A Corpus Driven, Aspect-based Sentiment Analysis To Evaluate In Almost Real-time, A Large Volume of Online Food & Beverage Reviews

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Abstract

Nowadays, more than ever, customers have access to other consumers' digital evaluations concerning the products or services that they have consumed. The use of online review websites, by the potential digital consumers, makes them aware of the choices they have. This, enables them to make comparisons between all the available products or services. However, the big volume of the opinionative data that is produced continuously, creates difficulties when being analyzed by stakeholders, mostly due to human's physical or mental restrictions. In this research, web scraping combined with an aspect-level sentiment analysis using the corpus-based technique, approached methodologically the problem, by identifying not only the relevant information, but also the particular expressions and phrases that the reviewers use over the Internet. The purpose is to recommend a corpus-based, sentiment analysis web system for detecting and quantifying customers' opinions which are written in Greek language and referred to the Food and Beverage (F&B) sector in almost real-time. The system consists of two modules that constructed using the aforementioned methods. As far as the web scraping module is concerned, the BeautifulSoup and the Requests libraries of Python programming language were used. For the constructing purposes of the corpus-based sentiment analysis module, 80,500 customers' reviews are extracted (data set) from 6,795 companies which selected randomly from the most popular Greek e-ordering platform. The evaluated functions are the quality of food, the customer service and the image of the company. The extracted sentiment orientation terms and phrases from the customers' reviews are used to form the corresponding dictionaries of the functions and the appropriate pattern of tags, in order to proceed in the sentiment classification. Finally, the system is tested in the dataset and the findings will be practical and significant, as not enough attention has been paid in sentiment analysis techniques used in combination with a non-English, like the modern Greek language.

Keywords: Sentiment Analysis, Aspect-level, Food and Beverage Sector, Modern Greek.

1. INTRODUCTION

Before the rapid evolution of the World Wide Web, people used to ask others about recommendations concerning the products or services that they wanted to consume. This type of communication is known in Marketing as Word of Mouth (WOM). In research, the WOM refers to interpersonal communication regarding products or services whether the receiver regards the communicator as impartial [1]. In today's digital century, where the conventional consumers transformed into digital, especially at young ages, the WOM replaced by the User-Generated Content (UGC). This is a positive or a negative statement made by potential, actual or former consumers about a product or a company, which can be available to a multitude of people and institutions via the Internet [2]. The online UGC is considered to be more reliable compared with the traditional methods of communication [3,4].

Online reviews, become more and more the most useful information source helping consumers to form their purchase decision and change their buying behavior [5,6]. Significant researches have shown also that 92% of consumers read online evaluations (reviews) to buy a product [7], 66% of people trust online product reviews [8], 63% of consumers are willing to purchase products or services from a website which contains user reviews [9] and interestingly, customers are willing to pay from 20% to 99% more for a five than a four or lower-star rated product [10].

As far as the Greek market is concerned, in 2018, 43% of Internet users made orders for food or take away goods from aggregators (online digital markets) or new delivery platforms. Greek small local restaurants or cafeterias tent to cooperate with aggregation platforms, mainly due to their lack of media awareness. These platforms, use their brand recognition strengthening by effective sales techniques, such as advertising campaigns, the use of social influencers, celebrities' endorsement, or product placement to transform the local companies into digital. Another advantage of the aggregator platforms is that allows customers to make their evaluation about the products or services that they have already consumed publicly, and this increases the competitiveness forcing the companies for constant improvements, and product differentiation. Thus, the online order-delivery and evaluation process can be characterized as one of the most favorable activity by the Greek digital consumers (ELTRUN, 2018).

Opinion mining, or sentiment analysis, is referred to as a scientific subject that utilizes Information Retrieval (IR), Natural Language Processing (NLP), Computational Linguistics, as well as Machine Learning (ML) techniques to identify and extract subjective information from source materials. It is a new field of research, which uses advanced techniques for mining texts and handle large amount of unstructured UGC appearing in social media networking sites. Sentiment analysis tries to analyze emotions, opinions, and reviews to classify them into one of two polarities: positive or negative. Opinion can be expressed at four different levels, which are heavily interconnected. In the most popular case, the document-level, the whole review is treated as a solid unit and is classified either as positive, negative, or neutral. In the second case, the sentence-level, subjective sentences have to be identified from objective ones and classify them into positive or negative sentences. It considers each sentence as containing one opinion and therefore, the polarization of the whole document depends on the polarization of the sentence. The case holds in small sentences but not in comparative ones. In the third case, sentiment analysis at a document and sentence levels cannot identify the targets of the extracted opinions, i.e., the entities, and their features. Finally, in the last case, the aspect-, or feature-, based level, all opinions on all aspects of various sentences of a document are summarized to provide positive or negative feedback. Noteworthy, that in this case a single sentence may include many aspects, and each one with its own polarity, corresponding to the particular opinion acquired.

In this research, the major problem related to the detection and analysis of the continuously generated high volume of the opinionative data is considered. As has been noted, a large portion of the online UGC does not fully follow the rules of spelling and grammar, making also difficulties not only in the classification but also, in understanding the meaning of the reviews. This makes it difficult for the stakeholders (companies or consumers) in extracting, analyzing, and inferring meaningful information. The situation is getting even more difficult by the fact that the Greek language, is a typical high inflection language, because of the grammatical and syntactical rules of complexity [11]. As an example, in English, there are only four forms of the regular verb ask (ask, asks, asking and asked) while there are 93 different forms of the same Greek regular verb 'ρωτώ' [12]. The solution proposed is based on aspect-level, sentiment analysis methodology, using the corpus-based technique which is able to identify relevant information, as well as, particular expressions and phrases used by the Internet reviewers. More precisely, in the corpus-based technique, an initial set of sentiment terms with their sentiment orientations is detected manually and then, this set is increased by adding more terms such as synonyms or antonyms. Moreover, the extraction of useful information from the UGC must usually be held in real-time to facilitate the stakeholders and to make smart decisions on-time. Since the products that are traded by the companies in the Food and Beverage (F&B) domain are basic commodities (food and drinks), the consumers must have an immediate view of them. Thus, a web-based system able to mine and analyze customers' evaluations in almost real-time, need to be introduced. For this, two modules will be designed and implemented. The first is a web scraping module to mine the reviews and the second is a sentiment analysis module to analyze and quantify the customers' evaluations.

2. RESEARCH BACKGROUND

2.1 Web Scraping, Applications, and Research Challenges

Web scraping, which is also known as Web Data Extraction, or Web Harvesting, is an automated process based on software developments, aiming to extract data from a website into a new format. Specifically, it is the process of extracting data from the HTML DOMs of certain URLs, and stored the mined data into spreadsheets, JSON files, or databases. The data extraction from the web may also be considered to belong to the class of big data problems [13] because it is emerging as a powerful method for handling the unstructured data by analyzing it, in order to extract new knowledge and identifying significant patterns and correlations hidden in it [14]. The web scraping applications consist of two components: the crawler and the scraper. The crawler can download the specific data from targeted URLs and the scraper can concentrate the meaningful content of the unstructured web data by the elimination of needless content [15,16].

The main web scrapping methods can be classified into three categories: the libraries for the widely used programming languages, frameworks, and desktop-based applications. The most important method, commonly used by the research community, is the construction of individual web scrapers using a known programming language. Third-party libraries access the website by implementing the client website protocol, while the parsing of recovered substances is achieved using functions like tokenization, trimming, or comparison of a regular expression. Some known libraries for a general-purpose programming language, are presented in TABLE 1.

Programming language	Libraries
Python	*BeautifulSoup, Urlib, Selenium, Requests*
PHP	*Goutte, cURL, Requests, Buzz*
Perl	WWW: *Mechanize*
Java	*Apache Nutch, Heritix, ACHE Crawler, BUbiNG*

TABLE 1: Most known web scraping libraries in programming languages.

As for the second method, a lot of frameworks were designed to overcome the drawbacks of the web scraping libraries in programming languages, where there is a need of two components; the first one for providing access to the websites and the second, for configuring the parse and the deduce of useful contents from the URLs. Some known libraries that are used widely, as well as web scraping frameworks depending on the programming language, are presented in TABLE 2.

Programming language	Frameworks
Python	*Scrapy, MechanicalSoup, Jauntm, Apify*
Java	*Storm Crawler, Norconex*

TABLE 2: Most known web scraping frameworks in programming languages.

Lastly, the desktop-based applications are mentioned to the rich graphical user interface tools. These tools enable users to select elements from a webpage without the need of high programming skills. Their outputs can be displayed either in CSV, text, or XML formats or into the most used databases. Some known web scraping desktop tools are presented in TABLE 3.

Tool	Benefits
Octoparse	1. Turns un/semi-structured data into a structured data set. 2. Ready web scraping templates for Amazon, eBay, Twitter, etc.
WebHarvy	1. Point-and-click web scraping tool. 2. Web scraping tutorials.
Parsehub	1. Visual web scraping tool. 2. Extracts the data by just clicking fields on a website.

TABLE 3: Most known web scraping desktop tools and their benefits.

Finally, as far as the automated web scraping is considered, in literature, there are three major scraping levels: The semantic, the syntactic, and the service levels [17]. In the semantic level, a model is designed to map the HTML elements to semantic web sources, whereas, in the syntactic one, the data is mined from selected webpages by parsing the HTML, the CSS, or other web programming languages. Thus, some known wrapping and extraction techniques (e.g. Content Style, XPath, URI, or Visual selectors) are used. Lastly, the service level uses technologies/applications such as opinion, miners, recommenders, mashups, etc. and the use of semantic scraping level to mine the useful content from the webpages. The lack of web scraping templates devoted to the platforms in the F&B domain shows the need for the development of a particular web scraping module dedicated to this purpose.

2.2 The Corpus-based Technique of The Sentiment Analysis

The lexicon-based approach of the sentiment analysis method uses a dictionary that contains sentiment terms with their associated polarities and strengths for detecting the sentiment in a corpus of textual data [18]. As has been noted, these terms are also called opinion words since they are used to express positive or negative opinions. In literature, there are three techniques for the lexicon-based approach. The manual technique which is more accurate but time-consuming [19,20], the corpus-based technique which is relying on the syntactic, or co-occurrence patterns in a large corpus [21,22] and the dictionary-based technique which is based on a set of seed opinion words and a predefined online dictionary (e.g. SentiWordNet) [23,24]. Note that since the same or similar words in different domains might have different polarities, the major advantage of the corpus-based technique is that the opinion words are generated from a corpus of textual data related to a specific domain. It is also notable that the majority of work on sentiment analysis has targeted the identification of English texts, while the Greek language was showing a low position among the most languages spoken worldwide [25]. Also, food e-ordering platforms have drawn limited researchers' attention so far. To the best of our knowledge, there is no Greek lexical resource available for opinion research purposes except [26] which is different from the F&B domain. Finally, previous studies have shown that the dependent domain lexicons can achieve better accuracy [27]. For these reasons, the corpus-based technique, which belongs in the frame of lexicon-based techniques is adopted [28].

The aspect-level analysis fits perfectly well in the framework of the problem considered in this research because reviewers talk about entities that have many aspects (functions) and they usually show different opinions about the various aspects they may evaluate. This often happens in reviews about products or discussion forums dedicated to specific product categories (food, restaurants, smartphones, etc.). The aspect-level analysis presents also advantages in robustness (cope with the informal writing style in most UGCs), flexibility (deal with multiple functions), and velocity (high-speed performance) [29].

The main dictionary constructed for this research consists of three sub-dictionaries. The sub-dictionaries correspond to the same criteria that have already set and express the companies' functions in the F&B sector, namely, the food quality (DoQl), the customer service (DoS), and the image of the local company (DoI). The dictionaries contain the adjectives with their corresponding polarities that describe each of the examined functions. The adjectives were placed in each dictionary manually, depending on the context of customers' reviews that containing them. Moreover, the polarities were calculated based on the customers' overall evaluations (stars) that were appeared in the examined e-platform on a [-1: Extremely negative,1: Extremely positive] scale. Details about the sub-dictionaries are shown in TABLE 4:

Dictionary	No of terms	Average polarity of terms	Positive: Negative
DoQl	227	0.28	50:50
DoS	132	0.32	70:30
DoI	116	0.38	70:30
Total:	414		

TABLE 4: Details of the proposed dictionary.

Finally, for determining the aspects related to the restaurants' or cafeterias' examined functions, three lists of nouns were created (LF: List of Food aspects, LS: List of Service aspects and LI: List of Image aspects), using the Part of Speech (PoS) tagging methodology. More details about the construction of the dictionaries and the corresponding lists of aspects are presented in [11,27].

3. THE PROPOSED WEB-BASED SENTIMENT ANALYSIS SYSTEM

3.1 The Need for A Real-Time Web-Based Sentiment Analysis System

Due to the continuous generation of customers' evaluations, restaurants or cafeterias must have access to this data in real-time, if possible, to form a clear view of their brand awareness. The analysis of such data will certainly help them to maximize their competitive advantage and differentiate their products or services. Notably that, a real-time understanding of the UGCs from e-ordering platforms could help companies to adopt more easily an online personalized marketing model facilitating customers in saving time and effort, and driving companies to customer loyalty. Finally, the analysis of the large volume of e-opinionative data could help them to design an accurate customer segmentation based on an effective understanding of the customers [30].

On the flip side, digital consumers form an opinion by reading just one to three customers' evaluations in their attempt to choose a product or a service [7]. A study indicates that one to three negative online reviews could be enough to defer the vast majority of customers [31], and interestingly, a survey on Internet users in US reveals that customers' evaluations are more trusted than the description which comes from the companies. This, reveals the interest of customers in online reviews, in terms of relying on the online users' generated content to shape their consumer behavior.

The demand for a real-time sentiment analysis system in the F&B domain is significant due to the high surge of interest for the customers' e-evaluations and the large volume of the textual data generated very quickly. For the consumers, it could be beneficial for making intelligent decisions by knowing the products'/services' positive and/or negative attributes. Restaurants or cafeterias, on the other hand, will get valuable insights about how their customers feel about them to improve their marketing strategies and enhancing their products and/or services. Notably, the vast majority of restaurants/cafeterias are local with a lack of resources in data analytics and qualified staff too (except the multinational companies).

3.2 The Systems' Architecture

The flowchart of the architecture of the system is shown in FIGURE 1. The user (company or consumer), interacts with the system through an appropriate user interface and selects either a potential company from a list of all available companies by adding the company's URL from the selected e-ordering platform or a particular area/region. Then, using the web scrapping module developed to cope with almost real-time mining of reviews, the customers' reviews for the selected company or area/region proceeded for evaluation. Note that using the Python language, the access to the e-ordering platforms, was based on the *requests* library, whereas, the parse and deduction of the customers' evaluations from the restaurants' or cafeterias' accounts was based on the *BeautifulSoup* library.

Further, the proposed corpus-based module was designed and developed (see section 3.2.1) to identify and calculate the sentiments' strengths for each restaurants'/cafeterias' evaluated functions. In the last case, consumers are able to find the most qualitative restaurant or cafeteria, and companies are able to find how consumers feel about their competitors, helping them to improve their SWOT analysis and using the computed data in their strategies.

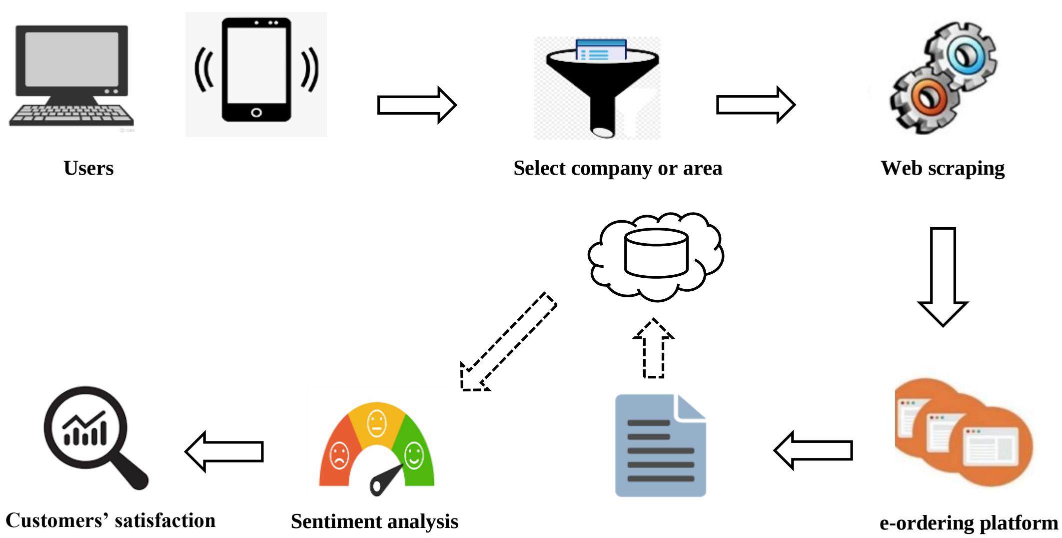

FIGURE 1: System's Architecture.

Note that the use of a cloud database is enhanced contemplating the fact that the majority of companies in the F&B domain tend to cooperate with more than one e-ordering platform to maximize their sales. Also, the use of a cloud database may be used in cases where various e-ordering platforms have been established, or in other domains (e.g. electronics), where a lot of electronic and physical companies have been established so far and the competition is very high.

3.2.1 Quantifying Customers' Opinions

Although an isolated adjective should indicate subjectivity, there may be insufficient context to determine the semantic orientation of the opinionative textual data. As an example, the word "ωραίο" (nice), can be characterized as a controversial term because it can be used to describe all the restaurants' examined aspects (nice food, nice staff, and nice image). However, many terms that are not mentioned explicitly in the reviews and can be inferred from the sentiment expressions that mention them implicitly. Also, from the analysis, we concluded that the adjectives may have different polarities depending on the aspect that evaluates.

As was suggested in [22], two or more phrases co-occurrence association rule mining can be used to match the implicit aspects with the explicit aspects. To support this statement for the

Greek language, the Pointwise Mutual Information (PMI) metric [27] was implemented to measure the relationship of the aspects (lists of nouns of each aspect) with the adjectives (dictionaries DoQl, DoS and DoI) that co-occur. Consequently, a strong relationship in co-occurrence between the nouns and the adjectives was found. For instance, the noun 'ΑΡΑΒΙΚΗ ΠΙΤΑ'/ARABIC PIE, which is a kind of food, shows a high probability of co-occurrence with the adjective 'ΩΡΑΙΟ΄ (nice). More details can be found in [27]. Then, we proceeded in the examination of the sequence of the adjectives, nouns, and other parts of speech in customers' e-evaluations and this resulted in some patterns of tags, expanding the results of [21]. It is important to note here that the vast majority of online text-based communications ignore the rules of spelling and grammar using the slang language and emoticons.

Following the results of the PMI metric which were shown that the adjectives and nouns could act as sentiment indicators and according to the proposed dictionaries, we proceeded in the evaluation of a certain customer's review. The first step is the pre-processing of the review as shown in FIGURE 2.

FIGURE 2: Pre-processing Procedure of a Review.

The next step after the pre-processing is to search for a noun in the corresponding list of words of the examined review using the lists of aspects (LF, LS and LI). Thus, the aspect is identified. In the sequel, the program locates the position "j" of the noun (aspect) in the list of terms of the examined review and searches for an adjective, first in location "j-1" to examine some possibilities (patterns of tags) that were found from the analysis of the data set (TABLE 5). The JJ tags indicate the adjectives (sub-dictionaries DoQl, DoS, and DoI) and the NN/NNS tags indicate the noun/nouns (aspects).

j-2	j-1	j	j+1	j+2	Sentiment Orientation Term/s
ANY	JJ	NN/NNS	(.) or (,) or ( )	-	j-1
ANY	JJ	NN/NNS	JJ	(.) or (,) or ( )	j-1, j+1
ANY	JJ	NN/NNS	JJ	NN/NNS	j-1
(.) or (,) or ()	JJ	NN/NNS	ANY	JJ	j-1, j+2

TABLE 5: Patterns of Tags for the j-1 Analysis.

The module moves also to the location "j+1", if there is no adjective in location "j-1". In this case, the following pattern of tags can be implemented for calculating the sentiment orientation of an aspect (TABLE 6).

j	j+1	j+2	j+3	j+4	Sentiment Orientation Term/s
NN/NNS	JJ	(.), (,), ()	ANY	-	j+1
NN/NNS	JJ	JJ	ANY EXCEPT NN	-	j+1, j+2
NN/NNS	JJ	JJ	NN		j+1
NN/NNS	ANY	JJ	(.), (,), ()		j+2

TABLE 6: Patterns of Tags for the j+1 Analysis.

To conclude, the analysis of the following customer review will be used as an example to explain in a better way the proposed module (FIGURE 3).

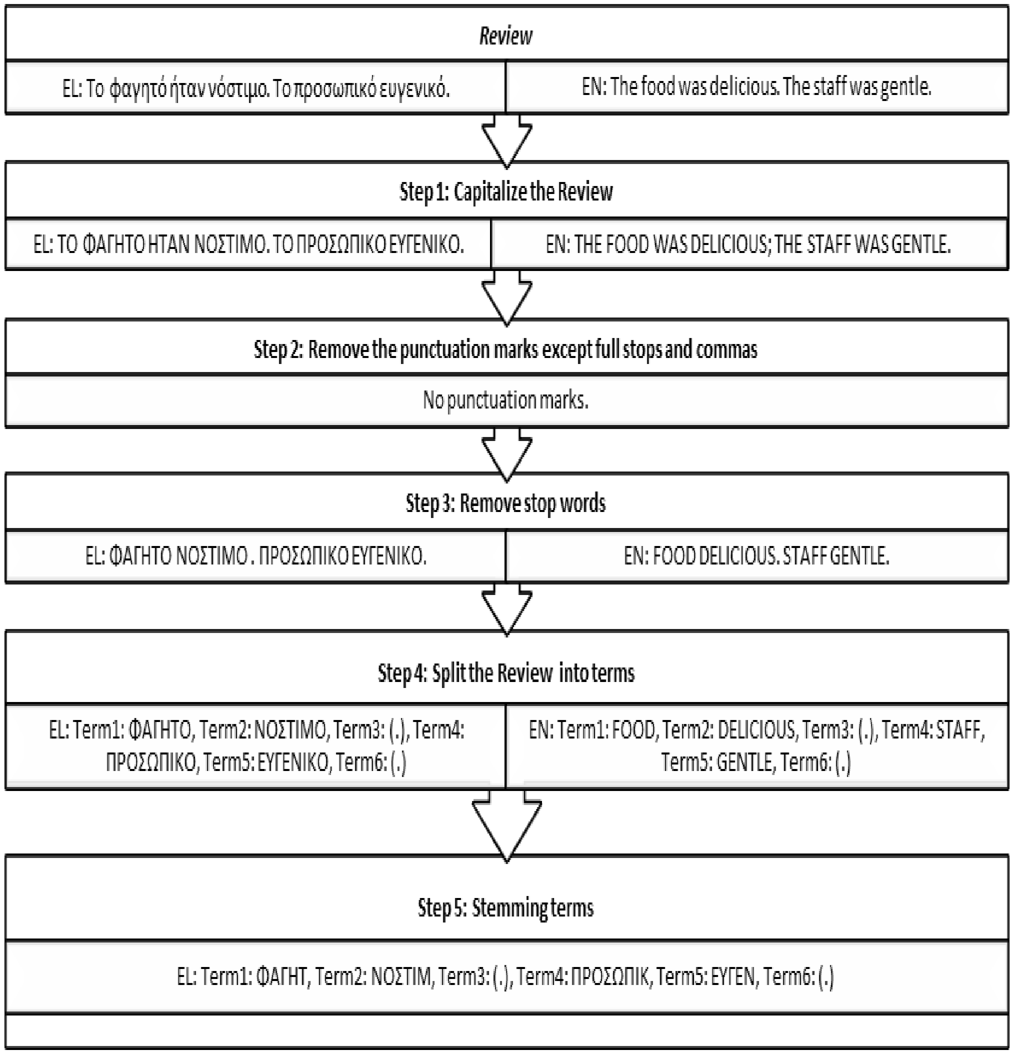

FIGURE 3: Analyzing a Customer's Review.

Based on the customer's review analysis that is presented above, the aspect that describes the quality's function (Term 1: ΦΑΓΗΤ/FOOD) is placed in position "j" and the adjective which contains the reviewer's judgment and evaluates the aspect is placed in position "j+1". According to the DoQl, the adjective 'ΝΟΣΤΙΜ' (TASTY), shows a polarity of +0.60. Similarly, the aspect which describes the service's function (Term 4: ΠΡΟΣΩΠΙΚ/STAFF) is placed in position "j" and the adjective which evaluates the reviewer's opinion is placed in position "j+1". According to the dictionary DoS, the adjective 'ΕΥΓΕΝΙΚ' (GENTLE), shows a polarity of +0.66. Therefore, the overall sentiment score of the review is calculated as the average score of each evaluated aspect and is equal to +0.63. More examples of customers' reviews which describe in more detail the proposed methodology and each pattern of tags respectively, are presented in [27]. Finally, the code and the supporting files (opinion dictionaries, lists of aspects, stemming list etc.) of the proposed system are available in the following repository of GitHub: https://github.com/aliapakis1989/Anastasios-Liapakis.

4. EXPERIMENTAL RESULTS

4.1 Data Extraction

Because of the multitude of dialects in the Greek language, there is no corpus containing all dialects. Create comprehensive corpus requires great abilities that must be gathered around all dialects in the Greek region. In general, the texts on the Internet are unorganized and contain a lot of noise and repetition in the letters. So, it needs to preprocess. Sentiment analysis of the Greek language and dialects works, some of them used the old corpora and the other created new corpora.

To design a representative sample and to detect most of the Greek local dialects and idioms, the last Greek census of 2011 was used. Thus, the data is extracted only from the most populated city, e.g. the capital, of each one of the 51 NUTS-3 (Nomenclature of Territorial Units for Statistics 3) Greek regions (prefectures). Note that, until the end of 2018, only three major e-ordering platforms had been established in Greece, owned by the same multinational firm, and having a common structure. To facilitate the creation of a data set concerning the F&B domain, we retrieved the customers' evaluations only from the most popular e-ordering platform in Greece. Thus, a database with 80,564 customers' reviews that were posted from 02/08/2013 to 31/12/2018 written in the Greek language was created. The reviews are mined from 1,359 companies selected randomly from a total of 6,795 companies (20%) presented in the e-platform. The analysis aims to evaluate the functions of food quality, customer service, and image of the local company. Note that the training set of the current research is used as a data set in a previous study showing a remarkable high performance on classification [27]. Also, in the same study, the proposed sentiment analysis module has implemented in an annotated set and it has shown also remarkable high performance on the classification of customers' reviews in the F&B domain. Finally, from the pre-processing procedure, a percentage of 7% (6,406) of customers' reviews was removed from the data set.

4.2 Data Set Evaluation

To compute the accuracy of the proposed system, the customers' reviews in the data set were classified as positive or negative based on their overall evaluations (stars) as were mined from the e-ordering platform considered. Notably, the overall evaluations from the examined e-ordering platform are computed on a 5-point Likert scale. In particular, the customers' reviews that present an overall sentiment score in a range of [1,2.5] were classified as negative whereas, the reviews with an overall sentiment score in a range of [3,5] were classified as positive. The reviews with an overall sentiment score in a range of [2.5-3] were classified as neutral (2,000 reviews) and therefore, were removed from the data set. Then, both classifications deduced from the examined platform and the designed module were compared. The confusion matrix (TABLE 6), presents the overall classification results of all customers' reviews in the data set. It appears that 58,157 positive reviews and 7,728 negative reviews have been classified correctly. Then, the performance metrics are calculated and presented in TABLE7.

	Total Number	Predicted Positive	Predicted Negative
Positive	61,876	58,157	2,554
Negative	10,282	3,719	7,728

TABLE 7: Confusion Matrix of The Data Set.

Metric	Percentage
Precision	84.56%
Accuracy	90.69%
Recall	83.30%
F-Score	83.91%

TABLE 8: Performance of Sentiment Classification in The Data Set.

The proposed system has shown an overall accuracy of 90.69% in the classification of the data set with high values in precision and recall metrics. The low values in the negative predictions are justified because of the small number of negative evaluations in the data set as well as of the identification difficulties of negation and sarcasm that are very challenging for any sentiment analysis system.

5. CONCLUSIONS

The use of social media networking improves restaurants’ brand names. Since in social networks is continuously produced a large amount of data daily, companies or other customers face difficulties to extract and analyse all the information needed to obtain valuable conclusions. In this research, we proposed a corpus-based, sentiment analysis system, able to evaluate in almost real-time a large amount of online F&B customers’ opinions in the Greek language. It may be considered as an initial attempt to introduce the sentiment analysis in the F&B sector using a non-English, like the Greek language.

The system built around two modules. The first is a web scraping module used to mine the reviews and the other is a corpus-based sentiment analysis module used in the analysis and quantification of the customers’ evaluations. The data set consisted of 80,500 customers’ reviews extracted from 6,795 companies selected randomly from the most popular Greek e-ordering platform. To include all different Greek dialects, the design allowed users to select either a restaurant/cafeteria that has a presence in the most known Greek food e-ordering platforms, or all the restaurants in a region. The evaluated functions were limited to the most important ones, namely, the quality of food, the customer service and the image of the company. The extracted sentiment orientation terms and phrases from the customers’ reviews were used to form the corresponding dictionaries of the functions and the appropriate pattern of tags, in order to proceed in the sentiment classification. Then, with the support of various tools (i.e. web scraping, preprocessing of the data etc.), the big data of customers' evaluations can be visualized.

Based on the confusion matrix of the dataset and using the well-known performance metrics of accuracy, precision, recall, and F-score that are used in common in information systems, we found a remarkable high performance on the classification. Specifically, the system showed an extremely high average accuracy of 90.69%. However, were calculated lower values in negative predictions, mainly due to the identification difficulties of negation and sarcasm. In more detail, the system showed an average recall of 70.81% in negative predictions against of 95.79% in positive predictions, in the data set. It is noteworthy that the performance of negative prediction remains at a high level, comparable to other similar researches. Notably, one of the very big e-ordering platforms (just-eat), with a global presence, may adopt the proposed web-based system and apply it in other than the Greek language, such as English, French, Italian, etc., because the customers’ evaluations concerning the F&B sector, have similar structure.

Future work will focus on a larger sample of online reviews in order to allow us to predict all the alternative Greek words, expressions or phrases that are used by the customers to express their sentiments about F&B companies in all known opinions and review websites. Also, a comparison among the proposed methodology and some other methods, including machine learning will be conducted.

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