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Sentiment Analysis of Restaurant Reviews in Artvin Province by Rule-based Sentiment Analysis and Machine Learning*

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Abstract
The purpose of this study was to investigate customer sentiments of restaurants in Artvin province. It was determined that 73.9% of the reviews were positive, and 26.1% were negative. 7 topics including place, view, price, food, service, staff and taste were extracted from the reviews. While the most reviews were about the place with 33.89%, it was followed by view with 15%, and the fewest reviews were about taste with 5.83%. It was found that the view topic was the most liked among these topics. 23.53% of those who commented on the price stated that the prices were high, while the percentage of those who indicated that the service was slow was 21.98%. In general, it was noticed that the service, place, food, and view topics were closely related to each other, and a customer who likes one of them is likely to appreciate the others and vice versa. It can be concluded that the application of RBSA and ML methods together is appropriate in terms of enabling both grammar rules and artificial intelligence methods and obtaining satisfactory results.

Keywords: *Artvin restaurants, sentiment, rule-based sentiment analysis, machine learning*

* This study is not included in the study group that requires TR Index Ethics Committee Approval.

1. Introduction

Artvin is a city with important natural, cultural, historical and tourist values of the Eastern Black Sea region. Artvin is emerging as an effective destination for tourism regionally, nationally and internationally and offers opportunities for alternative types of tourism with its nature, protected areas, registered cultural assets and plateaus (Akyol & Zengin, 2021). Although the tourism field actually includes many disciplines and business, food and beverage enterprises constitute an important part of it. Nowadays, guests and travelers share their holiday and restaurant experience through community-based social networks such as Google Maps, Tripadvisor, Yelp and Booking (Leung, Law, Van Hoof, & Buhalis, 2013). As a result of this situation, a very large amount of user-generated content is produced on social networks. In addition, developing social media technologies offer great advantages for collecting, managing and sharing information that will facilitate management activities (Gretzel, Sigala, Xiang, & Koo, 2015). The analysis of large amounts of data will both allow enterprises to develop more efficient strategies, increase competitiveness, and contribute to the country's economy due to the increase in domestic and foreign tourist satisfaction.

Recent years have seen a rapid increase in studies to uncover the relationship between guest experience and customer satisfaction, the intensity of sentiment in reviews, and the relationship between restaurant performance and reviews in the world using social media data in the tourism sector. It is of great importance to carry out studies in this field in Turkey as well. Analyzing social media data in the tourism and restaurant sector in Turkey will allow businesses to understand customer decision-making behavior and recognize opportunities and threats around competition (Büyükeke, Sökmen, & Gencer, 2020).

The aim of this study was to perform sentiment analysis of restaurant reviews in Artvin and to assist restaurant owners and managers in better understanding customer experiences and making data-driven recommendations.

2. Literature Review

In order to get more customer satisfaction and profit, researches about restaurants have recently increased and customer reactions have started to be examined. Consumer-generated ratings of restaurant meal quality, service, and ambiance are favorably connected to restaurant online popularity (Zhu, Yin, & He, 2014). Consumers can share text-oriented information or a combination of text and image information to express their restaurant experiences (Yang, Hlee, Lee, & Koo, 2017). Hotels, restaurants, and other travel-related companies may better understand what their guests like and dislike about them and their competitors by researching online community evaluations (Leung et al., 2013). User-generated content not only enhances the description supplied by the product or service provider, but also plays an increasingly crucial part in a potential customer's judgment process (Baek, Ahn, & Choi, 2012). Oğan and Durlu Özkaya (2018) performed a survey with 270 participants and stated that restaurant preferences in Artvin mostly affected by the taste of the food and drinks, the quality of the service and the attitude behaviors of the working staff. Oğan and Durlu Özkaya (2021) reported that tourists did not find at a sufficient level the number of restaurants, equipment, food prices, service quality, service types and features such as marketing activities in Artvin province in their survey study with 400 tourist participants. However, in the studies conducted, mostly the inclusion of surveys restricts the sample level. In addition, very often, the studies performed remain at the basic statistical level and it becomes difficult to gather the necessary inferences from the dataset. Therefore, more advanced techniques and larger datasets are needed.

Computers can learn from data provided and solve real world problems with the research area of machine learning. Machine learning techniques learn data patterns and use existing data to solve tasks (Mahmood & Khan, 2019). Specifically, the major purpose of machine learning is to provide approaches that enable computers to learn automatically by inferring behavior from instances (Romero et al., 2013). For this purpose, the study of restaurant sentiment analysis, in which machine learning methods are used, has been increased in recent years. In recent studies, deep learning techniques that have proven themselves have mostly been used to obtain results with high accuracy (Alamoudi & Alghamdi, 2021). Deep learning is a subgroup of machine learning. Nakayama and Wan (2019) found that Japanese reviewers placed a higher value on food quality, were more positive about pricing fairness, and were more negative about ambiance than American reviewers. Alamoudi and Alghamdi (2021) obtained the reviews on Kentucky Fried Chicken restaurants from yelp.com and as a result of machine learning methods, they reported the positive, negative and neutral sentiment percentages in ambience, food, price, and service topics as 36.5-49.8-13.7%, 28.9-57.2-13.9%, 32.8-56.3-10.9% and 28.4%, 61.8-9.8%, respectively.

3. Methodology

The method of the study is explained in the following headings.

3.1. Materials

The data used in this study was collected from Google maps (Google maps, 2022). There were 64 restaurants and 1425 customer reviews totally. All restaurants and reviews were belonging to Artvin province city center. In the data pre-processing step, the data was spell checked and translated to English (**Error! Reference source not found.** 1). Afterwards, the punctuations were removed and all words were lowercased. The sentences tokenized and subsequently lemmatization was carried out. By tokenization, a string of words is divided into smaller units, also known as tokens, for example "*The price was excessively high*" to be "*The*", "*price*", "*was*", "*excessively*", "*high*" (Hasan, Matin, & Joy, 2020). Lemmatization, on the other hand, refers to the transformation of a word into its basic form. For example, *"rules"*, *"books"*, *"believes"*, *"cries"* and after the lemmatization, it transforms into *"rule"*, *"book"*, *"belief"*, *"cry"* (Zahoor, Bawany, & Hamid, 2020). In this study, two different approaches were used to determine the customer sentiment. The first one is rule-based sentiment analysis (RBSA) and the second is machine learning (ML).

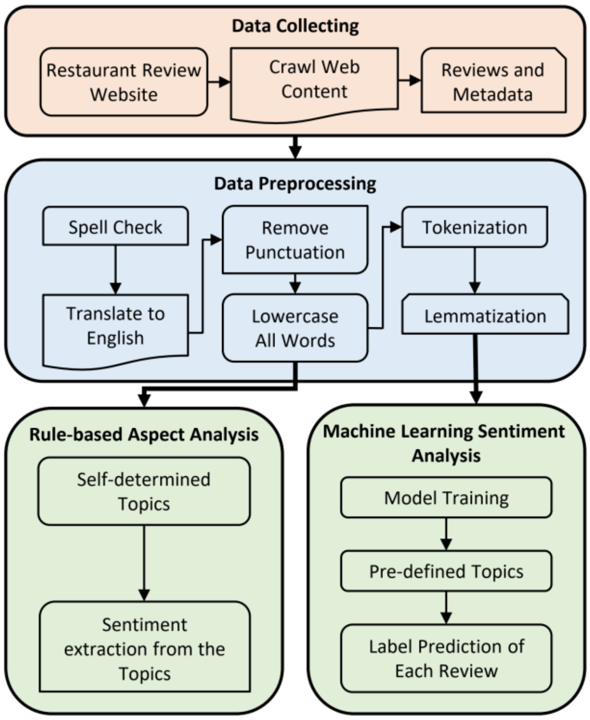

Figure 1. Architecture Diagram of The Research Framework

3.2. Rule-based sentiment analysis (RBSA)

Part-of-speech tagging, also called grammatical tagging, is the process of tagging a word in a text based on its task and definition in the sentence (Schmid, 1994). Here I am showing an example of a review; "*There was too much music and the meat was tasteless. It is a place worth seeing when you come to Artvin with its magnificent view and polite employees*". After part-of-speech tagging: ('there', 'EX'), ('was', 'VBD'), ('too', 'RB'), ('much', 'JJ'), ('music', 'NN'), ('and', 'CC'), ('the', 'DT'), ('meat', 'NN'), ('was', 'VBD'), ('tasteless', 'RB'), ('It', 'PRP'), ('is', 'VBZ'), ('a', 'DT'), ('place', 'NN'), ('worth', 'NN'), ('seeing', 'VBG'), ('when', 'WRB'), ('you', 'PRP'), ('come', 'VBP'), ('to', 'TO'), ('Artvin', 'NNP'), ('with', 'IN'), ('its', 'PRP$'), ('magnificent', 'JJ'), ('view', 'NN'), ('and', 'CC'), ('polite', 'JJ'), ('employees', 'NNS').

In this study I focused on adjectives (tagged as "RB", "RBR", "RBS", "JJ", "JJR", "JJS") and nouns (tagged as "NN", "NNS", "NNP", "NNPS") for extracting features since other words do not comprise any logical information for sentiment. In this implementation, Python programming language version 3.9 with NLTK module (Natural Language Toolkit) was used.

3.3. Machine Learning (ML)

The use of ML is common throughout natural language processing (NLP) because RBSA cannot fully capture all the information from the sentences. For this purpose, an artificial neural network (ANN) model was built by using Python 3.9. Word2Vec class from Gensim module was used for the model training (Rehurek & Sojka, 2010). The model was built with the parameters of vector size = 50, minimum count = 2, learning rate = 0.03, number of epochs = 25, and window = 5. The computer to run the program is a MSI laptop with Intel Core i7-8750-H CPU. The computer has 16GB physical memory.

3.4. Principle component analysis (PCA) and T-distributed stochastic neighbor embedding (t-SNE)

Variations among the captured topics by RBSA were analyzed through principal component analysis (PCA) to establish the relationships between the topics. The topic vectors obtained by the previously built ML model were decomposed into principal components (PCs) and the biplot was drawn using the first 2 PCs (Jolliffe & Cadima, 2016).

t-SNE was used to demonstrate word vectors and all reviews (totally 1425 reviews) from ML model in 2D and 3D spaces (Belkina et al., 2019). Both PCA and t-SNE were performed with Scikit-learn Python module with setting all parameters to their default values.

4. Findings

The findings of the study is explained in the following headings.

4.1. Rule-based sentiment analysis (RBSA)

After data processing, it is common to find out the most frequent words in order to get a general idea of the dataset. For this purpose, a word cloud is a convenient way to visually display the representation. In word clouds, words that are used more often are larger and bolder than words that are used less often. Figure 2 shows the most frequent 100 words from the dataset. We see that some neutral words such as food, chicken, tea, meat, service, etc., positive words such as beautiful, great, good, perfect, etc., and negative words such as slow, bad, expensive, etc. appear in the word cloud.

On the other hand, RBSA can reveal detailed information about the corpus. Part-of-speech tagging (POS tagging) is a method that evaluates the sentence and assigns parts of speech tags to each word, such as adjective, verb, noun, etc. (Bagheri, Saraee, & De Jong, 2013). After receiving information from the POS tagging, it is used as a feature to find the sentiment information from the sentence. By using the RBSA method, the topics present in the reviews can be determined and it is also possible to collect the words for each topic according to the word frequency.

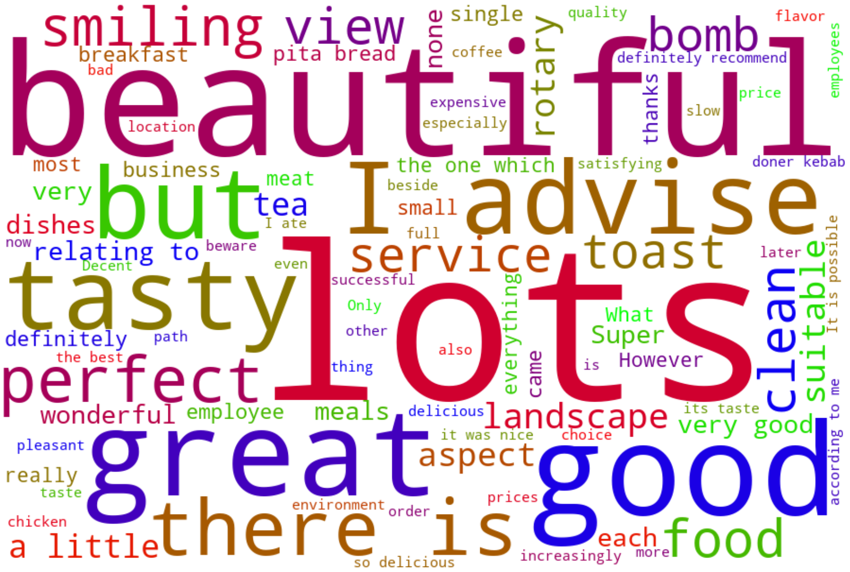

Figure 2. Word Cloud for Restaurant Reviews

It was found that the percentage of negative and positive reviews were 26.1%, and 73.9%, respectively (Figure 3). Pantelidis (2010) carried out content (topic) analyses of online reviews on restaurants in London from 2005 to 2007 and 2008 to 2009. He found the percentages of positive and negative comments as 77.62%-22.38 for 2005 to 2007 period and 63.13%-36.87 for 2008 to 2009. Dosoula et al. (2016) studied restaurant reviews and found the percentage of positive sentiments in their data as 58.7%.

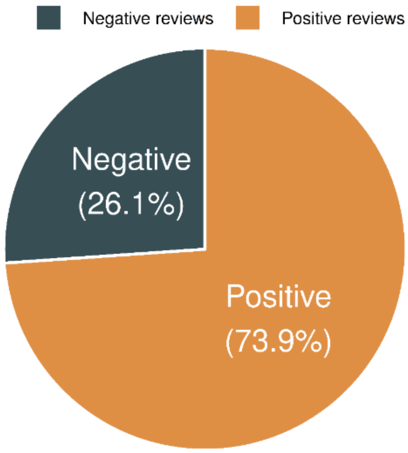

Figure 3. Percentages of Negative and Positive Reviews Obtained by Rule-Based Aspect Analysis

The topics extracted from the corpus are *place, view, price, food, service, staff,* and *taste* (Figure 4). This means that these topics have a higher frequency than other nouns since nouns were considered as topics in present study. Mathayomchan and Taecharungroj (2020) used Google maps restaurant reviews and extracted the topics as *food*, *service*, *atmosphere*, and *value*. Besides, Alamoudi and Alghamdi (2021) determined these topics as *food*, *service*, *ambiance*, and *price* in their study and Dosoula et al. (2016) detected as *food*, *service*, *ambiance*, *price*, and *anecdotes/miscellaneous*.

In this study, subgroups have been determined for each topic and thus it was aimed to reveal customer sentiments about the topics. Similarly, the subgroups consisted of adjectives that have a higher frequency than the other adjectives in the corpus. *Place, view,* and *staff* topics had overall good feedbacks from customers (Figure 4).

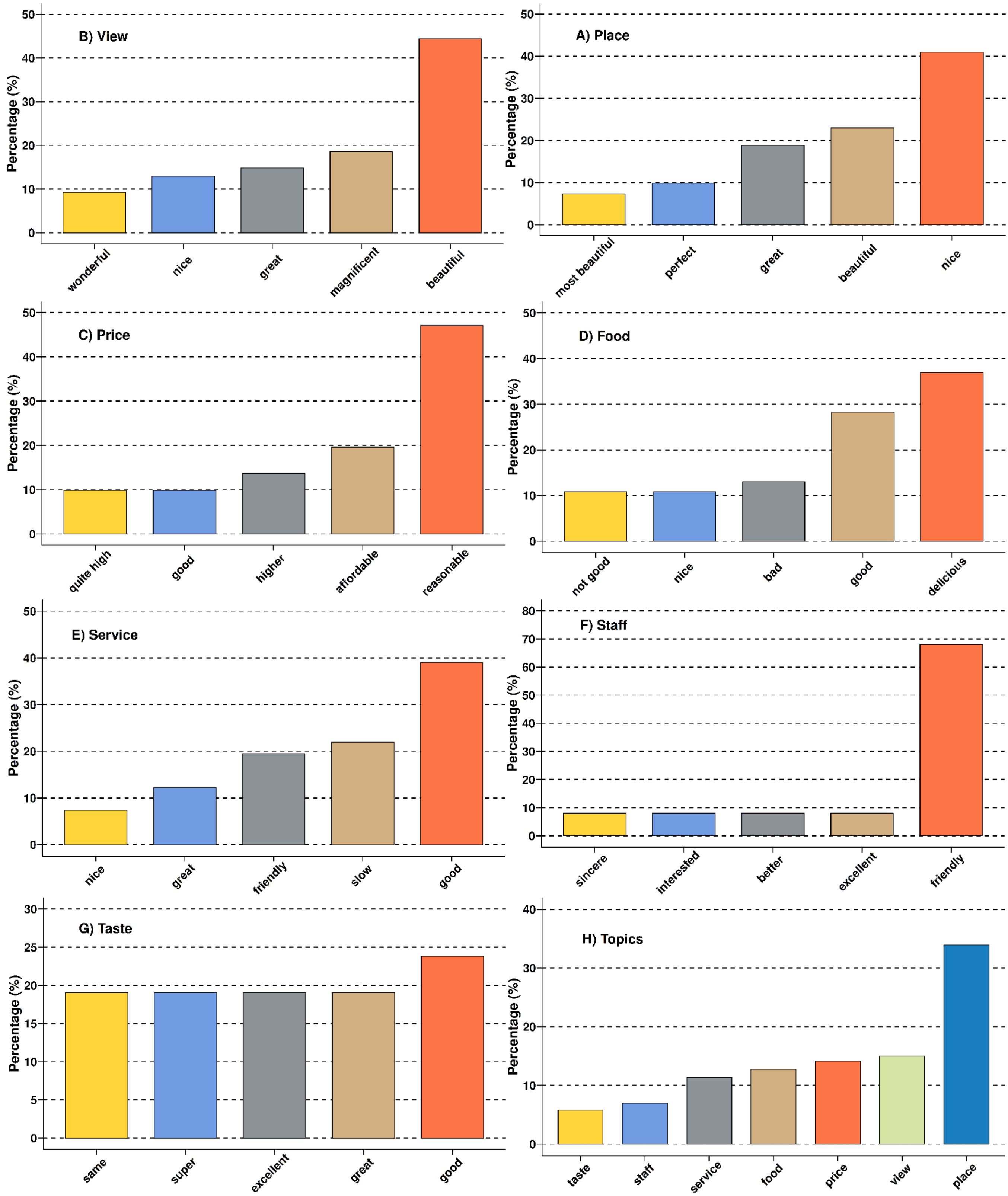

Figure 4. Sentiment Analysis Results of Reviews by Using Rule-Based Aspect Analysis A) Place, B) View, C) Price, D) Food, E) Service, F) Staff, G) Taste, H) Topics

Food topic had a negative sentiment with "not good" (10.87%), *service* with "slow" (21.95%), *taste* with "same" (19.05%), and *price* with "quite high" (9.80%) and "higher" (13.73%). Figure 4.H. shows percentages of all topics with respect to each other. The most reviews were given for the *place* with 33.89% in the data, followed by *view* with 15.0% and *price* with 14.17%. Due to the fact that Artvin is located next to the Çoruh river and in a mountainous area, the city has beautiful views in general, which is reflected in restaurant reviews. The reviews about the *place* have 33.89%, and the total of other topics is 66.11%. Although there are a total of 7 topics extracted from reviews, the fact that one third of customer reviews are about *place* is probably due to the fact that customers make comment on restaurants without giving information about *view, price, food, service, staff,* and *taste*. Dosoula et al. (2016) obtained the topics as *food*, *service*, *price*, and *ambiance* in their restaurant review data set. The authors determined the percentages of these topics as 53.10%, 22.54%, 8.14%, and 16.22, respectively. In addition, Tian, Lu, and McIntosh (2021) used review data from the Yelp restaurant dataset (https://www.yelp.com) for the city of Las Vegas, Nevada in USA. They indicated the topics as *food*, *service*, *expenditure*, *social*, and *miscellany* with the percentages of 37%, 13%, 2%, 3%, and 45%, respectively.

4.1. Machine learning (ML) sentiment analysis

In this study, all words in the restaurant reviews were converted into vectors by Gensim's Word2Vec implementation after the lemmatization process. This implementation is a kind of artificial neural network (ANN) and deep learning that is only used for text processing. Word vectorization, also called model training, was used to convert each word into a vector that was consisted of 50 float numbers. Since it is not possible to visualize 50 size dimensional data into human-readable form, the vectors converted to 2D and 3D spaces with the t-SNE algorithm. t-SNE is a dimensionality reduction algorithm for nonlinear data representation that provides a low-dimensional distribution of high-dimensional data (Belkina et al., 2019). The word vectors for this study are presented on 2D and 3D spaces in Figure 5.

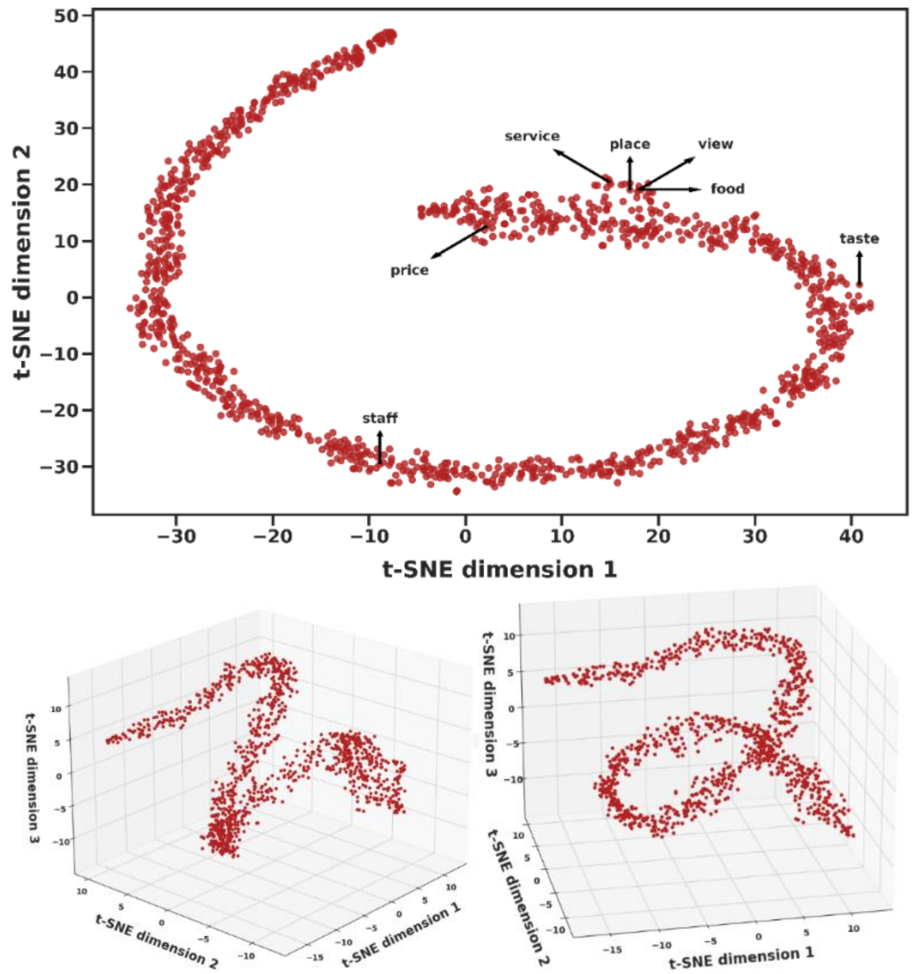

Figure 5. 2D and 3D Spaces Word Vector Visualization with t-SNE

As shown in Figure 6; *place, view, food,* and *service* words are located close to each other. It has been observed that the words *price, taste* and *staff* are located far away, especially the topic *staff* is located quite far away. The reason for this is most probably due to that the contents of comments about *staff* are not highly concerned with other topics. On the other hand, the PCA method was used to better understand the relationship between these topics. PCA is a linear dimensionality reduction technique for extracting important information from data and displaying the similarity of the observations and variables as points on maps (Abdi & Williams, 2010). Figure 6 shows that the topics *place, view, food,* and *service* have correlation to each other, generally meaning that a review has a high score in one of them is also high in the others and vice versa. However, the *price, taste,* and *staff* topics are located on the biplot at a distance from each other, as well as far from other topics, which indicates that they do not have a considerably high correlation. It is considered interesting that the topic of the *view* is closely related to *food* and *service*.

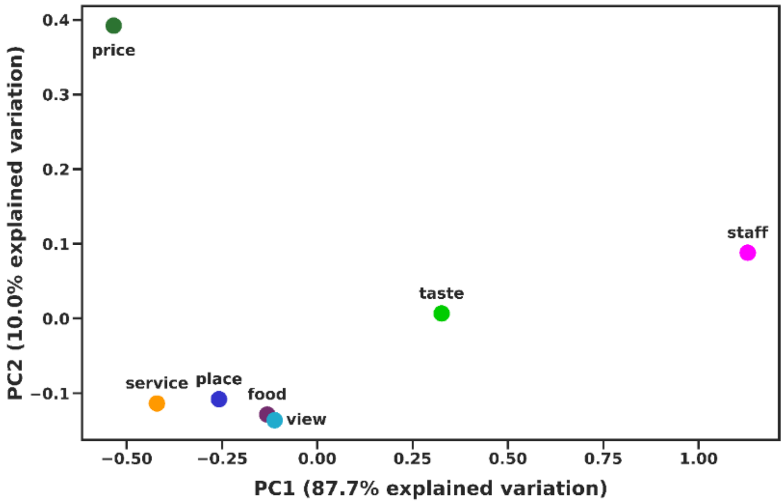

Figure 6. Biplot of Principal Component Analysis (PCA) Illustrating the Variation Among the Captured Topics by Using Rule-based Aspect Analysis

Due to the fact that Artvin province is located near the Çoruh river and is located in a mountainous area, it has quite beautiful views. It is thought that this was positively received by customers and positively affected the *food* and *service* topics. In the PCA biplot, the *service* and *staff* topics are located far from each other which means that there is a high negative correlation between *service* and *staff*. The reason for this is most probably the fact that the negative reviews about the *staff* are mostly related to the *service*. We see that the *price* topic is located quite far from other topics. Accordingly, it can be concluded that the *price* topic was not much related to other topics, in other words, other topics found to be not very effective in *price* assessments. In this study, 1425 reviews have been analyzed and these reviews can be seen in the 2D view in Figure 7.

As previously described, each word after model training is expressed as a vector in the model. Since each review consists of these vectors, all reviews were made vectorized by means of these vectors. There are 1425 points in Figure 7 and each point represents a review. Hence, the closer the reviews are in terms of meaning, the closer the distance between the points is and vice versa. We can say that clusters that appear to be a circle consist of almost the same review with each other in terms of meaning.

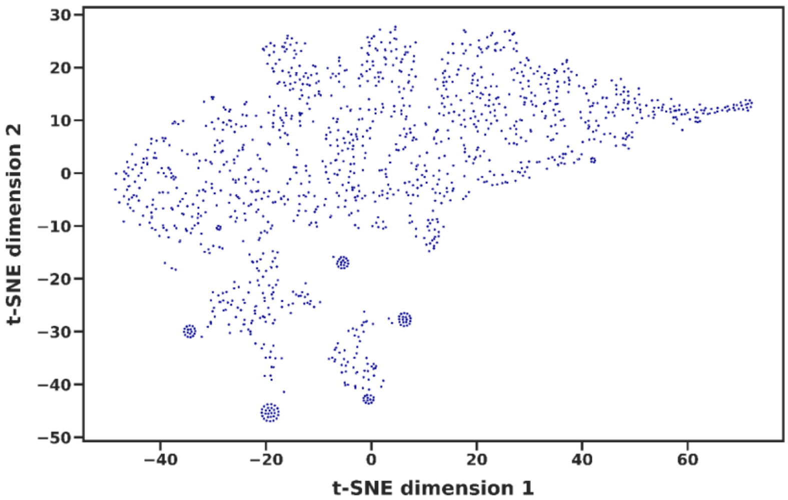

Figure 7. Vector Visualization of Each Review (1425 Reviews) with t-SNE

For each topic, a classification has been performed according to whether it is positive, neutral or negative (Figure 8). It has been observed that the *price* topic has the highest negative ratio (14.32%) followed by *staff* (6.53%). This can be reasonable, since customers are mostly interested in the price first. The *staff* topic has the lowest percentage value among the positive rates (17.23%). In addition, the *view* topic has the highest positive ratio (60.28%) followed by *place* (49.04%). Mathayomchan and Taecharungroj (2020) conducted a restaurant sentiment analysis using the price, service, atmosphere and food topics and determined the customer sentiment analysis scores from high to low as food, service, atmosphere and price, respectively. Tian et al. (2021) collected restaurant reviews belonging to 10 metropolitan areas in the United States and Canada from Yelp (https://www.yelp.com) and informed that consumers rated food lower than they rated restaurant service.

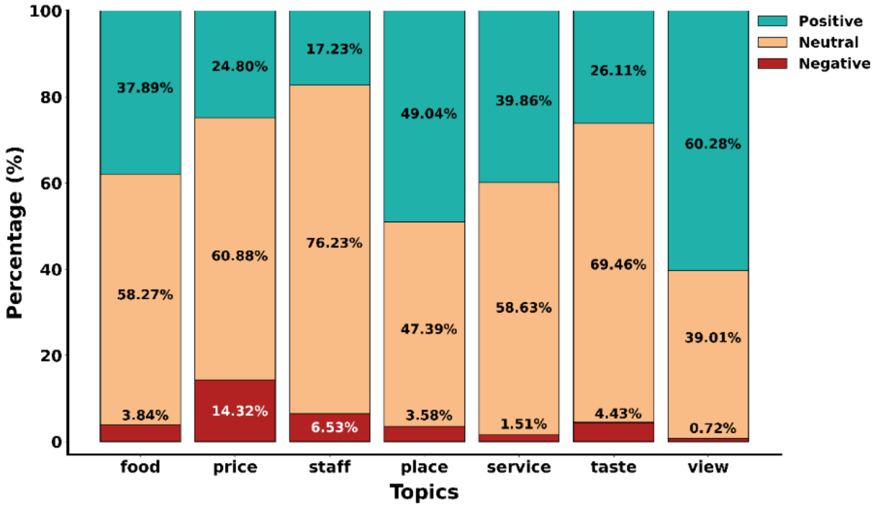

Figure 8. Sentiment Analysis Results of Each Topic After Label Prediction by Using ML

5. Conclusion

This study focused on the sentiment analysis of restaurants in Artvin province. Detailed information about customer reviews has been provided and the favorable and unfavorable aspects of the restaurants have been identified. Two different methods were employed: rule-based sentiment analysis (RBSA) and machine learning (ML), which are respectively based on grammatical rules and artificial intelligence algorithms. The RBSA method was used to extract the subjects covered in customer reviews and investigated what the customers thought about each subject. These topics were found to be as *place, view, price, food, service, staff,* and *taste*. Accordingly, the proportion of those who mentioned that the *food* was "not good" was determined as 10.87%, the *service* was "slow" was determined as 21.98%, and the *price* was "high" was determined as 23.53%. In addition, it was observed that customers commented most about the *place*, followed by the *view* and *price*, and at least comments were made about the *taste* and *staff*. All words in the reviews were vectorized using the ML method. In this way, the relationships of the topics with each other were examined and the distribution of negative, positive and neutral sentiment percentages in each topic was determined. It has been observed that the *service*, *place*, *food* and *view* topics are closely related to each other and whether customers like one or not had an impact on the others. Furthermore, customers had the most negative opinions on the *price*, followed by the *staff*. Due to the fact that restaurants are often visited by many people, it is necessary to carry out studies similar to this study at various levels using the most up-to-date methodologies both in terms of the country's economy and to increase customer satisfaction. Machine learning algorithms in the Gensim library can prove to be quite effective in text mining and the library was employed properly in this study.

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Ethical Approval: In the article, the authors declare that they comply with national and international research and publication ethics. In case of detection of a contrary situation, **GSI Journals Serie A: Advancements in Tourism Recreation and Sports Sciences Journal** has no responsibility and all responsibility belongs to the article's authors.

Ethics Committee Approval: Ethics Committee Approval was not required for the study.

Conflict of Interest: There is no conflict of interest or gain in the article.

Contribution Rate of Researchers: The study was prepared with the contribution of a single author. Contribution rates: 1. Author = 100%.

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