-García, 2020). These systems make it possible for users to choose the best of many options (Altan, & Karasu, 2019). The choice of restaurant among numerous and unknown selections is one of the important uses of the recommender systems, especially for tourists and travelers (Esmaeili, Mardani, Hashemi Golpayegani, & Zanganeh Madar, 2020). However, extracting user's preferences is a challenging issue in these systems. Traditional approaches such as using questionnaires (Miao, Gao, Chen, Cui, Guo et al., 2016) or user's provided rates to restaurants, Mahadi, Zainuddin, Shah, Naziron, and Rum (2018) cannot dynamically extract their preferences.

Nowadays, online comments on websites and social networks are considered a rich source of implicit information (Walek, & Fojtik, 2020). In this regard, the user's preferences of food can be derived from the processing of these comments and the analysis of their underlying sentiments. To this end, natural language processing methods (Cambria, Poria, Gelbukh, & Thelwall, 2017) could be exploited to process and discover the implicit feelings hidden in the user's comments. In fact, with the help of sentiment analysis techniques, the author's feelings about a variety of topics could be deducted. On the other hand, human language is complex, so people may use different words to express a concept. Therefore, it is suitable to use a semantic approach to sentiment analysis.

Previous recommendation systems that are based on sentiment analysis analyze users' opinions based on restaurant characteristics such as quality of service. Food is the most important factor in choosing a restaurant (Anderson, 2018). The previous recommender systems (Hedge, Satyappanavar, & Setty, 2018) utilize general methods such as Term-Frequency (TF) or Bag of Word to extract the names of the food. Repetitive patterns on the one hand indicate the user's preferences and on the other hand, indicate items that the user is not interested in and are extracted only because of repetition. As a result, the accuracy in recommendation is low in these systems. In this paper, we augment the extraction of user's preferences by sentiment analysis.

The proposed recommender system is designed to first extract the users' preferences from their textual comments and then it suggests restaurants tailored to these preferences. For this purpose, after doing the text mining and extracting the nouns in the user's comments, unrelated nouns to the food domain are identified and filtered using the WordNet (Pedersen, Patwardhan, & Michelizz, 2004) ontology. These nouns are then clustered together based on their semantic similarity. Afterwards, the sentences containing them are transmitted to the cluster and scored using sentiment analysis. Based on the scores earned, the cluster with the highest score reflects user preferences. Then, by converting the user's preferences as well as the restaurant's menu into

* Corresponding author.
E-mail addresses: elham.asani@birjand.ac.ir (E. Asani), vahdatnejad@birjand.ac.ir (H. Vahdat-Nejad), j_sadri@encs.concordia.ca (J. Sadri).

https://doi.org/10.1016/j.mlwa.2021.100114
Received 29 April 2021; Received in revised form 22 June 2021; Accepted 14 July 2021
Available online 19 July 2021

vectors and calculating the similarity between them, the suitability of the restaurant for the user could be calculated. Finally, the restaurants that their menu is the most similar to user's preferences are proposed to them.

The data from comments available on the TripAdvisor[1] website is used to evaluate the proposed recommender system. The evaluation results indicate that the proposed system can provide users with highly accurate recommendations.

The contributions of this paper are as follow:

- The proposed personalized system extracts user preferences by analyzing their opinions and refines the obtained list by sentiment analysis. The accuracy of extracting user preferences by analyzing each user's comments is far higher than methods such as TF.
- In extracting users' preferences, a semantic method is used to cluster the names in the comments in order to increase the accuracy.
- A relevant dataset has been collected from the TripAdvisor website to evaluate the proposed system in real situations.

The remainder of the paper is organized as follows: Section 2 investigates the related research. In Section 3, the proposed recommendation system is described. Section 4 evaluates the proposed system and Section 5 concludes the paper.

2. Related work

Recommender systems seek to identify the preferences of users to suggest them set of items that best suit their priorities. There are several ways to extract user preferences, including explicit queries (Zeng, Li, Liu, Wen, & Hirokawa, 2016), star ratings (Liu et al., 2020) and user opinion analysis (Abbasi-Moud, Vahdat-Nejad, & Sadri, 2021). In the query-based methods at the beginning of the login, the user's preferences are extracted via answering some questions in the form of a questionnaire. In this regard, in a restaurant recommender system (Miao et al., 2016), when the user enters the system, they are asked to choose their desired price and food type among the options. The extraction of preferences by this method has some disadvantages, as food preferences might be inconsistent with the questions of the static questionnaire. Besides, based on the stars that users have already rated, some other recommender systems extract users' preferences and adapt the suggestions (Castro, Cordon, & Martinez, 2015). For example, in some research in the restaurant area (Mahadi et al., 2018; Zhang, Zhang and Wang, 2018), customers are grouped according to the similarity of ratings that they have already done. Similarly, restaurants are grouped according to their similarity to user ratings in terms of quality, service, food, and price. Then, based on the similarity between the restaurant group and the user group, various restaurants are offered to them.

With an increase in the volume of users' comments and reviews on websites and social networks, extracting their preferences by sentiment analysis has become feasible. Since users comment on their priorities and interests, extracting their preferences by using opinion mining and sentiment analysis could provide more flexible and accurate information than previous approaches. Hence, some of the restaurant's recommender systems have been utilizing user comments analysis to extract their preferences (Ashok, Rajanna, Joshi, & Kamath, 2016; Zhang, Salehan, Leung, Cabral and Aghakhani, 2018). If the system's purpose is to identify the preferences based on users' opinions, then sentiment analysis techniques could be exploited to determine the polarity of the opinions, i.e., its positive or negative orientation. To this end, machine learning (Ghiassi, & Lee, 2018; Zhang, Miao, Wang, & Zhang, 2019) and dictionary-based methods (Phu, Chau, Tran, & Dat, 2018; Zhang, Wei, Wang and Liao, 2018) are widely used. In these methods, sentiment analysis is performed at three levels: document level (Yessenalina, Yue, & Cardie, 2010), sentence-level (Meena, & Prabhakar, 2007), and aspect level (Hu, & Liu, 2004). For example in a research (Trevisiol, Chiarandini, & Baeza-Yates, 2014), after extracting food names by natural language processing, sentiment analysis is performed at the sentence level using the LIWS 2007 (Pennebaker, Francis, & Booth, 2001) dictionary, and users' sentiment ratings are collected in relation to each dish. In another study (Kiritchenko, Zhu, Cherry, & Mohammad, 2014), after identifying features such as food prices and restaurant environment in users' opinions, sentiment analysis is done at an aspect level using support vector machine. In a similar work (Hedge et al., 2018), for each restaurant, the top n foods that customers have been mostly satisfied with are extracted. To do this, first TF and Bag of Word are used to extract the feature. The SVM algorithm is then used to analyze user feedback based on the extracted features. Finally, in every restaurant, top n better food is recommended to other users from the customers' point of view. Another study (Nurifan, Sarno, & Sungkono, 2019) also uses TF to extract restaurant features. Different restaurants are examined from 4 aspects of the physical environment, food quality, service quality and price fairness. It should be noted words related to these 4 aspects are extracted through topic modeling and TF. Then, using the emotion analysis algorithm (Qiu, Liu, Bu, & Chen, 2011), user comments for each restaurant are analyzed on 4 different aspects and different restaurants are ranked.

Some restaurant recommendation systems use collaborative filtering to provide suggestions to users. For instance in one study (Deac-Petruşel, & Limboi, 2020), first, the scores of different users' emotions for different features of the restaurant are collected using SentiWordNet. The KNN algorithm then calculates the similarity between the two users based on Attractiveness, Relevance and Popularity. Finally, based on the similarity of users, top n restaurants are recommended to each user.

In another research (Liu, & Gan, 2016), restaurant features are extracted from users' opinions and the polarity of each opinion on these features is calculated by machine learning and sentiment analysis at the sentence level. This work also utilizes contextual information such as time, user's companion and user objective. Then, the correlation between restaurant features with user preferences and contexts is calculated by the Analytic Hierarchy Process analysis, and therefore, restaurants with a higher correlation coefficient are suggested. Finally, in our previous work (Asani, Vahdatnejad, Hosseinabadi, & Sadri, 2020), the foods that receive the most emotional points from the users are extracted as user food preferences. To this end, the name of foods extracted from the users' comments are scored by sentiment analysis. The results show that the accuracy of this method in extracting users' food preferences, is better than the previous works.

To the best of our knowledge, none of the previous restaurant recommender systems has used the full potential of opinion mining and sentiment analysis to extract user's food preferences. According to a recent survey conducted in the field of food science based on text mining (Tao, Yang, & Feng, 2020), only one research (Mostafa, 2018), uses sentiment analysis to find out how users feel about the quality of foods. Besides, an article (Ara, Hasan, Al Omar, & Bhuiyan, 2020) published in 2020, uses sentiment analysis on restaurants comments, to extract the level of customers' satisfaction with the quality of foods. Both of these studies address different issues regarding the current paper. In this research, the extraction of food preferences is done using the user's textual reviews analysis. On the other hand, the restaurant menu is used to extract the features of each restaurant. In addition, previous feedback of users about restaurants is exploited as contextual information and the restaurants that their sentiment analysis score for quality features and services is less than a threshold, are removed from the list of suggestions.

3. Proposed system

The proposed system consists of two parts including extracting preferences and recommending. In this section, they are described in detail.

[1] https://www.tripadvisor.com/.

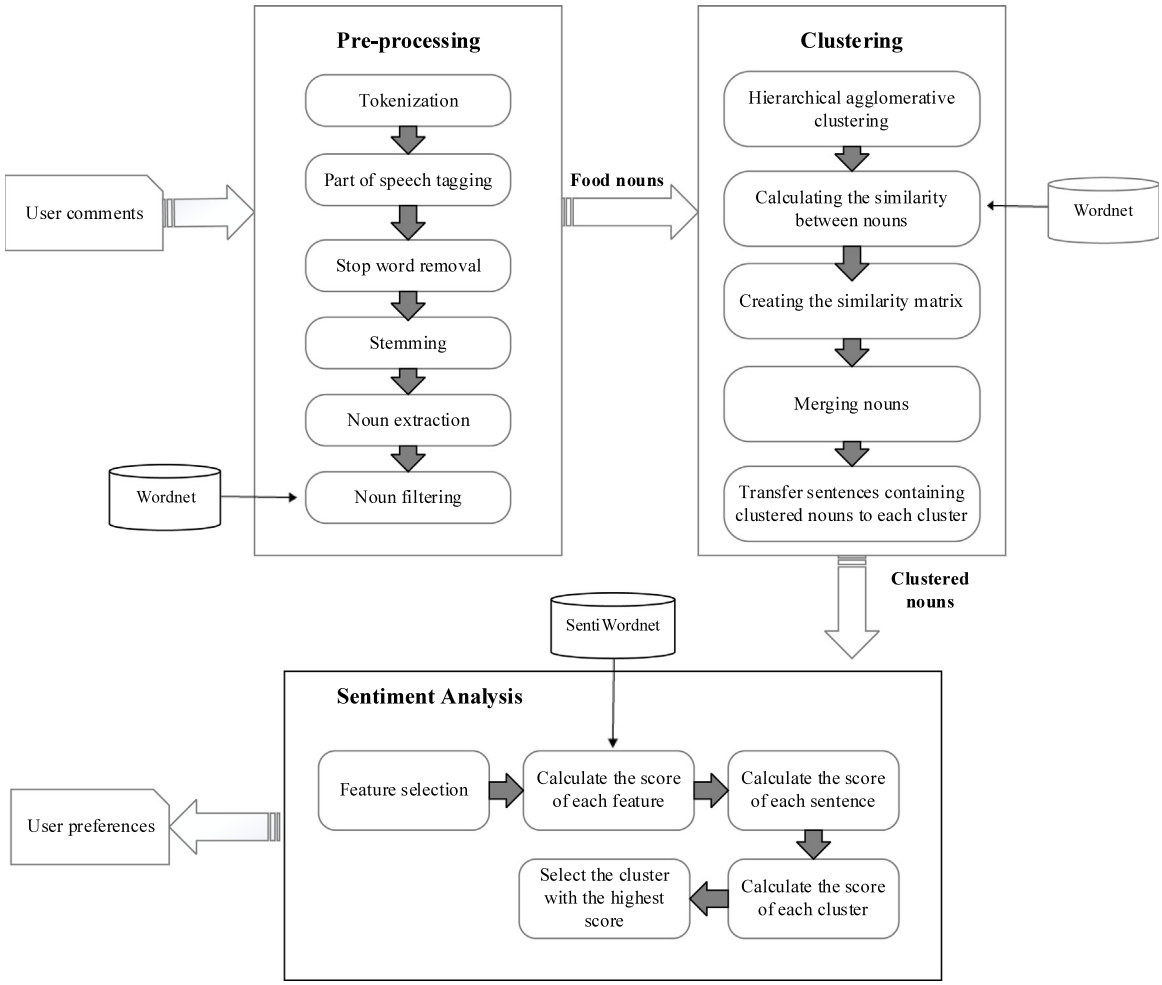

Fig. 1. The overall scheme of the extracting preferences phase.

3.1. Extracting preference

This part consists of three stages including preprocessing, clustering, and sentiment analysis. Fig. 1 shows the overall scheme of the extracting preferences.

3.1.1. Preprocessing

The preprocessing includes tokenization, part of speech tagging, stop word removing, stemming, noun extracting, and noun filtering. Tokenization mainly focuses on detecting words. Then, the words get tags that determine their syntactic role (such as verb, subject, adjective, etc.) in the sentence. The stop words including “a”, “an”, “and”, “but”, “the”, “that”, “of”, “from” are deleted (Vijayarani, Ilamathi, & Nithya, 2015). Then the suffix and prefix of the words are deleted and the stem of them remains.

The stemming helps to reduce all derivatives of a word, which are not semantically different, into a common concept (Katariya et al., 2015). For example, if a document contains words like “eating” and “eaten”, they are all considered as “eat”. As we are looking for preferences of the user that are usually in the form of nouns, the words that have received the noun tag are extracted.

Since the number of these nouns may be very large, unrelated nouns are filtered (Karasu, Altan, Bekiros, & Ahmad, 2020). For this purpose, these nouns are looked up in the food domain of the WordNet. If a noun is not available in the food vocabulary classification and its synonyms of the WordNet, it is deleted.

3.1.2. Clustering

Clustering techniques are divided into hierarchical and partitioning categories. In partitioning clustering, the number of clusters is determined at the beginning of the work, but in hierarchical clustering, it is not necessary to specify the number of clusters. Moreover, clusters produced in hierarchical clustering often have higher quality, but their time complexity is usually more than partitioning techniques (Steinbach, Karypis, & Kumar, 2000). As data filtering reduces the number of nouns, agglomerative hierarchical clustering (De Knijff, Frasincar, & Hogenboom, 2013) is exploited for categorizing nouns.

To this end, each noun is firstly considered as a cluster. Afterward, the semantic similarity between the nouns in the food domain is calculated according to the Wu–Palmer (Wu, & Palmer, 1994) index. This index uses the distance between the two concepts in the word hierarchy tree of the WordNet ontology. In general, the similarity between the two concepts of C_1 and C_2, with the least common subsume of C_3, is equal to:

$$\mathrm{Sim}(C_1, C_2) = \frac{2N_3}{N_1 + N_2 + 2N_3}, \tag{1}$$

whereas Fig. 2 illustrates, N_1 represents the number of nodes on the C_1 to C_3 path, N_2 is the number of nodes on the C_2 to C_3 path, and N_3 is the number of nodes on the path between C_3 and the root of the tree.

Afterwards, the pair of clusters that have the smallest distance from each other are merged and the distance between the new cluster and the other clusters is calculated This process is repeated until the similarity between the clusters becomes less than a threshold value.

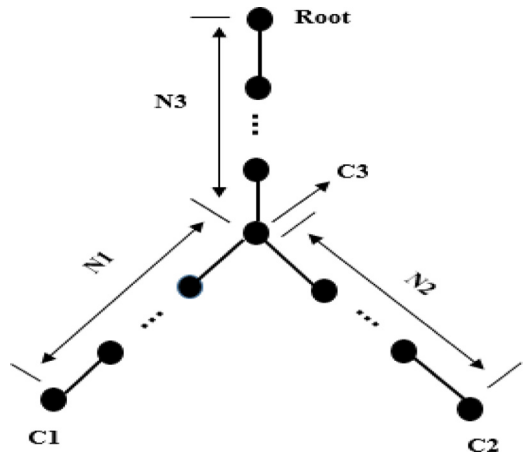

Fig. 2. The word hierarchy tree in WordNet (Wu & Palmer, 1994).

3.1.3. Sentiment analysis

Finally, the sentences that include any of the words of a cluster are transferred to that cluster. It should be noted that as a sentence typically consists of several words, it may be assigned to more than one cluster. Afterward, each sentence is analyzed, and its positive and negative sentiments are extracted. Because after calculating the score of all sentences, the sentiment score of the total cluster is calculated, sentiment analysis is done at the document level. In this research, after applying different methods for sentiment analysis, the results obtained by the SentiWordNet dictionary have shown a higher precision. Therefore, SentiWordNet dictionary is used for sentiment analysis, as follows (Denecke, 2008):

In the SentiWordNet, the synonyms of each word are assigned positive, negative, and objective polarity scores. Each score is within the range of [0,1] and the sum of the three scores should be equal to 1. For example, the triple score assigned to the word "good" is equal to ($score_{pos}$, $score_{neg}$, $score_{obj}$ = 0.875, 0.0, 0.125 (Siersdorfer, Chelaru, Nejdl, & San Pedro, 2010). For sentiment analysis using SentiWordNet, all words of sentences that have received "adjective", "verb", or "adverb" tags are selected as attributes (Dang, Zhang, & Chen, 2010). Then the triple score is specified for all the synonyms of each of these words using the SentiWordNet.

The positive score of each word A is equal to the total positive scores of all its synonyms divided by the number of synonyms. Objective and negative scores of each word A are calculated in the same way, as follows:

$$\text{score}_{\text{pos}}\ (\text{A}) = \frac{1}{n}\sum_{i=1}^{n}\text{score}_{\text{pos}}\ (\text{i}) \tag{2}$$

$$\text{score}_{\text{neg}}\ (\text{A}) = \frac{1}{n}\sum_{i=1}^{n}\text{score}_{\text{neg}}\ (\text{i}) \tag{3}$$

$$\text{score}_{\text{obj}}\ (\text{A}) = \frac{1}{n}\sum_{i=1}^{n}\text{score}_{\text{obj}}\ (\text{i}) \tag{4}$$

where n is the number of synonyms. After calculating the triple polarity score for all features in a sentence, the calculation of the score of the sentence is performed similarly. That is, the positive score of each sentence is equal to the average positive score of all the words in the sentence. Objective and negative scores are calculated in the same way.

After determining the triple score for each sentence, if the positive score of the sentence is higher than the negative score, the whole sentence is considered positive and vice versa. If the positive and negative scores are equal, the sentence is objective, and this sentence is not considered in the calculation of the cluster score. Then, the sentiment analysis score of each cluster is computed as follows:

$$\text{S}_{\text{c}} = \frac{Np - Nn}{Np + Nn} \tag{5}$$

where N_p and N_n are the numbers of positive and negative sentences inside the cluster, respectively.

At the end of this stage, the cluster that earns the highest score is chosen as the food preferences cluster of the user. If another cluster's score is very close to the selected cluster (less than 0.1 difference), then the second cluster is also selected, and the nouns of both clusters are combined and returned as user's preferences. Fig. 3 illustrates an example that describes these processes.

3.2. Recommender system

Fig. 4 shows the overall scheme of the recommender system, and Fig. 5 illustrates the extraction of context information.

The proposed content-based recommender system analyzes the content of user-written comments and recommends restaurants based on the similarity of their menu to the preferences extracted from the user's comments. Furthermore, based on the food items that the user has chosen in the past, the system offers him restaurants with a similar menu. This type of recommendation is exploited in item-to-item collaborative filtering systems. Therefore, the proposed system is a hybrid filtering system.

3.2.1. Context information

As shown in Fig. 4, the proposed recommender system is context-aware and suggests nearby restaurants based on the location of user. Working times of restaurants are also available on their websites and are considered in the recommendations. That is, if the restaurant is not open when recommended, it will be deleted from the list of offers. User preference itself is also an important element of contextual information that is used in the recommendation. In order to analyze users' opinions on different restaurants, first, a preset list containing words related to a service is provided. For example, #cleanliness and #staff refer to services. In addition, another list containing food names in each restaurant is also provided to examine the quality of foods for each restaurant. As an example, the sentence "Staff fairly disorganized" expresses a negative feeling about the feature of the service, and the sentence "Pizza was very delicious" expresses a positive feeling about the feature of quality. Finally, the opinions of previous customers are analyzed for each restaurant. Given the positive or negative opinions about their quality of food and services, restaurants whose sentiment analysis scores for these two features are less than 0.7 are filtered. This score for quality and service features is calculated using the following equation:

$$\text{Score of sentiment for each feature} = \frac{number\ of\ positive\ comments\ per\ feature}{the\ total\ number\ of\ comments\ related\ to\ that\ feature} \tag{6}$$

After extracting user preferences, the similarity of preferences is calculated with the menu of restaurants located around the user that are open at that time. Then, restaurants that their menus are the most similar to user preferences and have gained high scores based on comments from previous users are recommended to them. The restaurant menus are already available in the database, and pre-processing is performed including tokenizing multi-part names (for example, chicken pizza), removing stop words (such as with and to), and deleting unrelated characters (such as numeric characters and $).

In order to calculate the similarity between the cluster of user preferences and the restaurant menu, first all the features (food names) of them are extracted. Then the features (food names) in the preferences cluster are considered as columns of a matrix that includes row vectors of restaurant menus and the user preferences. The array in the preference row is filled according to the Term Frequency of features in the cluster of preferences. It should be noted that as some of the features are repeated, by determining the weight using TF, their importance is determined. The elements of the row arrays corresponding to menus are

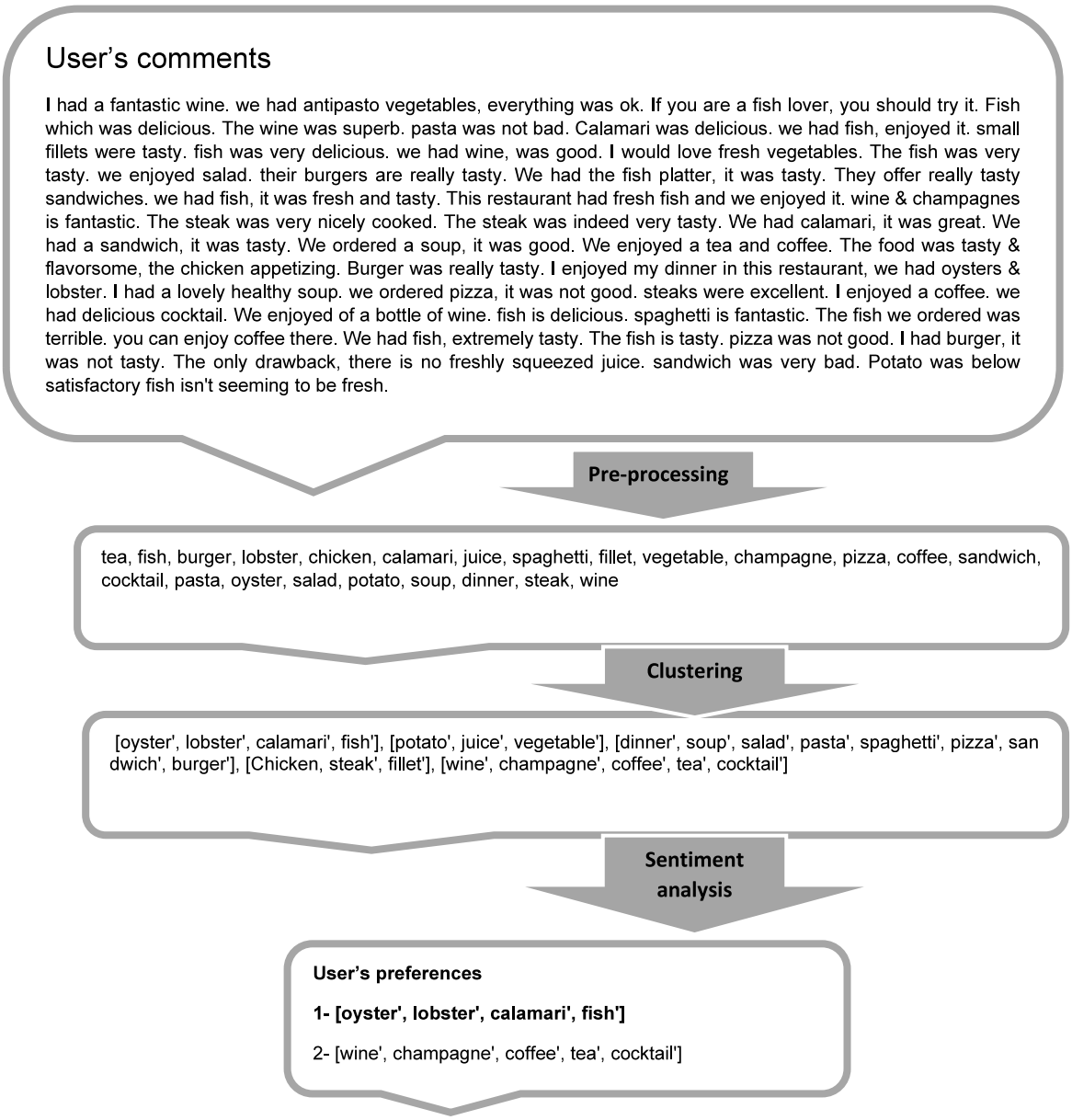

Fig. 3. An example of extracting user's preferences.

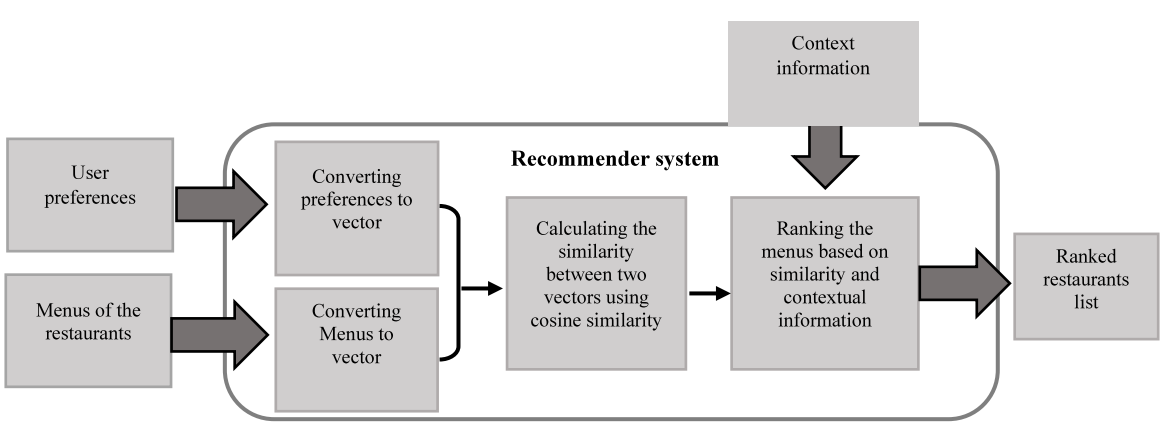

Fig. 4. The overall scheme of the recommender system.

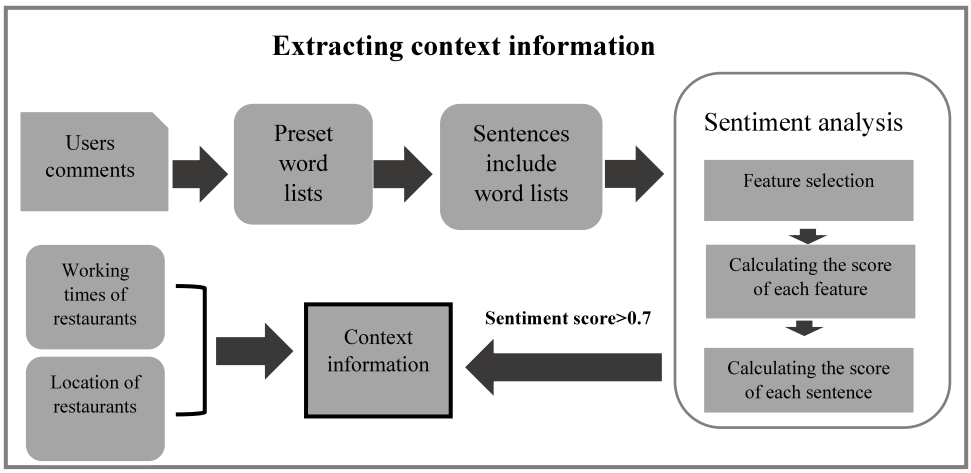

Fig. 5. Extracting context information.

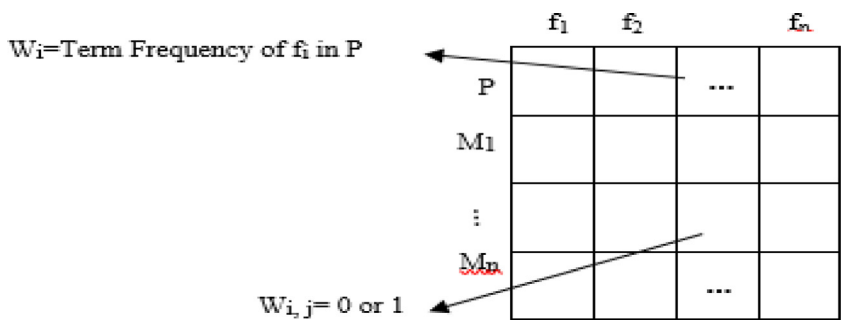

Fig. 6. The feature matrix of the user preference and restaurant menus.

either 1 (if the corresponding feature exists in the menu) and otherwise zero. This process is shown in Fig. 6.

Then, the matrix arrays are normalized using the following formula:

$$\mathrm{TF}_{i,j} = \frac{W_{i,j}}{\sum_{k=1}^{n} W_{i,k}} \tag{7}$$

The cosine similarity criterion is then used to calculate the similarity between the user preferences and the restaurant menu (Salton, & McGill, 1986):

$$\mathrm{Cos}(\theta) = \frac{P \cdot M}{|P|\,|M|} = \frac{\sum_{i=1}^{n} P_i M_i}{\sqrt{\sum_{i=1}^{n} (P_i)^2}\sqrt{\sum_{i=1}^{n} (M_i)^2}} \tag{8}$$

In this case, P is the vector of user preferences, M is the vector of the restaurant menu, P.M is the internal multiplication of the two vectors, |P| is the size of the preference vector, |M| is the size of the menu vector, and θ is the angle between the preference and menu vectors. P_i is the ith element of the vector P, and M_i is the ith element of the vector M.

The result will be a number between 0 and 1. The number 1 indicates that the words in the preferences and the menu are exactly identical, and the zero number represents the existence of totally dissimilar words in them.

Among the names of foods in the preferences cluster, there might be names that consist of two or more sections such as mushroom burger. In the tokenization stage, each of these sections is considered as a separate name. In the clustering process, these two names may be separated by assigning them into two clusters. Therefore, in the conversion stage of the features of the preferences cluster into a vector, other names found in the vicinity (immediately before or after) of the food names of the cluster are also included in the preferences vector. In the conversion of the menu to a vector, the multi-part names in the menu are separated, and each part is considered as a separate name. This will increase the precision of the recommendations. This idea is presented in the following example and is shown in Table 1.

Table 1
Example of a preferences and menu vectors.

	Mushroom	Hotdog	Ham	Burger
Preferences	1	1	1	1
Menu	1	0	0	1

Preference = mushroom burger, hotdog, ham

Menu = mushroom burger, lasagna, pizza, sandwich, chicken

According to Table 1, if the word mushroom is considered as a feature in the user's preferences, the similarity between the two vectors will be equal to 0.707, otherwise, it will be equal to 0.577.

4. Experiment

The comments of users on the TripAdvisor website have been used to evaluate the proposed system. Every user's comments comprise reviews on restaurants, tourist areas, and hotels, of which restaurant reviews are extracted. 100 users have been randomly selected and their reviews were collected during the period from January to October 2018. The data of the first 6 months (January–June) has been used for training to extract the preferences of each user. Then for testing the system data from July to October has been used for each user to measure the precision of the system.

The proposed system offers recommendations based on the current location of the user. For this purpose, the Google maps service is used to identify the current city of the user. Then, assuming a is the radius of the current city, three types of recommendations are suggested,

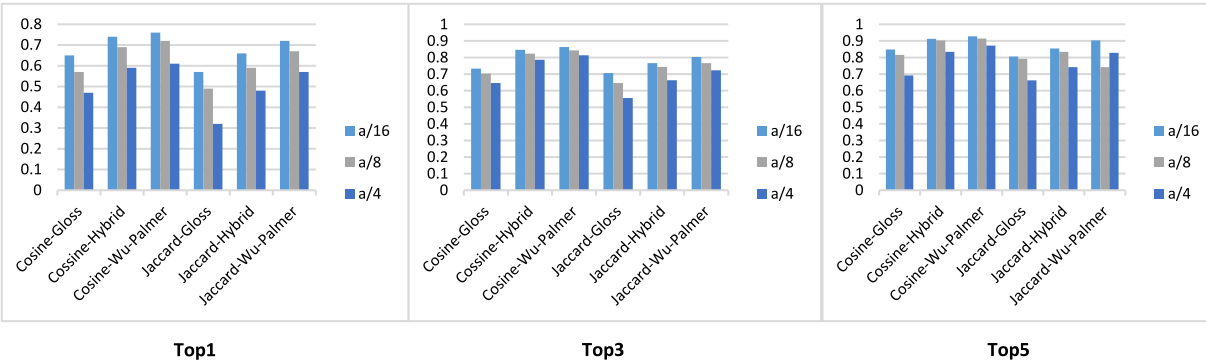

Fig. 7. Precision of the proposed system at different distances using different methods.

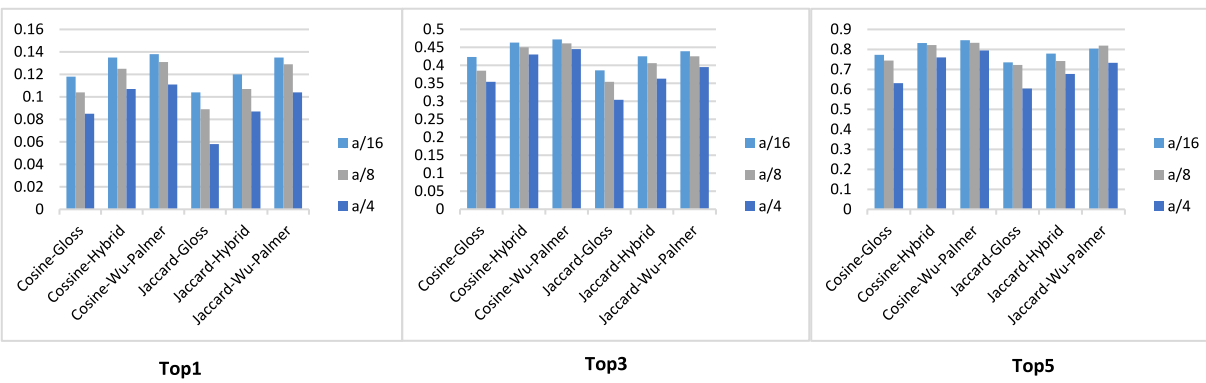

Fig. 8. Recall of the proposed system at different distances using different methods.

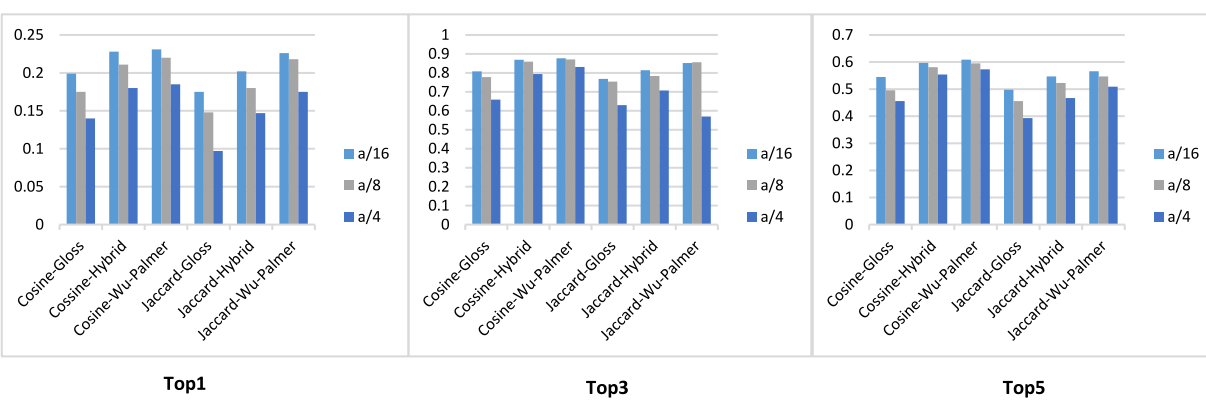

Fig. 9. F-measure of the proposed system at different distances using different methods.

including the restaurants with a maximum distance of a/16, a/8, and a/4 to the user's current position. To this end, by comparing the user preferences derived from the training data, with the menu of each of the accessible restaurants, the system provides a ranking list of nearby restaurants.

To assess the similarity metrics for the proposed system, the clustering stage is performed using three criteria of Wu–Palmer, Gloss, and the combination of these two criteria (Wei, Lu, Chang, Zhou, & Bao, 2015) based on the threshold value of 0.75. In the recommendation stage, the similarity between menu and preferences vector is measured using the cosine and Jaccard methods (Niwattanakul, Singthongchai, Singthongchai, & Wanapu, 2013). Then, the precision is measured using the combination of each clustering method with each similarity measurement method at different distances. Based on the results obtained by each of these methods, the precision of the system is measured in the following modes:

- Top 1: If the user has gone to the first recommended restaurant on the list, the system has done a successful recommendation.
- Top3: If the user has gone to one of the first three proposed restaurants on the list, the system has done a successful recommendation.
- Top5: If the user has gone to one of the first five proposed restaurants on the list, the system has done a successful recommendation.

Then the precision and recall are defined as follows:

Precision = What percentage has been visited out of recommended restaurants.
Recall = Out of visited restaurants, what percentage has been recommended.
F-measure = 2*

$$\text{F-measure} = 2 * \frac{Precision * Recall}{(Precision + Recall)}$$

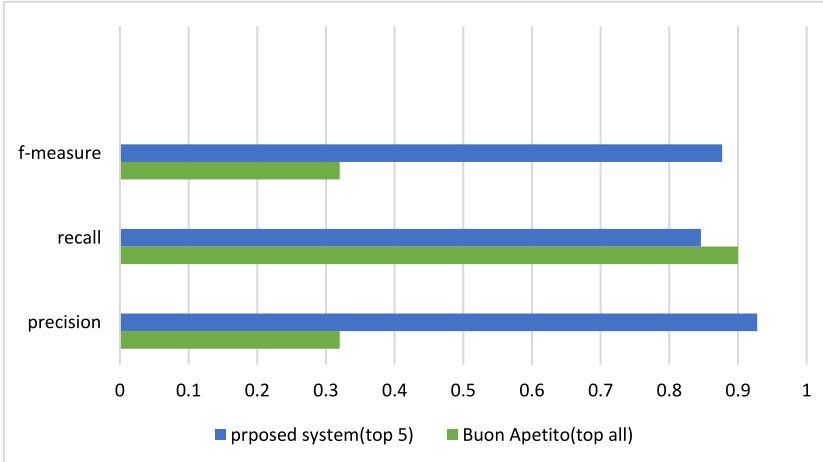

Fig. 10. Comparison results of the proposed system with Buon Appetito (Trevisiol et al., 2014).

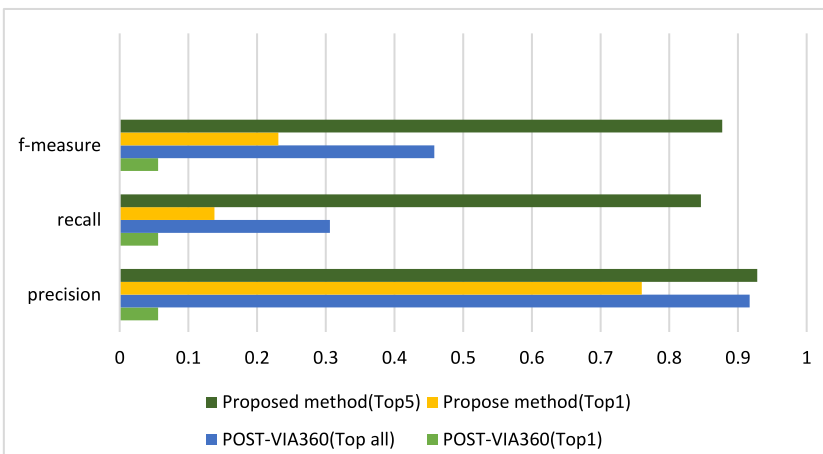

Fig. 11. Comparison of the results of the proposed system with POST-VIA 360 (Colomo-Palacios, García-Peñalvo, Stantchev, & Misra, 2017).

Fig. 7 shows the precision results in all modes using different methods at different distances. Similarly, Fig. 8 illustrates the recall results.

According to the diagrams, the combination of Wu–Palmer and cosine methods has higher precision than the combination of other methods. Hence, in this research, the similarity criterion of Wu–Palmer is selected to cluster the nouns and the similarity criterion of cosine is opted to calculate the similarity between menus and user preferences. In all cases, the precision of the system decreases as the distance increases. This is due to the fact that with increasing the distance, the number of restaurants around the user increases. Hence, the number of restaurants that have foods in accordance with user preferences will increase. Therefore, though logically the system produces proper suggestions, the probability that the user has gone to any of the top1, 3, or 5 restaurants decreases. Since food names are categorized based on semantic similarity and restaurants also offer a special range of foods (e.g. fast foods and traditional foods (lamb, beef and so on)), the results show that the proposed method can identify the desired restaurants for users with high precision.

The precision of the system in the Top 5 mode is more than Top3, which in turn is more than Top1. The reason is the increase in the number of recommendations in the Top 5. Because in Top5, the system generates 5 recommendations, the possibility for the user to go to one of them is more than the two other modes. As a result, the precision of the system is more. It is also observed that the changes in precision at different distances for Top5 are less than Top3, which in turn is less than Top1. As the distance increases, the number of available restaurants increases. However, in the Top5 (and also in Top3) modes, because of further recommendations, the user is more likely to go to a restaurant that the system offers. Also, according to Fig. 8, the recall values are reduced at greater distances. This is also due to the fact that with increasing the distance, the number of available restaurants around the user that have foods according to his preferences also increases. As the user has visited a limited number of them, the recall value tends to decrease. Similarly, recall values increase in Top3 and Top5 modes. In these modes, the number of recommended restaurants increases; thus, the likelihood that the visited restaurants are recommended increases.

Fig. 9 shows the f-measure diagrams. The higher the distances, the lower the f-measure is, since f-measure directly depends on the value of recall and precision and these parameters are reduced by increasing the distance.

As the evaluation methods and nature of the sentiment analysis-based restaurant recommender systems are different, their comparison is complicated. Among the previous research, Buon Appetito (Trevisiol et al., 2014) and POST-VIA 360 (Colomo-Palacios et al., 2017) are the most similar works to the proposed system. In Buon Appetito, the foods with the highest sentiment analysis score are recommended to users using the Fuzzy Apriori algorithm. Fig. 10 shows the comparison results between the proposed system and Buon Appetito. The proposed system yields a much higher precision as well as f-measure comparing with Buon Appetito [27]; however, the recall has a bit decreased. It should be noted that precision is a much more important parameter than recall in the restaurant recommendation domain.

POST-VIA360 (Colomo-Palacios et al., 2017) is a sentiment analysis-based as well as context-aware recommender system, which recommends points of interests such as restaurants. Fig. 11 presents the results of comparison between the proposed system and POST-VIA360. The results show that the accuracy of the proposed system in Top1 is by far more than POST-VIA360. Also, in Top5, there is an improvement in accuracy, and the recall has increased compared to the previous work.

According to the evaluation results, the proposed system suggests the surrounding restaurants to the users with an accuracy of 92.8. Among the methods used to implement the proposed system, the combination of the Wu–Palmer and cosine methods shows the highest accuracy. Also, comparing the results of this work with previous methods shows an improvement in the accuracy of the recommendations.

5. Conclusion

In this paper, a method to extract user preferences of food from their online comments about restaurants has been presented. This method is based on the use of natural language processing techniques for processing the text of user comments and extracting the desired food names. The semantic similarity approach has been exploited to conceptually cluster food names. The clustering results with the Wu–Palmer method have shown higher precision. To obtain the opinion of the user regarding each food, the sentiment analysis has been performed to indicate whether their opinion is positive or negative. Finally, a recommender system has been proposed that suggests the nearby restaurants that match the food preferences of the user. The proposed recommender system is context-aware, so that, by using user preferences, location, time and feedback of all users, it recommends nearby restaurants that are open at that time and are well-matched with user's preferences. The data extracted from the TripAdvisor website in 2018 has been used to evaluate the proposed system. The results have shown that making use of the Wu–Palmer criterion for clustering and the cosine criterion for calculating similarities between preferences and menus yields the best results regarding precision, recall and f-measure. The results also revealed that the proposed system can provide users with 92.8% precision in the Top5 mode. Finally, comparing the proposed system with previous related works has shown an improvement in most of the above criteria.

As users usually visit restaurants in groups, group-based restaurant recommendation is a main future direction for this research. To this end, the similarity between users' preferences and their favorite foods in each restaurant should be specified.

CRediT authorship contribution statement

Elham Asani: Conceptualization, Methodology, Software, Writing – original draft. **Hamed Vahdat-Nejad:** Supervision, Conceptualization, Methodology, Writing – review & editing. **Javad Sadri:** Supervision, Methodology.

Declaration of competing interest

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

References

Abbasi-Moud, Z., Vahdat-Nejad, H., & Sadri, J. (2021). Tourism recommendation system based on semantic clustering. *Expert Systems with Applications*.

Altan, A., & Karasu, S. (2019). The effect of kernel values in support vector machine to forecasting performance of financial time series. *The Journal of Cognitive Systems*, *4*(1), 17–21.

Anderson, C. (2018). *A survey of food recommenders*. Ithaca, NY, USA: Cornell University, 2018.

Ara, J., Hasan, M. T., Al Omar, A., & Bhuiyan, H. (2020). Understanding customer sentiment: Lexical analysis of restaurant reviews. In *IEEE region 10 symposium (TENSYMP)* (pp. 295–299). Sonargaon Dhaka, Dhaka: IEEE.

Asani, E., Vahdatnejad, H., Hosseinabadi, S., & Sadri, J. (2020). Extracting user's food preferences by sentiment analysis. In *2020 8th Iranian joint congress on fuzzy and intelligent systems (CFIS)*. Mashhad, Iran: IEEE.

Ashok, M., Rajanna, S., Joshi, P. V., & Kamath, S. (2016). A personalized recommender system using Machine Learning based Sentiment Analysis over social data. In *IEEE students' conference on electrical, electronics and computer science*. United States.

Cambria, E., Poria, S., Gelbukh, A., & Thelwall, M. (2017). Sentiment analysis is a big suitcase. *IEEE Intelligent Systems*, *32*(6), 74–80.

Castro, J., Cordon, O., & Martinez, L. (2015). CLG-REJA: A consensus location-aware group recommender system for restaurants. In *9th ACM conference on recommender systems*. Vienna, Austria: ACM.

Colomo-Palacios, R., García-Peñalvo, F. J., Stantchev, V., & Misra, S. (2017). Towards a social and context-aware mobile recommendation system for tourism. *Pervasive and Mobile Computing*, *38*, 505–515.

Dang, Y., Zhang, Z., & Chen, H. (2010). A lexicon-enhanced method for sentiment classification: An experiment on online product reviews. *IEEE Intelligent Systems*, *25*(4), 46–53.

De Knijff, J., Frasincar, F., & Hogenboom, F. (2013). Domain taxonomy learning from text: The subsumption method versus hierarchical clustering. *Data & Knowledge Engineering*, *83*(1), 54–69.

Deac-Petruşel, M., & Limboi, S. (2020). A sentiment-based similarity model for recommendation systems. In *22nd international symposium on symbolic and numeric algorithms for scientific computing* (pp. 224–230). Timisoara, Romania: IEEE.

Denecke, K. (2008). Using sentiwordnet for multilingual sentiment analysis. In *IEEE 24th international conference on data engineering workshop*. Cancun, Mexico.

Esmaeili, L., Mardani, S., Hashemi Golpayegani, S. A., & Zanganeh Madar, Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications*, *149*(1), A novel tourism recommender system in the context of social commerce.

García-Sánchez, F., Colomo-Palacios, R., & Valencia-García, R. (2020). A social-semantic recommender system for advertisements. *Information Processing & Management*, *57*(2), Article 102153.

Ghiassi, M., & Lee, S. (2018). A domain transferable lexicon set for Twitter sentiment analysis using a supervised machine learning approach. *Expert Systems with Applications*, *106*(1), 197–216.

Hedge, S. B., Satyappanavar, S., & Setty, S. (2018). Sentiment based food classification for restaurant business. In *International conference on advances in computing, communications and informatics* (pp. 1455–1462). Bangalore, India: IEEE.

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. In *Tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. Seattle, WA, USA.

Karasu, S., Altan, A., Bekiros, S., & Ahmad, W. (2020). A new forecasting model with wrapper-based feature selection approach using multi-objective optimization technique for chaotic crude oil time series. *Energy*, 1–12.

Katariya, N. P., Chaudhari, M. S., Subhani, B., Laxminarayana, G., Matey, K., Nikose …, M. A., & Deshpande, S. P. (2015). Text preprocessing for text mining using side information. *International Journal of Computer Science and Mobile Applications*, *3*(1), 1–5.

Kiritchenko, S., Zhu, X., Cherry, C., & Mohammad, S. (2014). NRC-Canada-2014: Detecting aspects and sentiment in customer reviews. In *8th international workshop on semantic evaluation*. Dublin, Ireland.

Liu, Q., & Gan, X. (2016). Combining user contexts and user opinions for restaurant recommendation in mobile environment. *Journal of Electronic Commerce in Organizations*, *14*(1), 45–63.

Liu, H., Wang, Y., Peng, Q., Wu, F., Gan, L., Pan, L., & Jiao, P. (2020). Hybrid neural recommendation with joint deep representation learning of ratings and reviews. *Neurocomputing*, *374*(1), 77–85.

Mahadi, M. I., Zainuddin, N., Shah, N. B., Naziron, N. A., & Rum, S. F. (2018). E-halal restaurant recommender system using collaborative filtering algorithm. *Journal of Advanced Research in Computing and Applications*, *12*(1), 22–34.

Meena, A., & Prabhakar, T. V. (2007). Sentence level sentiment analysis in the presence of conjuncts using linguistic analysis. In *European conference on information retrieval*. Berlin, Heidelberg.

Miao, X., Gao, Y., Chen, G., Cui, H., Guo, C., & Pan, W. (2016). I 2 p: a restaurant recommendation system using preference queries over incomplete information. *VLDB Endowment*, *9*, Surajit Chaudhuri, Jayant Haritsa.

Mostafa, M. M. (2018). Mining and mapping halal food consumers: A geo-located Twitter opinion polarity analysis. *Journal of Food Products Marketing*, *24*(7), 858–879.

Niwattanakul, S., Singthongchai, J., Singthongchai, E., & Wanapu, S. (2013). Using of Jaccard coefficient for keywords similarity. In *International multiconference of engineers and computer scientists*. Hong Kong, China.

Nurifan, F., Sarno, R., & Sungkono, K. R. (2019). Aspect based sentiment analysis for restaurant reviews using hybrid ELMo-wikipedia and hybrid expanded opinion lexicon-senticircle. *International Journal of Intelligent Engineering and Systems*, *12*(6), 47–58.

Pedersen, T., Patwardhan, S., & Michelizz, J. (2004). WordNet::Similarity—measuring the relatedness of concepts. In *19th national conference on artificial intelligence*. San Jose, CA, USA.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). *Linguistic inquiry and word count: LIWC 2001, Vol. 71* (pp. 1–13). Mahway: Lawrence Erlbaum Associates.

Phu, V. N., Chau, V. T., Tran, V. T., & Dat, N. D. (2018). A Vietnamese adjective emotion dictionary based on exploitation of Vietnamese language characteristics. *Artificial Intelligence Review*, *50*(1), 93–159.

Qiu, G., Liu, B., Bu, J., & Chen, C. (2011). Opinion word expansion and target extraction through double propagation. *Computational Linguistics*, *37*(1), 9–27.

Salton, G., & McGill, M. J. (1986). *Introduction to modern information retrieval*. New York, NY, USA: ACM.

Siersdorfer, S., Chelaru, S., Nejdl, W., & San Pedro, J. (2010). How useful are your comments?: analyzing and predicting youtube comments and comment ratings. In *19th international conference on World wide web*. Raleigh, NC, USA.

Steinbach, M., Karypis, G., & Kumar, V. (2000). A comparison of document clustering techniques. In *KDD workshop on text mining*. Boston, MA, USA.

Tao, D., Yang, P., & Feng, H. (2020). Utilization of text mining as a big data analysis tool for food science and nutrition. *Comprehensive Reviews in Food Science and Food Safety*, *19*(2), 875–894.

Trevisiol, M., Chiarandini, L., & Baeza-Yates, R. (2014). Buon appetito - Recommending personalized menus. In *25th ACM conference on hypertext and social media*. Santiago, Chile.

Vijayarani, S., Ilamathi, M. J., & Nithya, M. (2015). Preprocessing techniques for text mining-an overview. *International Journal of Computer Science & Communication Networks*, *5*(1), 7–16.

Walek, B., & Fojtik, V. (2020). A hybrid recommender system for recommending relevant movies using an expert system. *Expert Systems with Applications*, *158*, Article 113452.

Wei, T., Lu, Y., Chang, H., Zhou, Q., & Bao, X. (2015). A semantic approach for text clustering using wordnet and lexical chains. *Expert Systems with Applications*, *42*(4), 2264–2275.

Wu, Z., & Palmer, M. (1994). Verbs semantics and lexical selection. In *32nd annual meeting on association for computational linguistics*. Las Cruces, New Mexico.

Yessenalina, A., Yue, Y., & Cardie, C. (2010). Multi-level structured models for document-level sentiment classification. In *Empirical methods in natural language processing*. Cambridge, Massachusetts.

Zeng, J., Li, F., Liu, H., Wen, J., & Hirokawa, S. (2016). A restaurant recommender system based on user preference and location in mobile environment. In *5th international congress on advanced applied informatics*. Kumamoto, Japan.

Zhang, Y., Miao, D., Wang, J., & Zhang, Z. (2019). A cost-sensitive three-way combination technique for ensemble learning in sentiment classification. *International Journal of Approximate Reasoning*, *105*(1), 85–97.

Zhang, S., Salehan, M., Leung, A., Cabral, I., & Aghakhani, N. (2018). A recommender system for cultural restaurants based on review factors and review sentiment. In *Twenty-fourth americas conference on information systems*. New Orleans, USA.

Zhang, S., Wei, Z., Wang, Y., & Liao, T. (2018). Sentiment analysis of Chinese microblog text based on extended sentiment dictionary. *Future Generation Computer Systems*, *81*(1), 395–403.

Zhang, C., Zhang, H., & Wang, J. (2018). Personalized restaurant recommendation method combining group correlations and customer preferences. *Information Sciences*, *454*(1), 128–143.