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Determination of Social Media Users' Perceptions About "Black Friday" Activity via Sentiment Analysis

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ABSTRACT : The aim of this study was to analyze the "Black Friday-Kara Cuma" perception of Twitter blog site users via the method of sentiment analysis. A total of 491 tweets posted between 03 and 25 November 2018 from Turkey as location was subjected to analysis as data. Data were collected using the Java-based Twitter4J library. These data had pre-processed with Zemberek NLP natural language processing library. Sentiment analysis was performed based on pre-processed data. "Türkçe Duygu Sözlüğü V1" was used as a lexicon for this purpose. In conclusion, the data used was evaluated as 54% negative, 42% positive and 4% neutral perception. In addition, when examined in terms of their reasons, the tweets related to "Black Friday" cluster around certain headings to form groupings. This study emphasizes the effect of socio-cultural factors on behavior patterns in on-line shopping platforms.

KEYWORDS: Sentiment Analysis, Sentiment Lexicon, Text Mining, Twitter4J, Zemberek NLP.

I. INTRODUCTION

Nowadays, social media and internet usage has reached the highest level. As the mobile smart devices have become cheaper and more popular in the market, a significant population of internet users came into being in Turkey (TUIK 2019a, 2019b). Advanced mobile smart devices are preferred by all the demographic categories (TUIK 2019a, 2019b) . In addition to the technological IoT devices, many social network software serving in the web environment have been developed. These social networks have become an acceptable medium through which people carry on their social lives. Sharing their sentiments and opinions over these social networks, people use these networks to meet their many needs. Via these social networks, users transmit thousands of different messages every day. Therefore, a collective information batch accumulates in the databases of this social network software. This information batch formed is called social network data. Social network displays itself n0ot only as an objective but also as a means. It provides a large data to understand social perceptions, orientations or attitudes. As a result of uncovering the data present but unseen patterns in the data via techniques of text mining, unknown information is accessed.

As the information technologies have entered all parts of human life these days, it is known that many daily transactions are carried out on-line via internet; and this on-line participation is increasing day by day. People usually leave many traces behind on the on-line environments they enter. For example, when shopping, we engage in activities such as liking products, recommending them to people in our network, making comments about a product we have bought stating that we are satisfied or unsatisfied about it. Every step we leave behind as consumers may not be very meaningful for us, but it is very important for the manufacturer or marketer. What we face with does not always have to be a manufacturer or marketer; sometimes it can be a film, a music band or a political actor acting in the political arena. What we feel and think about the object, the situation or the person we face is important. These feelings and opinions become even more important when they occur at a mass scale. People's feelings and opinions can be used as a measure of success for the object we face. In this respect, sentiment analysis (SA) has become a definitive field of study. SA is defined as the process of uncovering the sentiments in the texts by using various text mining techniques or statistical algorithms on the texts(Pang and Lee 2008). Sentiment analysis (SA) methods are used to process the contents of the texts, and thus the emotions are extracted. For the text in question, 3 different polarities are calculated as negative, positive and neutral (Liu 2012; Pang and Lee 2008). It is considered that this study will contribute to the understanding of the importance of SA studies and contribute to the limited number of studies in SA literature.

Black Friday: Black Friday is the special and meaningful name given to the first Friday following Thanksgiving in the United States (Thomas and Peters 2011). In the United States, Thanksgiving takes place on the third Thursday of November each year (Thomas and Peters 2011). In the United States, the Friday that follows Thanksgiving has been considered the beginning of the Christmas shopping season since 1932, and many famous brands offer significant discounts and opportunities in their products (Thomas and Peters 2011). It's known that a serious supply and demand occur on this special day, which is a marketing strategy. During the events of 1961-1965, social violence and conflicts erupted due to heavy traffic and large crowds in Philadelphia (Thomas and Peters 2011). Following that year, when people crushed each other, these events came to be called "Black Friday" (Thomas and Peters 2011). Until the 1980s, retailers preferred this term and used it to refer to the bookkeeping practices, where losses were recorded in red and profits in black ink (Thomas and Peters 2011). For this reason, Black Friday refers to the day of the year when retailers want to pass from being "red" (that is, losing money) to being "black" (that is, making money) (Thomas and Peters 2011). Having survived to the present day, this event is also experienced in many countries outside the United States. Within the context of this activity, brands or markets provide practical benefits by providing significant discounts. The activity to date has been a tool used to reduce stocks abroad. Firms aim to reduce their stocks by offering serious discounts (Thomas and Peters 2011).

In Turkey, however, the "Black Friday" campaigns are rather held on on-line shopping sites. In the sectors where the competition is at the highest level, companies aim to increase their customer potential by organizing discount campaigns. Yet, many companies use different definitions and names instead of "Kara Cuma," which is the equivalent of "Black Friday" in Turkish, as it conflicts with the blessed meaning of the day in Turkish culture and the society's religious values. Among the commonly used attributions are "Legendary Friday" and "Fantastic Friday." A concept that originated in the western societies, the idea of "Black Friday" is maintained in Turkey via different concepts with a consideration of religious sensitivities, since the majority of the society is Muslim. No matter how much consideration is observed, the media reports reflect that there is still a large segment of the society that reacts to and opposes this practice (CNN Türk 2017). Furthermore, it is another object of curiosity how the activities held in other countries are reflected in their counterparts in Turkey when they are compared. What we call activities here are discount practices.

Sentiment Analysis: Also known as opinion mining, Sentiment Analysis is a field of study that analyzes people's sentiments, evaluations and attitudes about entities such as products, services, organizations, individuals, subjects and events, and their characteristics (Liu 2012). It contains solutions to many different problems. Many similar topics such as sentiment mining, opinion analysis, opinion extraction, or opinion mining have been collected under the heading of sentiment analysis or opinion mining (Liu 2012). It is the process of classifying and determining the human sentiments by analyzing the contents of the texts based on machine learning or statistical methods. It is the analysis of written texts via algorithmic or statistical solutions by processing them by means of computer software. In analyzing sentiments, the contents in the texts are analyzed, and thus the extraction of sentiments is provided. Usually the sentiments in the texts are divided into 3 classes; and they are calculated as 3 different polarities: negative, positive and neutral (Liu 2012; Pang and Lee 2008) .

Three technical levels are used in the analysis of sentiments. These are considered to be document level, sentence level and entity and aspect existence respectively(Liu 2012; Turney 2002) . The document level aims to extract an idea for the whole text. Generally a positive or a negative opinion is reached. On the other hand, the sentence level analysis establishes whether each sentence carries a positive, negative, or neutral content. In this level of analysis, the purpose is to distinguish between subjective sentences and objective verb sentences. This distinction is made by attribution classification techniques. In this level of analysis, sufficient sensitivity cannot be shown regarding the subjective sentences containing innuendos or irony (Liu 2012). However, the entity and aspect level deals directly with the idea given by the text, instead of dealing with the text structures in it. It is concerned with whether the text contains a sentiment (positive-negative) and an opinion (objective) (Liu 2012). A text with an unidentified objective is restricted. Trying to catch and realize the message that the text wants to convey enables us to understand the problem of sentiment analysis better. The aim of this level of analysis is to understand the entities and their aspects.

There are two different views when the opinion signaling a sentiment is expressed, which are divided into two as regular and comparative opinions (Jindal and Liu 2006). According to Liu, there are also certain well-accepted words that express sentiments best. For example, while words "good," "beautiful," "fine" directly evoke a positive perception by the brain, words like "ugly," "damned," "disgusting" create a negative perception. In

addition, there are neutral words and phrases that do not create any perception (Liu 2012). For instance, words like "pen," "arm," "bag," "go, "come" form a neural perception. A compilation of words consisting of a list of words signifying such sentiments are called a "sentiment lexicon" (Liu 2012). Many studies have been done to compile a lexicon of sentiments; and sentiment lexicons are one of the methods used in analyzing sentiments. In this study, we have taken "Black Friday" concept as an entity, and it was analyzed on the basis of sentiment lexicon with reference to its forms of application, the ideological reactions it drew, and the sense of trust in it.

Twitter Sentiment Analysis: Twitter is one of the most popular social media networks, where people share their sentiments and opinions in the form of brief summaries. It was reported to have 330 million active members per month in 2018 (Clement 2019). Also, 90 % of these active members are mobile users who constitute Twitter users (Clement 2019). Turkey ranks 5th among the countries that use Twitter most (Bayrak 2018). During the third quarter of 2018, Twitter reached the number of 326 billion monthly active users (Clement 2019). Besides 473 400 tweets are sent per minute, and it is known that more than 500 million tweets are sent by 100 million active users per day (Clement 2019). The Twitter blog network, which has a large pool of users, forms an incredibly large stack of data, which has led us to prefer twitter data as a source where sufficient interaction for sentiment analysis occurs.

II. LITERATURE REVIEW

Sentiment analysis is applied to many areas. To cite just some of the studies: by collecting data via Twitter, a social media blog, Mogaji and Erkan (2019) conducted an analysis of sentiments concerning the business brands to investigate the experiences and attitudes of passengers toward train companies in the UK (Mogaji and Erkan 2019). Bag *et al.* (2019) developed an attribute level decision support prediction model for accurate estimate of the consumers' purchasing intention about durable goods in retail sales. In order to develop the aid model, the study used brands' social perception score and reviews' polarity by computing them from social network mining and sentiment analysis. Then, an appropriate regression analysis and suitable instances were identified for each attribute to predict the appropriate product attributes (Bag, Tiwari, and Chan 2019) In another study, customers' satisfaction was analyzed in terms of the features of location, hospitality and comfort on social media data belonging to a hotel application. In this study, customer satisfaction was investigated by sentiment analysis method; and it was emphasized that large data and visualization could be used effectively in tourism and hotel applications (Cheng and Jin 2019). Jimenez-Marquez *et al*. (2019) conducted another similar study on hotel applications (Jimenez-Marquez *et al*., 2019). By collecting data from different social media networks, a research was carried out on hospitality in hotel management. In the mentioned study, massive data were analyzed (Jimenez-Marquez et al. 2019).

In a study by Liu *et al*. (2019), sentiment analysis of the touristic experiences of the Chinese Tourists in Australia was made by using the comments made for travel agencies on online social media platforms as data. Sentiment analysis was conducted by using the techniques of lexicon filtering, co-occurrence analysis and semantic clustering. The study concluded by emphasizing that the characteristics and preferences of Chinese tourists in marketting did not coincide with international touristic preferences and characteristics(Liu et al. 2019). For the sentiment analysis on the effective use of drugs Akhare and Saravanan (2017) used SentiWordNet (Akhare and Saravanan 2017; Baccianella, Esuli, and Sebastiani 2010; Esuli and Sebastiani 2007) lexicon and naive bayes classifier. The application Map-Reduce processing was performed in the framework of Apache Hadoop (Hadoop 2011). The mentioned study states that it can make suggestions about which drugs can be preferred according to the comments made to the drugs (Akhare & Saravanan, 2017). Using the Hadoop and Map Reduce to collect data instantly for the Indian Premier League 2015 from Twitter, Paul (2017) resorted to sentiment analysis in his study in order to show how popular the Indian Premier League is (Paul 2018).

In the study conducted by Trupthi *et al*., hadoop based sentiment analysis is studied by using fluid data. Filtering was done employing the words "education", "ISIS" and "Obama." For the "Obama" filter, of the 114 tweets used, 30 were negative, 28 were positive, and 56 were neutral. In the "education" filter, of the 238 tweets used, 150 were positive, 26 were negative and 62 were positive. For the "ISIS" filter of the 276 tweets used, 169 were negative, 83 were neutral, and 24 were positive (Trupthi, Pabboju, and Narasimha 2017). By using logarithmic differential term frequency and term existence distribution models and random forest classifiers, Oğul and Ercan conducted a sentiment analysis on a dataset containing 331 elements based on machine learning, and they concluded that the random forest classifier was the best classifier(Oğul and Ercan 2016).Enneji et al. (2016), using the Sentigem (Sentigem 2020) glossary for the idea of Social CRM (Customer Relationship Management),

a Map-Raduce based multi-agent emotion analysis model was established. In the study, the timing performance was measured. The Twitter4J library was used to collect data (Ennaji et al. 2016).

Beyhan (2014) has applied sentiment analysis to investigate the case of GSM companies in Turkey and developed a new model based on clustering. In their study, they used, via Botego Company, the tweets about 3 operator companies within a certain date range and the results of sentiment analysis about these tweets. They analyzed the same twit dataset by clustering approaches and compared these results with the results of sentiment analysis and made inferences (Beyhan 2014). Göçenoğlu made Turkey's sentiment analysis by collecting social network data for a study in 2014, in which machine learning based and lexicon based approaches in sentiment analysis were compared. The study made sentiment analysis by using Twitter API data as a big data source and visualized the results using Google Maps JavaScript API. In this study, SMO algorithm was proposed as the most appropriate method for sentiment analysis (SA)(Göçenoğlu 2014).

III. MATERIALS AND METHODS

Twitter API: Belonging to Twitter, Twitter API is an interface that offers an application development environment. Twitter offers two different options, two different applications for data access: API and Rest API. With Streaming API, it allows instant real-time data flow and tracking and allows for gathering data during Tweet flow. In a study to be made current issues, it might be useful to use Streaming API. On the other hand, the Rest API offers the possibility of searching on the current tweet data. The Rest API option provides 3 different usage rights as standard, premium and enterprise. In standard use, a simple search can be made using standard search operators and the right is limited to 7 days. Premium use is limited to 30 days and has full archive options, but it still has certain limitations (maximum number of queries that can be made and maximum number of tweets that can be posted).

In the case of Enterprise, the constraints are a little more flexible and there are additional, open search options (Twitter 2018a).The following visual summarizes the products, categories, dates supported, data and quantity constraints of the Twitter API.

Feature summary

Category	Product name	Supported history	Query capability	Counts endpoint	Data fidelity
Standard	Standard Search API	7 days	Standard operators	Not available	Incomplete
Premium	Search Tweets: 30-day endpoint	30 days	Premium operators	Available	Full
Premium	Search Tweets: Full-archive endpoint	Tweets from as early as 2006	Premium operators	Available	Full
Enterprise	30-day Search API	30 days	Premium operators	Included	Full
Enterprise	Full-archive Search API	Tweets from as early as 2006	Premium operators	Included	Full

Figure 1. Twitter API product details (Twitter 2018a)

Zemberek NLP: Zemberek NLP is a natural language processing library that started to be written in 2007. It is the first language processing library for Turkish language. Written in Java programming language, it is open source and open licensed. Its first version was released under BSD license as a LibreOffice plugin. The second version was changed to MPL license under the name Zemberek2. Finally, Zemberek NLP project is being developed as open source (Akın and Akın 2007). In this study, the latest version of Zemberek NLP Library was used. In this study, Zemberek NLP was used to analyze the data more healthily. With Zemberek NLP, pre-processing was applied to the data by root-body parsing, removing punctuation, removing null lines, non-words, or meaningless words such as conjunctions.

Collecting of Data Via Twitter4j Library: Twitter4J is an open source library supported by Twitter and written in Java(Twitter 2018b; Yamamoto 2007). In this study, filtering keys were used to scan the Twitter4J library from the Twitter API. It was used for providing API access and creating the existing encodings. By creating a java project with standard usage, various methods, constructors etc. were written. Thus, it was possible to make various queries. The following visual is a sample method that collects data.

```
public List<Status> search(String keyword) {
      ConfigurationBuilder cb = new ConfigurationBuilder();
 cb.setDebugEnabled(true)
            .setOAuthConsumerKey(x)
            .setOAuthConsumerSecret(x)
            .setOAuthAccessToken(x)
           . setOAuthAccessTokenSecret(x)
            .setTweetModeExtended(true);
      TwitterFactory tf = new TwitterFactory(cb.build());
      Twitter twitter = tf.getInstance();
      Query query = new Query(x);
      query.setCount(x );
      query.setLocale(x);
      query.setLang(x);
      query.setSince(x);
      query.setUntil(x);
     try {    QueryResult queryResult = twitter.search(query);
            return queryResult.getTweets();
         } catch (TwitterException e)
      return Collections.emptyList();
   }
```

Figure 2. Sample Code of Collecting Tweets

Sentiment Measurement: In this study, sentiment measurement was made on lexicon basis. In literature review, it was observed that the studies on sentiment lexicon in Turkish were limited; thus, there is need for more studies in this field. In the study by Dehkharghani et al. (2016), a sentiment lexicon entitled SentiTurkNet was created with the help of the translation of a sentiment lexicon in English (Dehkharghani et al. 2016). Sağlam et al. (2016) were reported to carry out a project of sentiment lexicon entitled SWNetTR-PLUS based on translation and a combination of the lexicons SWNET-TR and SWNetTR-GDELT (Saglam, Sever, and Genc 2016).
Uçan (2014) was reported to be working on an automatic sentiment lexicon translation study (Uçan 2014). In this study, the sentiment lexicon created by Uçan was used. Sentiment analysis was performed on twitter data collected using Turkce_Duygu_Sözlüğü_v1 version. The flow chart of the sentiment analysis is shown in *Figure 3*.

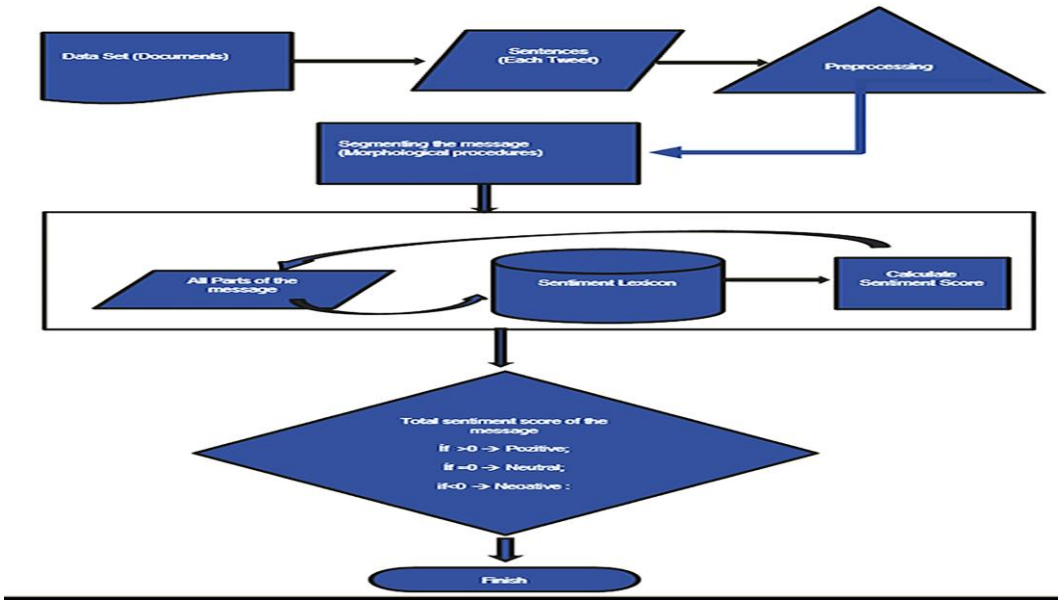


Figure 3. Sentiment Analysis Flow Chart

The data collected and compiled in this study was manually labeled as positive-negative-neutral according to their conditions. In addition, lexicon-based sentiment analysis was performed for each tweet text, and each tweet was automatically classified as positive-negative-or neutral. In order to analyze the contradiction between the predicted and the labeled, the confusion matrix was generated. Classification success was measured by confusion matrix metrics. To determine how successful the classification was, precision (π) and recall statistics were used by calculating from the confusion matrix. Sensitivity is used for measuring the accuracy of estimates. Recall (ρ) refers to how close the estimate within the group has been. The F1 score is the harmonic mean of the recall and precision statistics and is twice the ratio of their sum of their product. It enables the combined evaluation of precision and recall(Şimsek 2018).

$$Precision = \pi = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \rho = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = 2 * \frac{\pi * \rho}{\pi + \rho} = \frac{2 * TP}{2 * TP + FN + FP} \tag{3}$$

$$Accuracy = ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

VI. RESULTS

Within the scope of this study, we have tried to understand the perspectives of Twitter users on the activities within the context of “Black Friday.” In sum, we have tried to answer the following questions:

- What the sentimental attitude of Twitter users in Turkey towards "Black Friday" is like?
- Are customers or the users concerned satisfied with the “Black Friday” activities?
- What is the customer's sentiment perception of discount?
- How does the religious or national value perception in Turkey reflect on the concept of “Black Friday”?

Within the scope of this study, Twitter blog data was used as social network data. Twitter data was filtered from Twitter Streaming API and queried immediately. As query key, tweets whose language key and location were Turkey were chosen. To collect data on the concept of “Black Friday”, the query was made by using tags “BlackFriday” , “Black Friday”, “Kara Cuma”, “Efsane Cuma”, “BlckFrdy.” During the collection of data, many morphological pre-treatments were carried out by making use of Zemberek NLP library.

Tweet contents were cleared of image data, blank lines, meaningless characters, and only meaningful words and phrases were taken into consideration. After the data were collected, they were compiled and the duplicates were removed. Finally, the results of the analysis for “Black Friday” were summarized.

A data set made up of a total of 491 tweets, duplicates being removed, with search results and tags recorded between 03.11.2018 and 25.11.2018 was collected and evaluated, classified and the success of the classification was measured.

As shown in Figure 1, when the tweets on “Black Friday” other related concepts were examined, 54 % of the tweets were classified as Negative, 42 % were as Positive and 4 % were as Neutral. As the criterion of classification success, F-Score was used.

By calculating precision and recall via confusion matrix, F-Score value was calculated. In Lexicon-based sentiment analysis studies, it is generally accepted that the F1 score should be around 70% to be considered sufficient. In this study we conducted, F1 score was lower. The reason for this is that the data set contained too much irony. In fact, the messages that were semantically negative but seemed to be morphologically positive were an obstacle to correct classification.

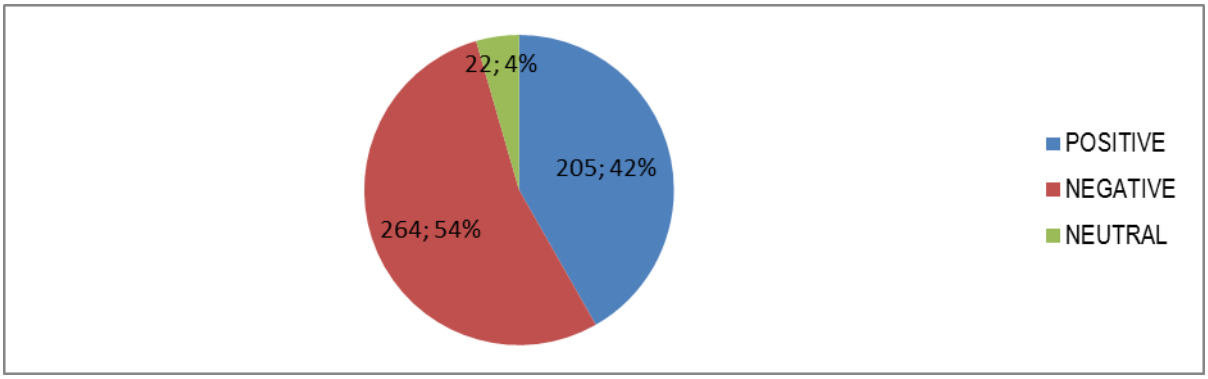


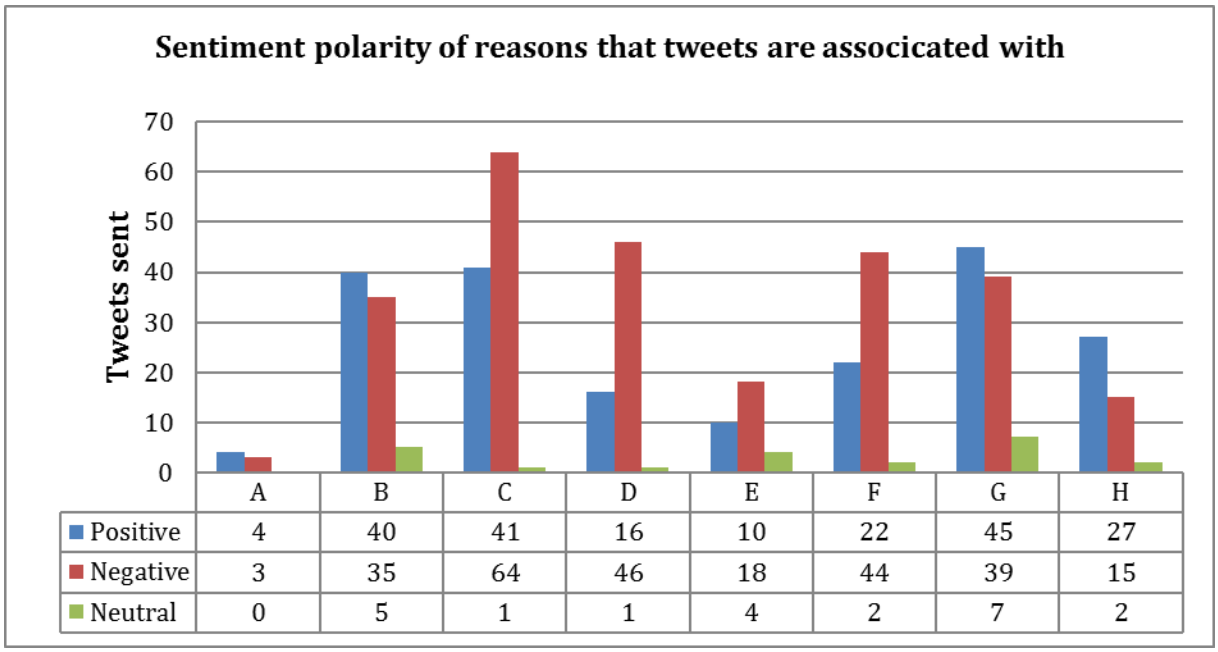
Figure 4. Sentiment classification

Table 1. Tweet dataset sentiment classification success statictics

Precision	Recall	F1-Score
0.6028708	0.7826087	0.6810811

Each tweet in the data set was examined, and it was observed that the tweets about the concept of "Black Friday" clustered around certain reasons. Following the detailed examination, these reasons are grouped as follows:

A: Complaints by Company Employees and Employers: This group we have created consists of positive and negative comments of the employees concerning the workload experienced during "Back Friday", pressure form the employers and customers and the resulting stress, and of positive and negative comments of the employers regarding demand and workload, expectations, and abuses.
B: Ideological and Religious Attitudes: This grouping consists of tweets containing opposing attitudes by the users who think that the concept of "Black Friday" is not compatible with national or religious values and disagree with them
C: Attitudes towards Confidence, Worry and Abuse: This grouping includes tweets that include the statements by the users expressing that in the "Black Friday" campaigns, companies attract customers by deception, and the discounts and the campaigns proclaimed do not reflect truth or they are not the way they should be.
D: Attitudes Towards Economic Constraints and Benefit Constraints: This grouping includes the messages of the users who think that "Black Friday" campaign offers serious opportunities, but they cannot fully benefit from it due to certain restraints like economy, transportation, etc.
E: Advertising and Marketing Pressure: It includes tweets reflecting the reactions of the users who complain that the extent of advertisements and announcements has reached the level of harassment. This group includes tweets that express the discomfort felt by messages sent without permission to Internet and mobile phone users.
F: Negative Practices: This group contains tweets posted for complaining about wrong product shipments, running short of products in basket application, fight for grabbing products, cancellation of the ordered product for its being out of stock, shipping of defective, deformed and problematic products, or the products that do not meet customers' expectations.
G: Irrelevant Tweets: This group includes tweets irrelevant to **"**Black Friday."
H: Tweets Containing Requests-Suggestions-Wishes: This group consists of tweets that are happy about the "Black Friday" campaign and express requests, wishes, likes or expectations for the improvement of the campaign.



	A	B	C	D	E	F	G	H
Positive	4	40	41	16	10	22	45	27
Negative	3	35	64	46	18	44	39	15
Neutral	0	5	1	1	4	2	7	2

Figure 5. Polarity distribution chart of the reasons that tweets are associated with

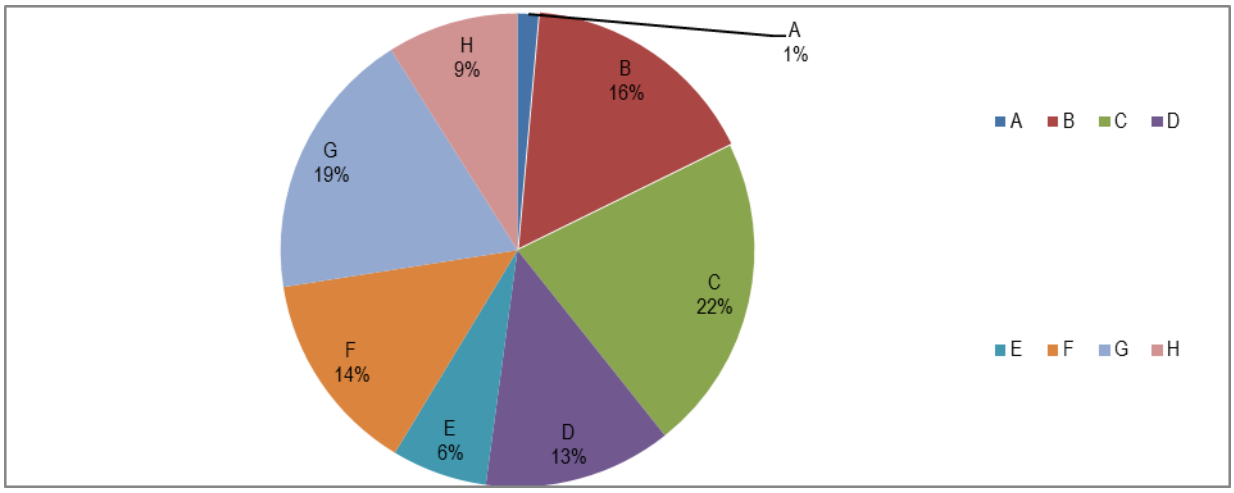


Figure 6. Categorical distribution chart of the reasons that tweets are associated with

A: The tweets concerning the complaints by the employees and employers are least in number. 4 out of 7 tweets have positive and 3 have negative emotion polarities, which makes the 1 % of tweets.
B: Those who think that "Black Friday" is not compatible with religious and national value judgments rank third in number and constitute 16% of the tweets. Out of a total of 80 tweets 40 are positive, 35 tweets are negative, and 5 tweets are neutral in terms of sentiment polarity.
C: Tweets on trust, worry and abuse make the majority of the tweets. Twenty-two percent of the tweets is about the abuse of trust. Of the 106 tweets corresponding to 22 % of all tweets, 64 are negative, 41 are positive, and 1 is neutral in terms of sentiment polarity.
D: Of the 63 tweets posted about the constraints, 46 are negative, 16 are positive and 1 is neutral in terms of sentiment polarity. This is the most negative group in the category. It corresponds to 13% of the posted tweets and ranks fifth.
E: Ranking seventh are the reports of weariness about advertisements and announcements via the media and the employee complaints about "Black Friday." In this category, there is a total of 32 tweets posted, 10 of which are positive, 18 are negative and 4 are neutral in terms of sentiment polarity.

F: Tweets on adverse situations encountered in campaigns related to “Black Friday” rank fourth and account for 14% of all tweets. Twenty-nine tweets of this category are calculated as positive, 22 as negative, and 2 as neutral in terms of sentiment polarity. This is the second category containing the highest number of negative tweets.
G: In this category, 45 of the 91 tweets are calculated as positive, 39 as negative and 7 as neutral in terms of sentiment polarity. The fact that tweets, which are not related to the concept of “Black Friday”, rank second in number with a ratio of 19%, suggests that this concept is not taken seriously enough. As an example, both the loss and the victory in football match that coincided with this period was posted about by different users with the label “Black Friday”.H: In this category, out of a total of 44 tweets posted, 27 are calculated as positive, 15 as negative, and 2 as neutral in terms of sentiment polarity. The tweets expressing requests, wishes, likes about the concept of “Black Friday” rank sixth with a ratio of 9 %. Although the tweets written in this category appear to be positive, all of the tweets in general are known to reflect a negative sentiment about the concept. However, the tweets posted indicate that there are also some that express positive opinions about the concept.

Table 2. Polarity distribution table of the reasons that tweets are associated with

	A	B	C	D	E	F	G	H	TOTAL
Positive	4	40	41	16	10	22	45	27	205
Negative	3	35	64	46	18	44	39	15	264
Neutral	0	5	1	1	4	2	7	2	22
Total	7	80	106	63	32	68	91	44	491

V. DISCUSSION AND CONCLUSION

In conclusion, it was found that people were generally prejudiced against the concept of “Black Friday”. To summarize the findings of this study: The most cited reason for the negative opinions about “Black Friday” is that the content of the concept of “Black Friday” is not the way it should be; to the contrary, it is a hollow concept, and a sales trick. It is perceived as a practice, in which the sale prices are inflated. It is important to use these activities positively as a market mechanism but it should not be abused. Sense of trust is important for the society. Therefore, the management should be able to take measures and make use of control mechanisms.A significant portion of the tweets is irrelevant to “Black Friday” and is related to the personal conditions of users. Positive and negative perception rates are very close. Events from the same period have been interpreted by different users with messages of different sentiment polarity. This suggests that the term “Black Friday” is not sufficiently embraced or taken seriously by the society. Fleshing out the content of the practice differently can attract the attention of users and the concept can be used as a tool to benefit from. To do this, companies should create a basis for institutional or legal regulation.

The number of those who interpret the concept of “Black Friday” in relation to the degeneration of religious and national values is too many to underestimate. In this respect, it is observed that the users are not well-informed about the real meaning and usage of the concept. People react to the concept due to the sacred meaning and place of “Friday” in Islam. There are also users who react to this situation since they see it as a medium of the capitalist system. The incidents causing disturbance during the practice such as fight for grabbing products have caused people to have a negative opinion about “Black Friday” and they have expressed their annoyance in the face of unpleasant incidents. The obstacles to the campaign, constraints such as the economic crisis and the lack of money, have reflected negatively on the concept of “Black Friday”. As a reaction, people have attributed a negative sentiment to “Black Friday.” It is seen that the discount and campaign ads, which are generally found to be exaggerated, create a sense of weariness in the users, and this creates a negative perception about the concept. Despite all these negative situations, there are also users display to a sense of hope and expectation. Thus, the concept of "Black Friday" is thought to find its place gradually in Turkish society.In this study, lexicon based sentiment analysis has been performed. As a result of the analysis, 54 % of the tweets were calculated to be negative, 42% were positive, and 4% were neutral. Twitter users in Turkey can be said to attribute a negative sentiment in general to the concept of “Black Friday.” In the sentiment analysis conducted, the F1 score has been 68%. In the studies conducted, that score to be generally 70% is an expected and desired result. The tweets posted have contained too much irony. It’s a known trouble of language processing process.

Besides, it should not be overlooked that the performance of the dictionary used, entitled Türkçe_Duygu_Sözlüğü_v1, may have affected this result. The adequacy of the dictionary used was excluded from this study.

Potential Conflicts of Interest : The authors declare no conflict of interest.

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