SOCIAL MEDIA ANALYTICS FOR BRAND IMAGE TRACKING: A CASE STUDY APPLICATION FOR TURKISH AIRLINES

İbrahim SABUNCU[1], Mahir ATMIŞ[2]

[1,2] Industrial Engineering Deparment, Engineering Faculty, Yalova University, Yalova, Türkiye

ABSTRACT

Along with technological developments, concepts such as big data, big data analytics, social media, and social media analytics have been included in the agenda of marketing and other management sciences. It is known that among the biggest obstacles encountered in applying new methods, which are generally called business analytics, is the lack of knowledge and experience. In this study, an exemplary application that could be useful to academics and business managers who want to work in social media analytics applications, a subdivision of business analytics, has been implemented. Within the scope of the study, 6667 Twitter messages shared between 23.03.2018 - 02.04.2018 in English about Turkish Airlines (THY) are fetched and recorded into a database using open source R programming language. Messages were classified as positive and negative by applying sentiment analysis implementation of syuzhet R package on these messages. Daily positive and negative message counts are computed and the changes in counts are interpreted. A total of 50 randomly selected samples' Twitter account names, negative/positive message counts, locations, latitude and longitude information, and profile photos are downloaded from the Twitter server. The samples are then viewed on the map via the Google Maps API. It is examined how these applications made within the scope of Data Visualization can be used in administrative processes[1].

Keywords: Data Analytics, Social Media Analytics, Image Management, Twitter, Sentiment Analysis

MARKA İMAJ TAKİBİ İÇİN SOSYAL MEDYA ANALİTİĞİ: TÜRK HAVA YOLLARI İÇİN BİR VAKA ÇALIŞMASI

ÖZET

Teknolojik gelişmeler ile birlikte büyük veri, büyük veri analitiği, sosyal medya, sosyal medya analitiği gibi kavramlar pazarlama ve diğer yönetim bilimlerinin gündemine dahil olmuştur. Genelde iş analitiği olarak adlandırılan yeni yöntemlerin uygulanması sırasında karşılaşılan en büyük engeller arasında, bilgi ve tecrübe eksikliğinin olduğu bilinmektedir. Bu çalışmada, iş analitiğinin bir alt dalı olan sosyal medya analitiği uygulamalarında çalışmak isteyen akademisyenlere ve işletme yöneticilerine yararı olabilecek örnek bir uygulama gerçekleştirilmiştir. Çalışma kapsamında, ücretsiz (açık kaynak kodlu) R programlama dili ile hazırlanan yazılımla, Türk Hava Yolları (THY) hakkında Twitter'da İngilizce olarak 23.03.2018 – 02.04.2018 tarihleri arasında paylaşılmış 6667 mesaj dakikalar içerisinde tespit edilip veri tabanına kaydedilmiştir. Bu mesajlara duygu analizi algoritması, syuzhet R paketi uygulanarak, mesajlar pozitif ve negatif olarak sınıflandırılmıştır. Mesajların günlere göre pozitif ve negatif sayıları tespit edilip, değişimler yorumlanmıştır. Bu mesajları paylaşan kişilerden, rastlantısal seçilen toplam 50 örneklemin, Twitter hesap adları, negatif/pozitif mesaj

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sayıları, konumları, enlem ve boylam bilgileri, profil fotoğrafları Twitter sunucusundan indirilip, Google Haritalar API uygulaması kullanılarak, harita üzerinde bu kişilerin görülmesi sağlanmıştır. Verilerin görselleştirilmesi kapsamında yapılan bu uygulamaların, yönetimsel süreçlerde nasıl kullanılabileceği incelenmiştir.

Anahtar kelimeler: Veri Analitiği, Sosyal Medya Analitiği, İmaj Yönetimi, Twitter, Duygu Analizi

INTRODUCTION

Thanks to technological developments such as the Internet, mobile applications, and social media, businesses can collect large amounts of data. Data can be obtained from many different sources such as customer service call center call records, emails, customer purchase histories, accounting records, website navigation history, and search engine searches. The cost of high-capacity digital storage technologies is decreasing. This resulted in the storage of an increasing amount of data at exponential speed. As a matter of fact, the size of the data in the digital universe is expected to increase 10 times from 2013 to 2020, from 4.4 trillion gigabytes to 44 trillion (International Data Corporation (IDC) 2014). Data stored in the digital environment has become a new asset of increasing importance with the development of technology.

The emergence of large amounts of data has led to the development of business management models based on data that benefit from this data. Businesses try to obtain useful information by analyzing big data with the methods called "Business Analytics". It is used as a framework for similar concepts such as business analytics, big data analytics, business intelligence, and customer analytics. Business analytics is the use of information technology, statistical analysis, quantitative methods, mathematical or computer-based models to help managers better understand business operations and make better, fact-based decisions (Evans 2016).

Business analytics methods can be used in all functions of the business such as marketing, production, quality control, research and development, logistics, finance, and accounting. An illustration can be found in Figure 1. However, it is seen that the most commonly used business function is marketing (Vaughan 2017). Referring to a survey conducted by the Bain & Company research company, the largest impact of big data was on marketing by 38.2%. Business analytics applications in the field of marketing can be called customer analytics or marketing analytics (Charan 2015).

Figure 1: Usage areas of the Business Analytics

Marketing analytics is the use of data obtained from many channels such as accounting records of businesses, social media transactions of customers, transaction records obtained from web pages and mobile applications, and processing of that data through appropriate methods and making marketing decisions with the resulting information (Venkatesan et al. 2014). The use of social media data in marketing analytics has been defined as social media analytics which is an important subfield of business analytics (Holsapple et al. 2018).

Within the scope of social media analytics, social media data can be used for sales, marketing communication and pricing (Salo 2017). It is possible for companies to identify potential customers and communicate advertisements to their potential customers by analyzing data sources such as social media, search engines, and other sources of information such as the pages, applications, and pages that they examine, like, interact with. Examples of technologies used for this purpose include Google AdSense and DoubleClick applications (Laudon and Traver 2017). Natural Language Processing and Artificial Intelligence algorithms are used to benefit from the data such as Brand Image Tracking, Net Promoter Score and Net Advocacy Index calculation (Charan 2015), potential customer identification (Lee 2018), (Syam and Sharma 2018). Social media posts can be categorized as positive, negative and neutral. In addition, prominent issues in the sharing can be identified with text mining algorithms (Charan 2015). Thus, in the brand image management, managers can make proactive decisions in order to eliminate the negativities related to the brand by seeing the issues originating from the messages that support or discredit the brand and the distribution of positive/negative shares according to regions.

LITERATURE REVIEW

Using business analytics methods, organizations can examine their current situation in more detail, make predictions about the future from the current situation and make business plans according to these forecasts. With this information, it is possible to optimize the resources of enterprises. Optimization is to use the resources in the best way to produce minimum cost and maximum benefit (Winston and Goldberg 2004). Optimization can be used not only in production but also in many different fields and marketing. If marketing resources (budget, staff, etc.) can be used for the right audience in the right place, it is possible to generate more revenue with the same resources. What needs to be done is to determine which customer segment is more valuable for the business and allocate marketing resources to customers in proportion to their values.

Research on IBM is an example of the optimization of marketing resources (Venkatesan et al. 2014). In this study, instead of customer expenditures, customer segment values are calculated according to customer lifetime value calculated with RFM model and optimization of marketing resources is made according to this new situation. The three factors to be considered when calculating the customer's value according to the RFM model and their importance are as follows: R (Recency: the last time the customer trades), F (Frequency: the frequency of processing within a certain period), M (Monetary Value): Monetary value of the transactions. This model argues that the customer who has recently purchased a product from the company is more valuable than the customer who has made more purchases in the past but has not made any transactions recently (Kumar 2007). As a result of this study for IBM (Venkatesan et al. 2014), the average revenue per customer increased by 10 times in the C and D customer groups (segments) where fewer resources were allocated in the previous case, while acquisitions increased by 60%. In total, IBM's revenues increased by $19.2 million at the end of one year.

Another example is the work of the American Target store chain (Armstrong and Kotler 2017). Target examines the purchase history and purchase behavior of customers and predicts their pregnant customers. Using the information obtained, it sends a catalog of baby and pregnancy products to its customers. Thus, it takes advantage of connecting with potential new customers long before its competitors.

With business analytics, it is possible to increase the examples of organizations that increase their profitability. These success indicators affected the interest in business analytics and the demand in this area. Research on 12796 marketing job advertisements in the USA indicated that 39% of the advertisements have big data and 35% have analytical concepts among the necessary skills(Vaughan

2017).

If the spread of using business analytics methods in Turkey is to be possible, it is also possible to expect the analytical concepts to be of high importance in the near future of the manager seeking advertisements. Probably in line with this expectation, Turkey's Istanbul Technical University, Middle East Technical University, Bahcesehir University, Istanbul University, Sabanci University and Sehir University has opened graduate programs in business analytics. Turkish studies in this area are very limited. As a matter of fact, when you search Turkish Business analytics (in quotation marks) in Google Scholar, only 7 results are seen. When "Business Analytics" in English is searched on Turkish pages, 26 results are obtained. However, searching for "Business Analytics" (in quotation marks) without language limitation can result in 24100 results.

In addition to the successful applications of a few companies in business analytics and/or analytical marketing methods, the impact of these methods on the success of organizations has been investigated through field studies on many companies. These studies will be briefly discussed below.

Elbashir et al. (Elbashir et al. 2008) developed a new scale to measure the impact of business intelligence systems on company performance. In order to apply this scale as a questionnaire, a sample was selected from the companies in the customer list provided by a company producing business intelligence software. As a result, it is observed that business intelligence has a positive effect on business processes and organizational performance. In the study conducted with 436 employees from 229 different organizations, the size of the organization was used as the control variable and it was found to have no effect on the developed model. It is stated that the number of employees and annual income was taken into consideration as the size of the organization, the majority of the organizations in the sample were large companies, the average number of workers was 663 and the average annual income was calculated as 2 Billion Australian dollars.

In his conceptual study (Bose 2009), Bose evaluated data mining technologies within the scope of predictive analytical methods, one of the three main topics of business analytics, and described them as advanced analytics. The benefits of these technologies and methods for companies are discussed, a conceptual framework is developed for advanced analytics, recommendations are made from data mining software that can be used for business analytics, and the steps that are required to follow and apply for advanced analytics are mentioned. It is seen that the recommendations are based only on the literature and the lack of field research.

The positive impact it has on company performance in supply chain management can be given as an example of the benefit of business analytics in non-marketing areas(Trkman et al. 2010). In their study, Trkman et al. conducted a survey on 310 companies with headquarters in America, Europe, Canada, Brazil or China from different sectors related to supply chain management such as manufacturing, distribution, and logistics. No information is given about the size of these companies. The results of the study indicated that business analytics had a significant positive effect on the supply chain performance of companies. However, when the survey questions related to business analytics are analyzed, it is seen that they limit business analytics only to classical statistical methods such as demand forecasts and customer profitability.

Germann et al. (2013) conducted a survey with 212 senior executives from Fortune 1000 companies and investigated the impact of marketing analytics methods on their performance. According to the results of the research, it has been found that using analytical methods has a positive effect on the performance of the companies. It is also stated that analytical methods provide an average increase of 8% in companies' return on assets. It has been argued that for the effective implementation of marketing analytics, the support of senior management, a supportive analytical culture, appropriate data, information technology support and analytical skills are all required.

Rubin (Rubin and Rubin 2013), argued that the use of "business intelligence" methods defined within the scope of business analytics reduces the financial risks of companies. For testing their hypotheses, they selected samples from companies traded on American stock exchanges. All of these companies are large and the average income of the companies in the sample is stated as 2.9 billion dollars. As a result, it has been shown that they can stabilize stock return rates and reduce uncertainty

in companies using business intelligence methods.

Suoniemi et al. (2014) are investigating the use of analytical methods and the influencing factors, which they refer to as big data customer analytics, within the scope of EU Horizon 2020 supported projects called big data-driven marketing for increased competitiveness. In the project, a questionnaire was developed to determine the factors that affect the adoption of big data analytical methods depending on the sector and the quality of the company. The developed questionnaire was applied to the sample selected from large-scale, US-based companies with more than 1000 employees who have invested in big data analytics. As a result of the research, it was determined that the use of customer analytics had a direct positive effect on customer relationship performance and an indirect positive effect on financial performance.

It was argued in the conceptual study conducted by Xu et al. (2016) that analytical methods have a positive impact not only on company performance but also on new product success. In this study, the processing of digital data is called big data analytics and is separated from traditional analytical marketing.

An important subfield of business analytics methods is social media analytics (Holsapple et al. 2018). Within the scope of social media analytics, it is stated that social media applications such as Facebook, Twitter, Instagram, YouTube, and TripAdvisor can be used effectively for brand communication and promotional activities and business performance is improved(Wang et al. 2016). There are large amounts of unclassified data on social media. In order to convert this data into useful information, methods such as text mining, natural language processing, artificial intelligence (Makridakis 2017) and machine learning are needed (Evans 2016). The first three analysis methods that the researches in the field of social media analytics have taken into consideration the most are 15.4% Content Analysis, 15.3% Natural Language Processing and 13.4% Sentiment Analysis (Misirlis and Vlachopoulou 2018).

Social media analytics applications can be applied on platforms such as Facebook (Ketter 2016), (Sitta et al. 2018), Twitter (Birjali et al. 2017), (Ahuja and Shakeel 2017), (Öztürk and Ayvaz 2018), (Kim et al. 2014), (Saif et al. 2016), Instagram (Kale 2016) and TripAdvisor (Chang et al. 2017).

The impact of social media analytics on business profitability, success and performance depend on various factors. For example, the findings of the survey conducted with 220 sales experts in the United States show that the use of social media can benefit B2B sales; the use of social media in sales is affected by the company's competence and the interaction of its customers with social media; companies should educate their managers on social media (Guesalaga 2016). In this study, the importance of social media expertise and the use of social media in brand development were mentioned.

Among other studies that social media and analytics increase sales performance (Itani et al. 2017); (Cuevas 2018), there are studies investigating the applications in the field of brand image. For example, research on 384 hotels in the United Kingdom showed positive effects of social media on hotel branding, innovation capabilities and performance (Tajvidi and Karami 2017).

An example of the analysis of social media data with the Natural Language Processing method for image management is the study of Chang et al with TripAdvisor data (Chang et al. 2017). In this study, the authors developed a method that automatically applies sentiment analyzes on hotel reviews published on TripAdvisor. They defined this method as helping hotel managers understand the feelings contained in new comments.

In another study on the processing of social media data, sentiment analysis of Twitter messages was performed (Birjali et al. 2017). The article writes that Twitter data is the largest ever-growing social networking site and is seen as an important source of big data. In this study, data was collected from social networks with Apache Flume and recorded in Hadoop repository. To analyze this data, InfoSphere BigInsight's big data technology was used. BigSheets was used to visualize the results. In this article, the usability of the technologies mentioned in the expert system planned to be developed will be investigated.

Research in the field of how social media can harm or benefit the image of organizations speaks of the effect of word of mouth on social media. Traditional word of mouth is defined as the sharing of feelings, thoughts, and experiences of individuals about a brand/product/organization. In social media, such posts are referred to as electronic word of mouth (E-WOM). While the traditional word of mouth effect is limited to a few people around the sharing person, such sharing can reach a large number of individuals due to the nature of social media and a large number of users (Melancon and Dalakas 2018). This shows the importance of social media in image management (Duan et al. 2008), (Bone 1995).

METHOD

In the researches, it is seen that business analytics, customer analytics, and social media analytics are the tools that provide important benefits to businesses. Despite its importance, social media analytics and similar methods are not widely used. The two most important reasons for this are the lack of information and personnel on how to use analytical methods and the inadequate understanding of the benefits compared to the perceived costs of analytical studies (Evans 2016). In this study, in order to help the problem of lack of information about social media analytics, an algorithm has developed about gathering and analyzing data by using free open-source R programming language (Shmueli et al. 2017), and to interpret the findings is explained with a case study application on Turkish Airlines (THY) company on Twitter. A developer account and API has been created on Twitter for this application. A software was then developed in the RStudio. After the data collection and data analysis stages were completed with the software, the findings were interpreted. The developed social media analytics software consists of data collection, sentiment analysis, geographic analysis and data visualization. The application steps are shown in Figure 2.

Figure 2: Social Media Application Steps
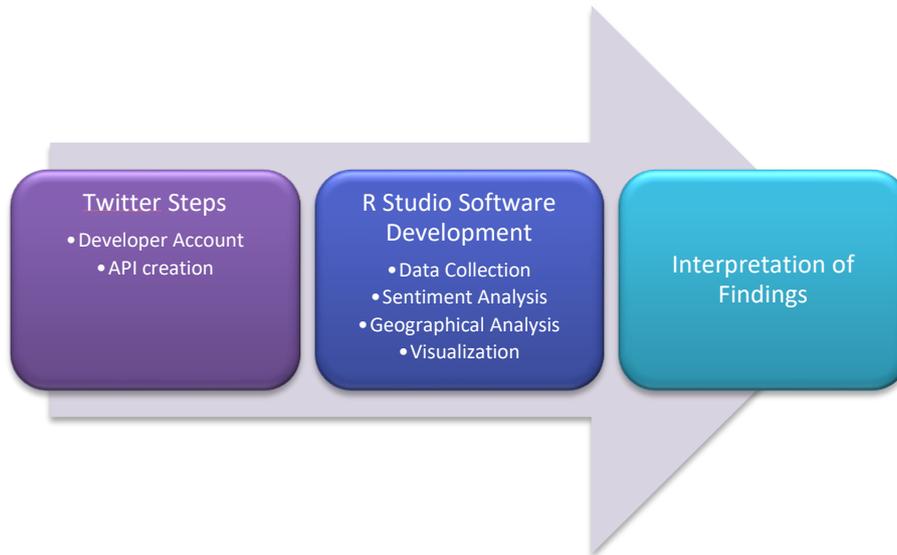
The verbal codes (pseudo-code) of the software developed with R Studio are given below. The steps of the algorithm are as follows:

1.   Start
2.   Install the required library files
3.   Set the Twitter API using the API key and token to pull data
4.   Download tweets with THY related statements using the API.
   a. Use **searchTwitter** function to search for the phrase on Twitter.
   b. Convert found tweets to the data frame format.
   c. Append all found tweets to the file *allthy*
   d. Repeat the previous three steps until all the statements to be searched are finished.

5. Clear tweets from unnecessary punctuation and spaces before sentiment analysis
6. Apply sentiment analysis to the tweets using the **Syuzhet** package
7. Calculate the total number of positive and negative tweets by day
8. Use the **ggplot2** package to visualize the change of tweets by day
9. Create a function to get coordinates from the Google Map API
10. Repeat the following three steps first for Positive Tweets then for Negative ones.
    a. Randomly select 25 twitter (search constraints) from twitter users (positive/negative)
    b. Import coordinate data and profile images of selected twitter users via the Google Maps API
    c. Create a map with user profile images that share (positive/negative) messages
11. Combine two (positive and negative) maps
12. Finish

The application's Twitter operations and the relevant program codes of the R software are described below. All code is freely available at https://github.com/mahiratmis/thyTwitterAnalysis.

Data Collection

During the data collection phase, it was aimed to download the Twitter messages referring to THY from the Twitter system to a database. For this purpose, the software has been developed by using TwitteR package written in R programming language. In addition, to be able to extract data from the Twitter server, a Twitter API application was created, and a developer account was obtained for a month.

To extract data from the Twitter social media application, a Twitter account is created, an application is made for the developer account, a Twitter application is created, and finally, the access codes of the application are obtained. The following links are used for these steps:

- Twitter Account: https://twitter.com/
- Twitter Developer Account: https://developer.twitter.com/
- Twitter API: https://apps.twitter.com/app/new

Twitter developer account membership has free and paid options starting from $339 per month. The free developer account is used in this application. The free account allows access to only the last one-week data on Twitter.

After the developer account and the new Twitter API application are created, it is necessary to obtain the access codes for this application. For this purpose, the customer keys and tokens of the API application (Keys and tokens) section and the alphanumeric values are determined. The last parts of the relevant key and tokens of the Twitter API application are hidden and given in Figure 3.

Open source RStudio software was used to extract and analyze data from Twitter. To use RStudio, first R, then RStudio should be downloaded free of charge using the following links:

- Link to download R: https://cloud.r-project.org/bin/windows/base/R-3.4.3-win.exe
- Link to download RStudio: https://download1.rstudio.org/RStudio-1.1.442.exe

After the programs are installed and executed, programming can be started by coding to the console panel in the left below or the script area in the left above in Figure 4.

In the developed software, R packages listed below are needed. Those packages can be downloaded from https://www.rstudio.com/products/rpackages/.

- data.table
- dplyr
- ggplot2

- leaflet
- lubridate
- reshape2
- RJSONIO
- rworldmap
- scales
- sp
- stringr
- syuzhet
- tm
- twitteR
- wordcloud

These packages can be downloaded and installed directly through the R program with the expression install.packages('the package you want to download'). For example, with the code install.packages('twitteR'), the twitteR package, which enables us to search Twitter and download data, is downloaded and installed on the program. library() is used in the software to activate the downloaded packages and use the functions in the content. For example, library(twitteR) will let you use functions inside twitter.

Figure 3: Twitter API Access Tokens
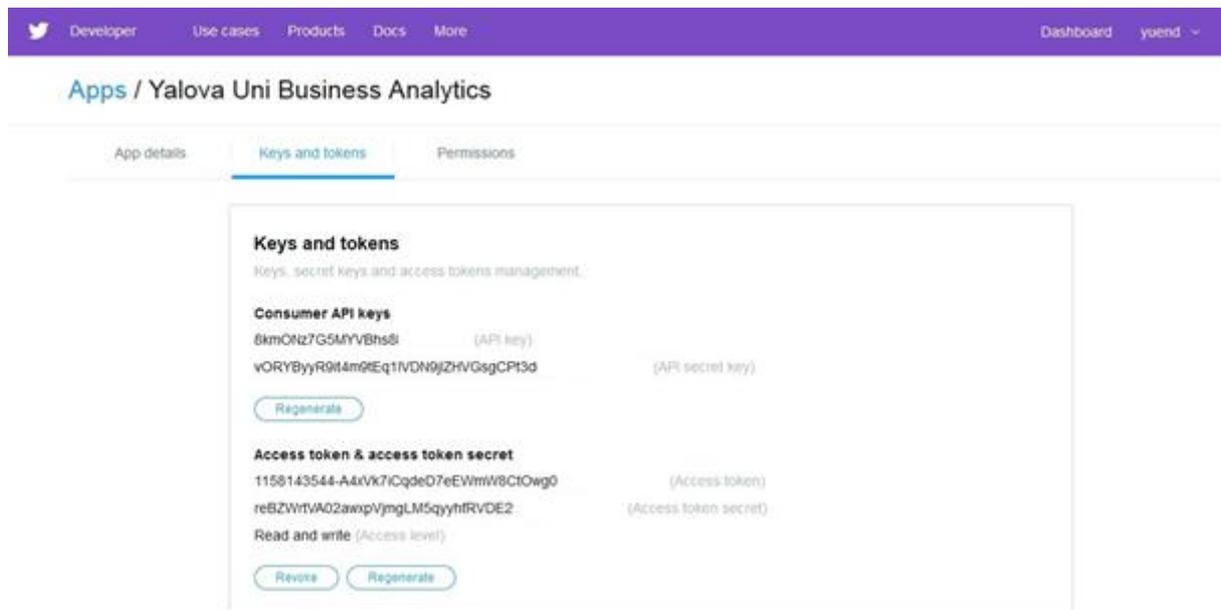
The next step is to provide access to the Twitter account on the R software using the keys and tokens of the API application and the *setup_twitter_oauth* function. The following codes are written for this:

- consumer_key <- '8km***************'
- consumer_secret <- 'vORYB************************************'
- access_token <- '11581435**'
- access_secret <- 'reBZWrt*********************************'
- setup_twitter_oauth(consumer_key, consumer_secret, access_token, access_secret)

Then, using the Twitter search function searchTwitter in the twitteR package, tweet messages containing the desired expressions in the desired language can be withdrawn from Twitter in the desired amount (this amount constitutes an upper limit).

- allthy <- searchTwitter("searchedword", lang='en', n = number of searched tweets)

These captured tweet messages can be converted to a variable, a multidimensional array or a table and saved. *allthy* name used in this study can be written as desired in different studies.

Figure 4: R Studio Screen
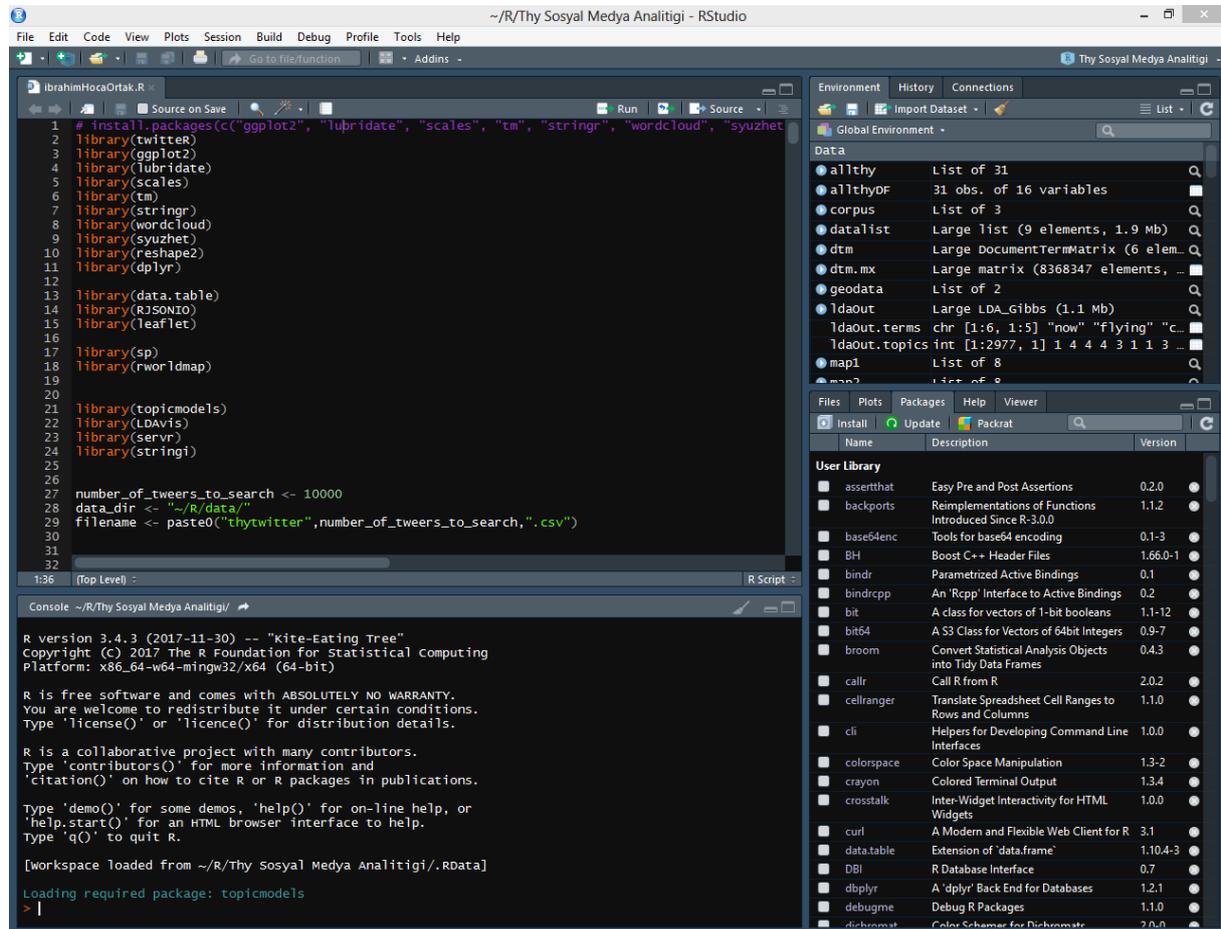
In order to evaluate the brand image of THY in foreign markets, only English shares were considered in this study. In accordance with research constraints, THY's Twitter accounts in English (@TurkishAirlines, @UKTurkish, @TK_US, @TK_HelpDesk, @TK_Netherlands, @TK_INDIA, @TK_Norway, @TA_IRELAND, @TK_CAN), or the English name of the company (Turkish Airlines) Twitter messages containing the company's English advertising slogan (#WidenYourWorld) were collected with R software and recorded in the database. Each of these expressions was searched separately and the results were transferred to an excel file called *allthy*. The collected data includes not only tweet messages containing the searched phrases, but also a total of 16 different attributes, such as who shares (account name), how many retweets were made, and the date it was created. Each attribute creates a separate column of the file *allthy*.

Sentiment Analysis

The analysis of the data (tweets) consists of the stages of sentiment and geographic analysis. The "Syuzhet" package of the R program (Jockers 2017) was used for sentiment analysis, which is used in many academic studies (Haripriya and Kumari 2017; Pabreja 2017; Ragupathy and Maguluri 2018; Hoffmann 2018; Grubert and Algee-Hewitt 2017; Madigan and Bliss 2016; Cajachahua and Burga 2017; Arun et al. 2017; Thinyane and Thinyane 2017; Salas 2018; Zehe et al. 2016; Gao et al. 2017; Singla et al. 2017; Hari et al. 2017; Das et al. 2017; Subbulakshmi and Raja 2016).

The package's sentiment analysis function (*get_nrc_sentiment*) was used. This function uses the lexicon (NRC). The NRC dictionary has pre-calculated scores for each word in 10 different emotion categories. These emotion categories are: "Anger", "Expectation", "Disgust", "Fear", "Joy",

"Sadness", "Surprise", "Confidence", "Positive" and "Negative". The emotion scores of the words were calculated manually by the Crowdsourcing method (Mohammad and Turney 2013). The Twitter messages collected in the previous stage can be used to evaluate a sentence as positive or negative as shown in Figure 5 after being processed before emotion analysis and cleared from unnecessary symbols and expressions.

Figure 5: Dictionary Based Sentiment Analysis Example
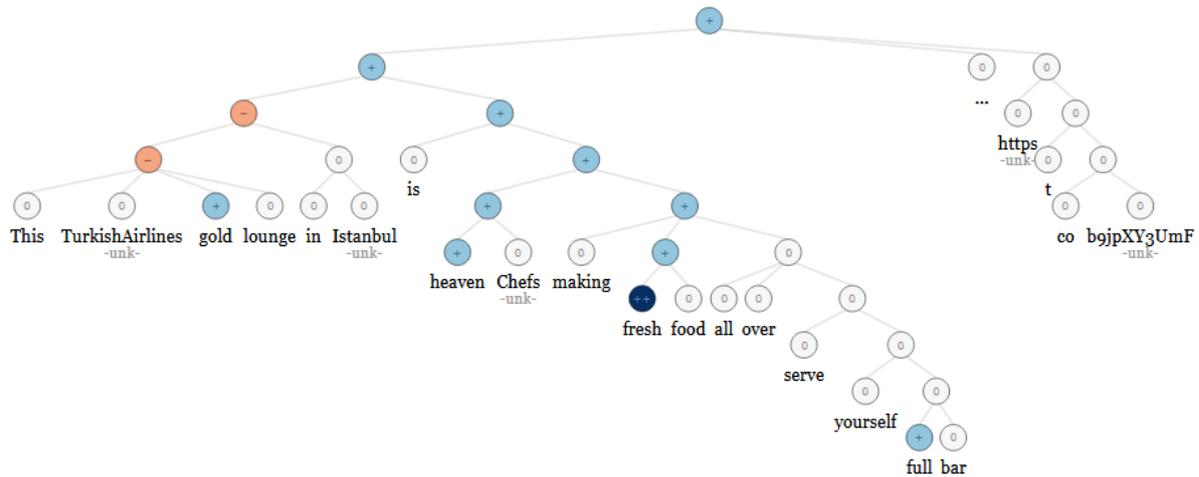
All tweet messages in the *allthy* file, which contains 16 data columns, for the cleanup process were copied to a new file named *purified*. A new column named *clean_text* is added to purified file. The tweet messages were then copied to that new column after unnecessary expressions and words are removed using the *str_replace_all* function. Sentiment scores of *clean_text* column are calculated using the *get_nrc_sentiment* sentiment analysis function.

Sentiment <- get_nrc_sentiment(purified$clean_text)

The calculated emotion scores were added to the file named tweets with all the data in the purified file. tweets with 12 emotion points added to separate columns contain 29 columns in total. Those whose score in the positive (negative) column in the tweets file are greater than the value in the negative (positive) column have been copied to a new file named tweetsPositive (tweetsNegative). The tweet messages in this file are grouped with the group_by function according to the days they are shared and graphed according to the days with the barplot function.

- tweets<- cbind(purified, Sentiment)
- tweetsPositive <- tweets[tweets$positive>tweets$negative,]
- tweetsPositiveCopy <- tweetsPositive %>%
- group_by(created=floor_date(created, "day")) %>%
- summarize(positive=sum(positive))
- barplot(tweetsPositiveCopy$positive, names.arg = tweetsPositiveCopy$created, xlab = "Date",ylab = "Number of Tweets",col = "blue",
- main = "Positive Sentiment Chart",border = "red", las=2)

Geographical Analysis

In the geographic analysis part of the software, Google maps API[2] is used. In this API, a separate query is required for each user profile. Since the free Google maps application has a limit on the number of queries, only 50 users have been analyzed for their profile.

A total of 50 Twitter users (25 from positive sharing and 25 from negative) were selected randomly and their location and profile photo were tried to be determined. Location information withdrawn from the Twitter server can only be composed of provincial or country abbreviations. The

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latitude and longitude of this location information and the country where the location is located according to these coordinates have been determined through Google Maps API application. Green/Red frame was added to the positive/negative sharing, and profile pictures of the coordinates were displayed on the map.

Using the data obtained in Subsection 3.2, the information of each user was obtained through the *getUser* function of the *twitteR* package. By using the *location* and *profileImageUrl* attributes of the obtained information, where the user is located (city and/or country information) and the link to the user's profile image is determined. Further, by using *geocode_helpers* and *modified_geocode* libraries, which was written by (Puente 2016) and uses Google Maps API application in the background, the location information was converted into latitude and longitude information. Using the open-source *leaflet* package, pointers were positioned at the corresponding locations on google maps to visualize this latitude and longitude information.

RESULTS AND DISCUSSION

Within the scope of the completed social media analytics applications, 6667 messages were shared on THY between 23.03.2018 - 02.04.2018 in English on Twitter and were transferred to the database. Sentiment analysis of the messages in the database revealed that 3603 of the messages were positive and 1205 of them were negative. The positive and negative numbers of the messages were determined according to the days and the net supporter net supporter score (NPS) (Charan 2015) was calculated daily as seen in Figure 6 by taking the difference of the percentage ratios of positive and negative messages.

Figure 6: Sentiment Analysis Results and NPS for THY
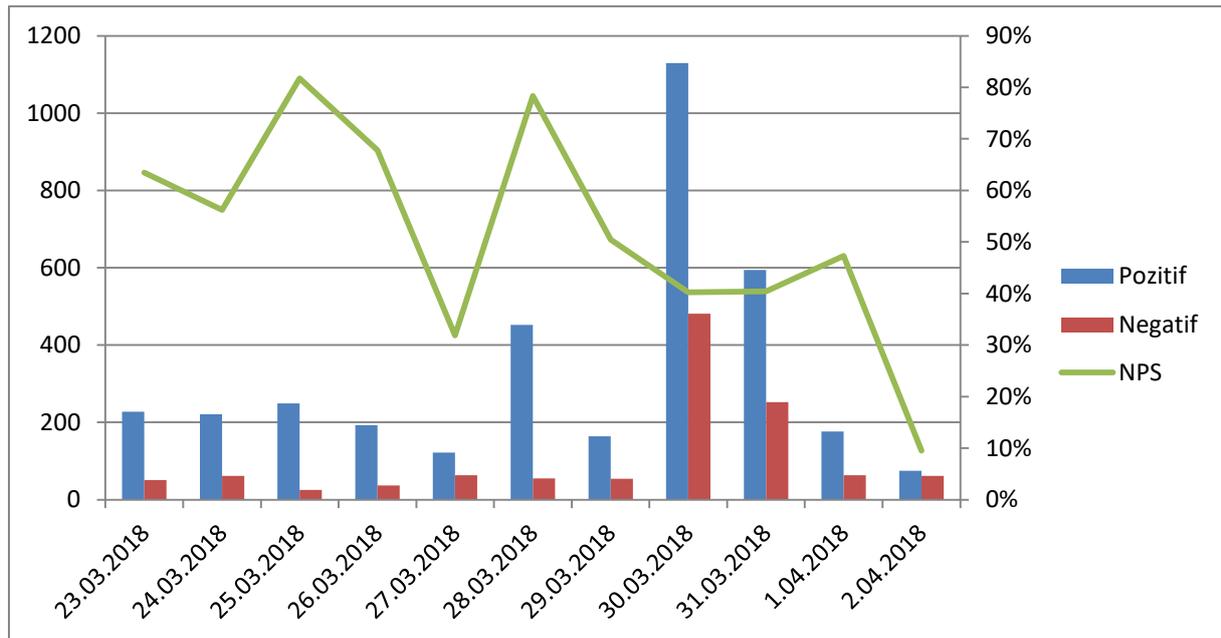
Following NPS changes monthly, quarterly, or before and after a particular campaign will give more meaningful results. According to current data, THY's image in the international market is positive and sudden changes in message volumes can be seen in the graph in Figure 6. Important information can be obtained by investigating the causes of these changes. Due to an incident involving a THY airplane landing in Kosovo on the night of March 29th, the messages started to increase suddenly, and this increase continued until March 31st.

The locations of the 50 Twitter users selected within the scope of the geographic analysis study are shown in Figure 7. The greens represent positive tweets and reds represent negative tweets. It is possible to calculate NPS and group them by subject according to the number of positive and negative messages by country. However, in this limited study, sufficient data could not be collected for the necessary geographical analyzes.

Figure 7: Geographic Analysis Result Map
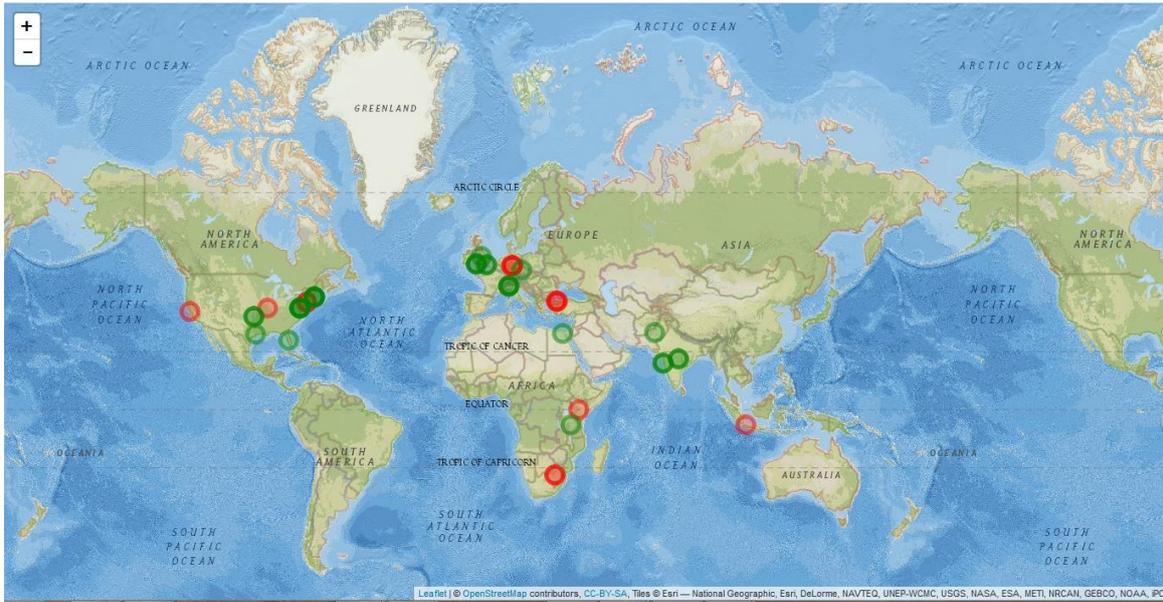
CONCLUSION AND SUGGESTIONS

Social media are digital environment where individuals can share their feelings and thoughts on a voluntary basis, that is, without being requested by any institution. By analyzing the sharing in these environments, the perceptions, attitudes, suggestions, complaints and comments of individuals using social media, that is, an important part of the society, can be learned. In addition, since social media posts are made continuously, social changes related to the researched subject can be followed instantly. These features are the advantages of social media analytics compared to traditional data collection methods such as surveys or focus groups. Indeed, literature review revealed that social media analytics is important method that provide significant benefits to organizations at low cost. Despite all this, studies also showed that there appeared to be a serious lack of knowledge and experience on how to use these methods in Turkey and other countries. So, in this study, in order to be useful by providing example to academicians and private sector representatives who want to work on this subject, in this study, implementation of social media analytics is explained by a case study.

Although a limited number of data were reached in this study conducted with free Twitter and Google Map API applications, useful information was obtained with social media analytical methods. It is seen that when the transaction steps are performed periodically and without the date limit by purchasing paid developer accounts by the enterprises, useful information can be obtained in brand and image management and social media marketing studies.

One reason for the selection of social media analytic applications is that social media can provide important data even to small businesses. As a matter of fact, for business analytics applications, businesses need to collect data using various software and technologies. It is difficult to benefit from business analytics for small and medium-sized enterprises (SMEs) who have not yet established the necessary IT infrastructure and do not store their data regularly. However, since data on social media are provided by the relevant social media companies, it is possible for SMEs to benefit from social media analytics applications without any investment. What is needed is only information gathering, analyzing and interpreting data from social media. The aim of this study is to help provide this information.

To conclude, social media data are precious metals waiting to be processed for not only companies, but also non-profit organization and governments. Further studies in this area are needed to increase the awareness of academicians and private sector representatives about the subject. Also, these subjects should be added to the education curriculum. An important obstacle in this area is the lack of Turkish software. The accuracy of the English emotion analysis function of the "Syuzhet" package of the R program used in this and many other academic studies is unfortunately controversial.

The Turkish emotion analysis function of the same package gives very incorrect results. So, although social media is an important data source, there is a need to develop better analysis methods, tools and software to turn this data into useful knowledge. In further studies, it is aimed to develop software that makes emotion analysis of social media sharing in Turkish by using machine learning. In addition, it is planned to apply topic modeling in order to understand the topics on which positive/negative social media messages are generally written and to have information on satisfaction/complaint issues.

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