Preprint accepted at CCI 2020 (IEEE). You can find the published version at:
https://ieeexplore.ieee.org/abstract/document/9238725

Extracting User's Food Preferences by Sentiment Analysis

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***Abstract*— With the growth and development of websites and social networks, the number of user comments on these platforms has grown significantly. These comments contain rich information, which can be analyzed to discover individuals' preferences in various areas, including food. Extracting individuals' preferences can be useful for many applications of the Internet of Things paradigm. This paper proposes a method for extracting individuals' food preferences from their comments. The method includes extracting foods names from individual comments, clustering them, and performing sentiment analysis for each name. Comments on the Trip Advisor website have been used in experiments. In this regard, 100 users have been chosen and their comments from January to September of 2018 have been collected. Data from the first six months has been used for training the proposed method, while the data from the last 3 months has been used for testing. The results indicate the high precision of the proposed method in extracting users' food preferences.**

Keywords— ***Sentiment analysis, Clustering, Semantic similarity, Food preferences.***

I. Introduction

Today, a huge amount of users comments is available on websites and social networks. These comments contain rich information in various areas such as tourism, commerce, and education. Therefore, analyzing them can help us to discover individuals' preferences in those domains. Since comments are expressed using natural languages [1], at first the natural language processing techniques should be used in order to process them. In addition, the emotions of users on their comments should be investigated. To this end, sentiment analysis is utilized to discover the writer's emotions and feelings.

Extracting users' preferences is an issue that has many applications in the internet of things (IoT). It can be used as input information for personalized and context-aware [2] IoT applications as well as recommender systems. These systems use contextual information collected by IoT sensors and devices to adapt their recommendations to the user's situation [3].

Food is among humans' vital needs. Eating the desired food is an important personal preference for many people. In this regard, discovering individuals' food preferences can be helpful for various applications such as those trying to find restaurants that match user's taste.

Previously, questionnaire-based methods have been used to infer food preferences [4]. They give the user the option to select from predetermined choices. This method is not flexible since available options might not completely satisfy the user. Considering the huge increase in online comments, inferring an individual's food preferences by analyzing them can be more accurate and flexible. According to our best knowledge, research has not published yet on inferring user's food preferences by analyzing their comments.

This paper intends to extract individuals' food preferences by analyzing their comments. For this purpose, foods names are firstly extracted from comments using text preprocessing. These food names are then clustered according to semantic similarity. Finally, clusters are scored by analyzing sentiments on them. The cluster that has the highest sentiment analysis score represents the user's preferences. Comments available on the Trip Advisor website [5] have been used to evaluate the proposed method. The evaluation results indicate high precision in predicting individuals' food preferences.

The rest of the paper is organized as follows: Previous works are reviewed in section 2. The proposed method is described in section 3. Section 4 includes evaluation, and section 5 presents conclusions.

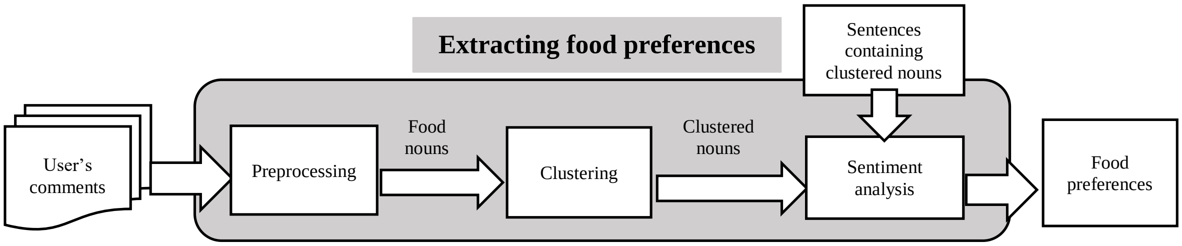

Fig. 1: Proposed method for extracting user's food preferences

II. Related Work

There are various approaches to inferring individuals' preferences, which include using questionnaires [6], star ratings [7] and individuals' text comments [8]. The most obvious approach is to explicitly ask from users their preferences via a questionnaire when they enter the system. For example, the user chooses their desired food from available options after entering the system [4]. One problem with this approach is the possibility of finding no matches between options available in the questionnaire and the individual preferences. Star ranking methods extract individuals' preferences according to their previous ratings. For example, users are categorized according to their previous ratings for features such as services, food quality, and price [9]. Besides, restaurants that have received similar ratings for these features are also categorized into the same group. Finally, suitable restaurants are recommended to the user based on the similarity between the restaurant category and user category.

The aforementioned methods are not flexible for choosing user food preferences since they can only use predetermined options to specify preferences. On the other hand, extracting individuals' preferences using their comments is now possible with the advent of domain-specific social networks. In this approach, comment positivity and negativity is determined using machine learning or dictionary-based methods after preprocessing comments and extracting desired features. For example, after extracting the restaurant's features, the user's sense on each feature is determined by the use of machine learning methods [10]. In this regard, in Buon Appetito [11] food names are extracted from user's comments. Afterward, a sentiment analysis at the sentence-level is performed to compute the score of each food. Finally, the top-k foods that have gained the most positive scores are returned as user's preferences. As a user's sentiment regarding a specific food could be different in different restaurants, sentence-level sentiment analysis cannot precisely represent user's preferences. In fact, it is necessary to investigate the user's general sentiment regarding that food in diverse restaurants. To this end, this paper proposes a flexible method for inferring individuals' food preferences by analyzing and clustering their comments and performing sentiment analysis at the document-level.

III. The Proposed Method

The proposed method extracts users' food preferences in several steps including preprocessing, clustering and sentiment analysis. The overall scheme is shown in Fig. 1.

Preprocessing: In this stage, tokenization is performed to convert the text into a series of words and signs. Then, each word's role in the sentence is determined using Part of Speech tagging. The stop words in the text are then removed and stemming is performed on the remaining words. Finally, the nouns available in the text are extracted. In order to remove unrelated nouns, food-related nouns in the WordNet [12] ontology are kept while other nouns are removed.

Clustering: In this stage, the nouns remained from the previous stage are clustered. Agglomerative hierarchical clustering is used to improve quality [13]. In the clustering method, each word itself is initially a cluster. Inter-cluster distances are then calculated using semantic similarity.

Afterwards, the clusters that are more similar than the threshold value are combined. The distance between the new cluster and others is then calculated. While the inter-cluster similarity is higher than the threshold value, this process continues.

Sentiment analysis: After clustering the nouns, sentences including these nouns are placed in the corresponding clusters for sentiment analysis. It is worth mentioning that it may be possible to put a sentence in several clusters.

Words that have the noun, adjective, adverb or verb tags are extracted as features. Sentiment score is then determined for each feature using SentiWordNet [14]. For example, if A is a word with n synonyms in WordNet, its positive, negative and neutral (objective) scores are calculated by SentiWordNet using the following equations [15]:

$$\mathrm{score}_{pos}(A) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{score}_{pos}(i) \quad (1)$$

$$\mathrm{score}_{neg}(A) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{score}_{neg}(i) \quad (2)$$

$$\mathrm{score}_{obj}(A) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{score}_{obj}(i) \quad (3)$$

According to the above equations, each feature's positive score is equal to the average positive score of all its synonyms. Negative and neutral (objective) scores are computed similarly. Afterward, the positive score of each sentence is calculated based on the average positive score of all its features, as are its negative and neutral scores. Therefore, a sentence is considered positive if its positive score is higher than its negative score, and vice versa. If the positive and negative scores for a sentence are equal, that sentence is neutral and is disregarded from cluster score calculation. The score of each cluster is then calculated using the following equation:

$$S_c=\frac{N_p-N_n}{N_p+N_n} \tag{4}$$

, Where N_p is the number of positive sentences of the cluster, and N_n is its number of negative sentences. Therefore, each cluster's score is a number between -1 and 1.

After calculating the score for all clusters, the cluster with the highest score will represent the user's preferences. If there is another cluster with a score sufficiently close to the selected cluster, it is combined with the selected cluster. To this end, a threshold value is considered to identify close clusters. The threshold value for this study is assumed to be 0.1.

IV. EVALUATION

Comments available on the Trip Advisor website have been used to evaluate the proposed method. People's opinions on hotels, restaurants and various world tourism destinations are available on this website. Comments of 100 users from January to September of 2018 have been collected. The data from each user's first 6 months has been used for training the proposed method; while the data from their last 3 months has been used for testing.

After extracting user preferences by each criterion, the precision, recall, and f-measure values have been measured according to the match between user preferences and the food that he/she has had in the last 3 months. To this end; we utilize the following criteria:

Precision= what percentage of the foods in the preferences are eaten in the test period

Recall= what percentage of the foods eaten in the test period are in the preferences

F-measure=2*(Precision*Recall)/(Precision+Recall)

Figures 2 compares the results of the proposed method in Top 5 for three different semantic similarity metrics exploited, namely as Gloss [16], Wu-Palmer [17], and their combination as Hybrid [16].

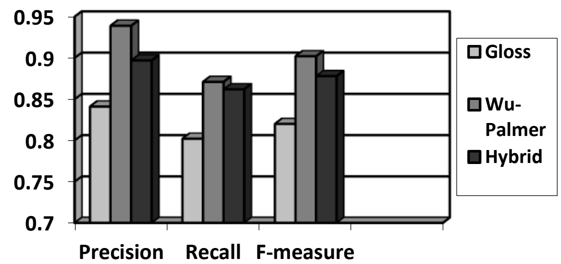

Fig 2: Comparing the exploitation of three different semantic similarity criteria

According to this figure, the proposed method's evaluation results indicate higher precision using the Wu-Palmer criterion. The results of all three criteria also show a reasonable precision, which indicates that most of the foods available in preferences are among those that users have eaten in the test period (last 3 months). Besides, recall value has also been higher for the Wu-Palmer criterion than the other two criteria. Furthermore, the high recall values obtained for all three criteria indicate that most of the foods eaten in the test period (last 3 months) match users' preferences. Finally, figure 3 also shows higher f-measure value for the Wu-Palmer criterion. It is expected, because f-measure is dependent on the precision and recall values.

In the next step, to evaluate the proposed method, we compare it with the Term Frequency-based (TF-based) [18], as well as Buon Appetito [11] methods**.** In the TF-based method, at first, food names are extracted from user's comments. Then by exploiting the Term-Frequency approach, the k most frequent foods are returned as user's preferences [11]. Buon Appetito [11] extracts users preferences from their comments by analyzing their sentiments at the sentence-level.

After extracting users' preferences by each of these methods on the reviews they provided in the first 6 months of the dataset, we compare the methods on the last three months of the dataset. Figures3, 4, and 5 represent the results for top3, top5, and top 7, respectively.

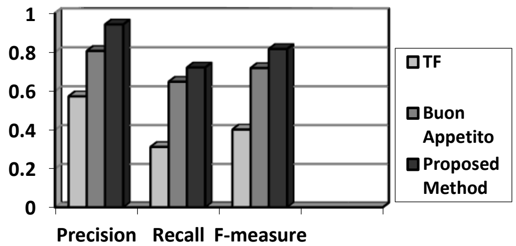

Fig. 3: Comparison results for top 3

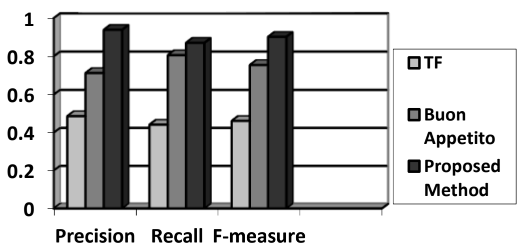

Fig. 4 Comparison results for top 5

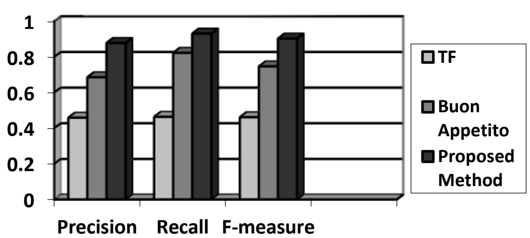

Fig. 5: Comparison results for top 7

For each method, the precision in top 7 is less than top 5, which in turn has a lower precision that top 3. As the number of foods in the preferences list increases, the "percentage of foods in the preferences that are eaten in the test period" decreases. Besides, the precision of the TF-based method in all cases is drastically less than the other two methods. It reveals that exploiting TF regardless of analyzing sentiments cannot be an efficient approach in extracting a user's food preferences. Finally, the precision of the proposed method is higher than the other methods. It indicates that analyzing sentiments at the document-level (cluster-level) results to better prediction of a user's food preferences. It should also be noted that semantic clustering assigns the foods of the same group (e.g. seafood, vegetables, etc.) into a cluster. This semantic clustering has resulted to better precision that the non-semantic clustering approach that has been used in Buon Appetito [11].

In contrary to precision, the recall value of all methods increases as the k parameter in top k increases. This is due to the fact that the likelihood for "the foods eaten in the test period" to be in the "preference list" increases. Besides, the recall results for the proposed method are better than the other methods. Finally, f-measure results also reveal that the proposed method outperforms the other two methods in predicting users' preferences. This is due to the fact that the proposed method uses semantic clustering approach and then performs sentiment analysis at the cluster-level.

V. CONCLUSION

A method for inferring individuals' food preferences from their comments has been proposed. It is based on extracting food names from user comments, clustering names based on semantic similarity, and analyzing the user's sentiment regarding each name. To perform semantic clustering, the Wu-Palmer and Gloss criteria as well as their combination have been investigated. The result has indicated that the Wu-Palmer criterion yields higher precision, recall and f-measure. Finally, for evaluation, the proposed method has been compared with similar previous methods. The results have shown that the proposed method achieves more accurate prediction of food preferences of individuals. Based on the results obtained in this research, the next step is to propose a restaurant recommendation system that suggests restaurants in line with user's preferences.

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