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HOW DO WE REACT @socialmedia? #catchthemoment

Mustafa COŞKUN

Meltem ÖZTURAN

Abstract

The impact of social media on society has been growing fast, especially in the information era. While there are several studies in the literature that show the effect of social media on society, the least touched point is about the effect of social events on social media. Since the relation of social events and social media is not in one direction, this study aims to find the reaction behaviors of social media users for positive and negative events in society. Sentiments of approximately 5 million tweets of 5000 users filtered from 127 thousand were analyzed and the results showed that most positive and negative days of 2015 and first quarter of 2016 in Turkey were detected by this sentiment analysis with 69.05% accuracy. Also in this study, the effects of those social events on social media were examined in terms of reaction speed. As a result, 4 main social media reaction types were classified as "sudden impact-sudden fall", "normal distribution", "hear, ask, prove, react" and "one shot-long stay".

Keywords: Social Media, Twitter, Sentiment Analysis, Social Psychology, Reaction

@sosyalmedyada NASIL TEPKİ VERİYORUZ? #anıyakala

Öz

Sosyal medyanın toplum üzerindeki etkisi, özellikle bilişim çağında, hızla büyümektedir. Literatürde sosyal medyanın toplum üzerindeki etkisi üzerine birçok çalışma olmasına karşın, toplumsal olayların sosyal medya üzerindeki etkisi pek değinilmemiş bir noktadır. Toplumsal olaylar ve sosyal medya ilişkisinin tek yönlü olmamasından dolayı, bu çalışma toplumda pozitif ve negatif olaylar için sosyal medya kullanıcılarının tepkisel davranışlarını bulmayı amaçlamaktadır. 127 bin kullanıcıdan filtrelenen 5000 kullanıcının yaklaşık 5 milyon tweetinin duyguları analiz edilmiş ve sonuçlar Türkiye'de 2015'in ve 2016'nın ilk çeyreğinin en pozitif ve negatif günlerini %69.05 doğruluk oranı ile göstermiştir. Bu zaman diliminde bu toplumsal olaylara sosyal medyadaki reaksiyon hızları da incelenmiştir. Sonuç olarak, 4 ana sosyal medya tepki türü sınıflandırılmıştır: "ani etki-ani düşüş", "normal dağılım", "duy, sor, doğrula, tepki ver" ve "tek vuruş-uzun duruş".

Anahtar Kelimeler: Sosyal Medya, Twitter, Mutluluk Analizi, Toplum Psikolojisi, Tepki (Reaksiyon)

INTRODUCTION

The impact of social media on society has been growing fast, especially in the current information era. Thus, it is on top of the agenda for many business executives today. Decision makers, analysts, advisors and consultants seek ways of gathering valuable information from social media to identify profitable results for the firms. As it is stated by Liu (2012), when we need to make a decision we often seek out the opinions of others. And, this situation is true not only for the individuals but also for the organizations. Additionally, social media term has been emerging in Turkey for a decade. The impact of this platform in Turkish society is growing not in a linear way (with a constant acceleration) but in an exponential way. Merging these two manners: “rich information (collected from social media) for decision making in business” and “the increasing ratio of social media usage in Turkey”; a novel study is designed in this paper on the base of the following research question: “how do people react to social events on social media?”

On the base of this research question, the scope of this article is to explore the effect of social events on social media, in contrast with the common studies in the literature whereas the social media literature mainly constitutes of the studies which analyze the effects of social media on the social events. But it is believed that the relationship between social media and society is not in “one direction”, that is a “correlation” between them.

In the following sections, literature about social media sentiment analysis studies and related works are reviewed for drawing the main goals and hypothesis. Then, research methodology and analysis progress are stated consequently. Afterwards, our research model is deployed and findings are discussed. Lastly, conclusions and discussions of the study are stated.

LITERATURE REVIEW

Social Media Sentiment Analysis

When we consider “social media” term today, we probably think a “social object” which is living with us in our environment. With the effect of computer and internet era, this object has been transforming from a virtual platform to a social spirit. Citizens, especially in the conservative countries, tend to use social media for screaming their feelings in a liberal way. This independence structure of social media caused a mutation in our daily lives and possible results provide rich information with the decision makers of the organizations.

The nature of decision making includes the main question “what others think?” Before the World Wide Web, this question was answered by researchers via data collected from experts’ reports, consumer questionnaires, field observations etc. But as it is defined by Pang and Lee (2008), the Internet and the Web have now (among other things) made it possible to find out about the opinions and experiences of those in the vast pool of people that are neither our personal acquaintances nor well-known professional critics - that is, people we have never heard of. Also, many people making and publishing their feelings publicly available to the strangers via big data and internet.

The idea of finding the public sentiment via social media big data concludes the sentiment analysis studies in academia. According to Liu (2012), the term *sentiment analysis* first appeared in (Nasukawa and Yi, 2003), and the term *opinion mining* first appeared in (Dave et al., 2003). On the other hand, the researches on *sentiments* and *opinions* appeared earlier in several studies (Das and Chen, 2001; Morinaga et al., 2002; Pang et al., 2002; Tong, 2001; Turney, 2002; Wiebe, 2000).

The early studies on sentiment and opinion analyses, of course, were not done on data collected from the web. Since the opinionated data are not only on the internet, those studies were done with the internal data of the organizations such as customer feedbacks collected by emails, call center surveys etc. The effect of the sentiment analysis results are not only used in industrial activities but also used for other social events such as political elections or marketing applications such as box-office studies of movie industry.

Moreover, in the academic research area, when we consider the most popular social media platforms in all over the world (for research purposes), Twitter can be called the most public with its open and rich access properties. Then, as another well-known fact, most of the social media sentiment analysis studies are based on Twitter data because of this easy and public access data structure.

For instance, O'Connor et al. (2010), made a Twitter sentiment analysis for linking with public opinion polls. In the study of Tumasjan et al. (2010), Twitter sentiment was also applied to predict election results. Additionally, Chen et al. (2010) studied political standpoints, while Yano and Smith (2010) reported a method in their study for predicting comment volumes of political blogs. Lastly, Twitter data, movie reviews and blogs were used to predict box-office revenues for movies in some studies (Asur and Huberman, 2010; Joshi et al., 2010).

Social Media Studies in Turkey

Turkey is a country which combines contrasts in both online and offline citizens. In accordance with the World Bank (2015), 73% lives in urban areas. On the other hand, the number of internet users is (35 million) relatively low compared to other European countries. But, it is surprising that Turkey was already home to nearly 30 million Facebook accounts, making it the fourth largest country in the world in terms of country-specific user numbers (SocialBakers, 2014). Probably the reason for this interesting result is that nearly half of the population is under the age of 29.

By late 2014, the market research firm GlobalWebIndex reported that 26 percent of the entire county has used the social network in the past month alone (Reuters Institute, 2015). And, Polat and Tokgöz (2014) reported that this was followed by Twitter at 17% or 6.5 million of Turkey's population, with the majority of Turkey's Twitter population (87%) being from Turkey's three largest cities: Istanbul, Ankara and Izmir (Dogramaci and Radcliffe, 2015). Lastly, Durahim and Coşkun (2015) designed a sentiment analysis study via Twitter big data collected from Turkish users' year 2013 and 2014 posts. The results of the sentiment analysis showed valid findings compared to Turkish Statistical Institute happiness survey results.

Research Questions

Considering the literature review, the research question "how do people react to social events on social media?", which has not been too much studied in literature, comes to mind. This question took us not only to the area of sentiment analysis but also the analysis of social behaviors as a society. Therefore the structure of the study is designed for exploring the followings:

- What are the characteristics of Twitter users?
- Which categories of social events by what accuracy can be captured via social media sentiment analysis?
- How do social events result in social media in terms of speed of reaction and staying time?

METHODOLOGY

Detection and Categorization of Social Events

The common way for finding accuracy of the sentiment analysis in literature is that the results are compared with findings from other sources such as news, archives, questionnaires, company secondary data, even manual provided and classified data etc. But, by this *backward* method of accuracy check, the real power of sentiment analysis cannot be detected. In other words, we cannot claim that our sentiment analysis results are accurate when we check the results with real data, because in this way we probably miss some real events to check. Therefore, a *forward* methodology for sentiment analysis accuracy check is more appropriate and valuable. In this forward method, first the data from the past are collected (and categorized- if needed), then the results of the sentiment analysis are checked with this data in terms of how much of the past could be detected.

Since this study is about social events and their effects on social media, a precise social event list was created with their categories in order to check the accuracy of sentiment analysis results.

First of all, a list containing "events of Turkey in 2015 and in the first quarter of 2016" was gathered from Wikipedia (2016b, 2016c). This list constitutes of 134 events with their given references and links. Since those lists are not only about social events but also all types of events in Turkey, a pre-filtering was done on the list by dropping 50 non-social events such as TRT 4K channel started broadcasting, CEBIT Fair started, foundation of TRJet Aero Technology Ltd.

After pre-filtering, 84 social events from given time interval left in the list. Those events were grouped into 8 categories. Categories and number of events in those categories are listed in Table 1.

Table 1. Social event categories and number of events

Category	**Number of events**	**Example**
Feasts	3	Ramadan (Holy Feast in Islam)
Financial Events	5	Savings Deposit Insurance Fund seized control of Bank Asya
Foreign Events	9	Turkey closed Consulate Building in Yemen because of dangerous atmosphere
Military Events	6	Turkish Military Forces entered Syria for transferring "Süleyman Şah Tomb" with the operation called "Şah Fırat"
Political Events	7	Parliament Elections
Tragic Events	5	An explosion at a coal mine in Zonguldak city
Sports Events	33	Galatasaray FC became champion in Super League
Terror Events	16	A bombing took place in Kızılay, Ankara, in which at least 37 people were killed and 125 injured.

Then those events are ready to be compared with sentiment analysis results to check how accurate the sentiment analysis algorithm captures social events.

Social Media Data Collection

The most common way of free access to Twitter data is using provided APIs. In this study, tweet dataset was collected via PHP APIs (for Twitter API version 1.1) and then stored in MySQL database for further analysis. In order to gather a sample of active users, a trend topic (TT) search API was written. Since it cannot be directly collected with a single REST API (single code and execution), multiple APIs were executed iteratively for creating active user dataset. Then, this TT API ("GET trends/place") was executed from Mon, 04 Apr 2016 07:12:38 GMT to Thu, 14 Apr 2016 06:44:20 GMT (256 attempts) to get data from 2015 and first quarter of 2016, and through this way, it collected 20 trend topics for every 400 seconds using Turkey's "woeid"[1]. This[2] woeid value was taken from Yahoo Geo Planet[3] and the code was written with the directions provided in "GET trends/place" API page of Twitter Developer web site[4].

Resulting dataset has 1431 trend topics with following attributes: "TT name", "TT created at", "TT search query", and "TT URL". For each iteration, TT search query was used to get 200 recent tweets about each TT with "GET search/tweets" API. This API helped to collect over 450 thousand (453578) tweets and 186 thousand unique publishers' information of those tweets. The json format of those users' dataset has lots of variables where the ones that are relevant to our study are; "User Id", "User name", "User location", "User screen name", "User followers count", "User friends count", "User tweets count", "User description", and "User account creation time".

Preprocessing of Big Data

In the first phase of preprocessing, the "users" dataset was filtered. First of all, the users whose Twitter language is not "Turkish" were dropped (59892 users). This came out with 127083 users. Then, the location fields of the dataset were edited. Since publishing of the location information is optional on Twitter, users who did not provide their location information (71302) were omitted (55781 users remained). Then, the users who did not write a city name as their location were dropped from the dataset. After this filtering 37203 users were remained in the database. The cities that most users are from can be seen in Table 2.

Table 2. Number of users from most populated cities

City	Number of Accessed Users
İstanbul	14596
Ankara	4000
İzmir	3390
Bursa	1343
Antalya	1320
Adana	1099

Since the sentiment analysis was aimed to be done on the tweets published in 2015 and first quarter of 2016, the users who created their accounts after 1st January, 2015 should be dropped from dataset. Filtering with this logic left the dataset with 27928 users. Afterwards, before the last filtering option, the users whose daily tweet-counts were one standard deviation (2.63 tweets) away from the mean (2.76 tweets) were filtered out. Then, the resultant dataset had 18918 users. Considering judgement sampling, the number of users for the analysis was chosen as 5000. Then, in order to supply generalizability, 5000 users were selected randomly from the resultant dataset. During selection process, the private accounts were checked on chosen users, because tweets of those accounts cannot be collected with "GET statuses/user_timeline" API. By this check, 344 users were eliminated from the dataset and

[1] Woeid is the acronym of "where on earth identifier".
[2] Turkey's woeid is 23424969.
[3] https://developer.yahoo.com/geo/geoplanet/.
[4] https://dev.twitter.com/docs/api/1.1/get/trends/place.

another 344 were selected from 18918. Lastly, the users dataset constituted of 5000 Twitter users;

- who use Twitter in Turkish
- who declare the location and write the city name
- who created his/her account before 1st January 2015
- whose tweet-count is not one standard deviation away from mean
- whose account is not private

After selecting users with given filtering options, tweets which were published by these users were collected by "GET statuses/user_timeline" API. Since this API was limited to providing 100 most recent tweets, a back-iterative API code was written which executed with "max_id" option. By this way, all of the tweets of every user that were published from 01.01.2015 00:00 GMT to 31.03.2016 23:59 GMT were collected. As a result, 5467055 tweets were collected for sentiment analysis.

Sentiment Analysis

In order to get the polarity of tweets, every tweet of each user was stored in text files and analyzed with a unique program designed for this study. The program uses a dictionary which consists of more than 3500 Turkish radical words. This dictionary was developed by Vural et al. (2013) on the base of the largest open source Turkish natural language processing library called "Zemberek", which is commonly used in Open Office and Libre Office software and used first in Thelwall et al. (2010).

In sentiment analysis results, every tweet has a positive (1 to 5) and a negative (−1 to −5) polarity value where a larger absolute value indicates stronger emotions. Moreover, Thelwall et al. (2010) stated that by restricting these values to at most 5 avoids possible outliers (absolute values greater than 5). Positive and negative polarity values are calculated as the sum of positive and negative polarities of the words in a particular tweet which are obtained from related dictionary, respectively.

RESULTS AND FINDINGS

Demographic Findings

Firstly, the demographic features of the users, who are in the resultant dataset, can be listed as follows. There are totally 5000 users in the resultant dataset. Those users are from 81 cities of Turkey in which the most populated sets can be listed as in Table 3.

Table 3. Number of users and percentages from most populated cities in the resultant dataset

City	Number of Accessed Users	Percentage over 5000
İstanbul	1925	38.5%
Ankara	549	11.8%
İzmir	438	8.8%
Antalya	181	3.6%
Bursa	166	3.3%
Adana	161	3.2%

Table 3 shows that 3420 users of total (5000) are from the most populated cities. Then, this can be a conclusion of a generalizable sample, because those cities constitute nearly 45% of Turkey's whole population (Wikipedia, 2016a).

In addition to the populations, the average features of the "users" dataset can be summarized as in Table 4.

Table 4. Average of demographic features of users in sample

Feature	**Average During Time Interval**
Twitter Age	49 Months (approximately 4 years)
Number of *"Favorited"* Tweets	2816
Number of Followers	1953
Number of Tweets	2829
Number of Friends[5]	916

Social Events and Social Media Sentiment Analysis

As it was explained in the previous section, a social event list containing 84 events from 2105 and first quarter of 2016 was prepared with the related categories.

In country level, the sentiment analysis results were checked in terms of detecting those social events. Since there are 546 days in the chosen time interval and since sentiment analysis algorithm found an aggregate happiness polarity value for all of those days, a threshold value was needed for determining the important days where after would be called as "*extraordinary"* days. To this respect, threshold value was calculated as "*one standard deviation away from mean*". The mean and standard deviation values of all the polarities of 546 days are listed in Table 5.

Table 5. Mean and standard deviation of polarities

	Value
Mean	0.0707
Standard Deviation	0.0475
Positive Threshold	>0.1182
Negative Threshold	<0.0232

Based on the values in Table 5, the days with polarities greater than 0.1182 and less than 0.0232 are stated as *extraordinary* dates. By this method, sentiment analysis found 89 extraordinary days over 546.

Within those 89 extraordinary days, the sentiment analysis found 58 of 84 social events given in the list prepared previously in methodology section. This result brought 69.05% detection accuracy for the sentiment analysis for all social events. On the other hand, the detection accuracies of the sentiment analysis on different social event categories were found as in Table 6.

[5] Twitter calls the ones you follow as "friend"

Table 6. Sentiment analysis detection accuracies for social event categories

Category	Accuracy
Feasts	100.00%
Financial Events	40.00%
Foreign Events	77.78%
Military Events	50.00%
Political Events	42.86%
Tragic Events	100.00%
Sports Events	69.70%
Terror Events	75.00%

The results showed that social media sentiment analysis can successfully detect all extraordinary days of Feasts (Positive) and Tragic Events (Negative) but is less successful for detecting Political and Financial Events.

Reaction Speed on Social Media

For analyzing the reaction speed on social media about positive and negative events, 2 most positive and 2 most negative days of the examining timeline was chosen.

Figure 1. Hourly tweet distribution of important dates

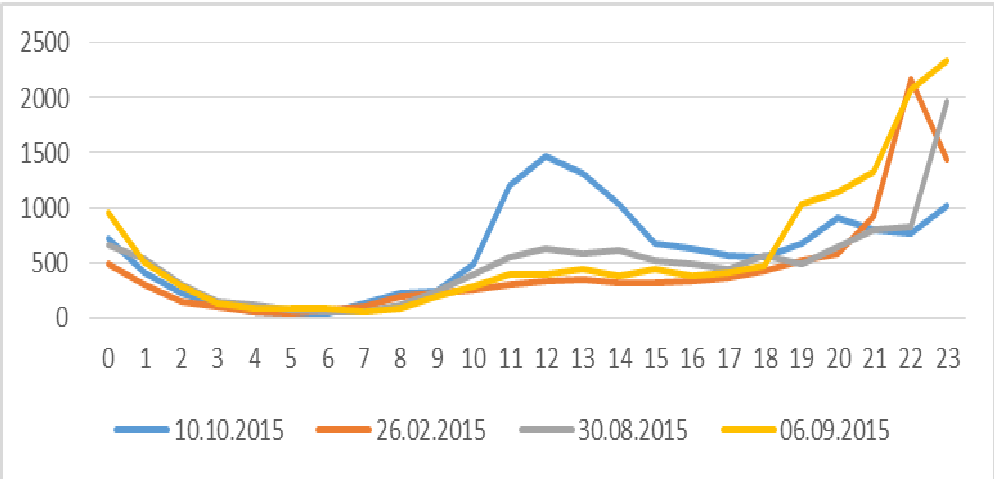

Figure 1 shows the distribution of hourly tweet publishing numbers in those days. The most negative days are 10.10.2015 (Ankara "Emek Meeting" Suicide Bombing) and 06.09.2015 (Dağlıca Attack by Terrorists), and, the most positive days are 26.02.2015 (Beşiktaş GC vs Liverpool FC Match) and 30.08.2015 (Victory Day).

Figure 2. Hourly polarity distribution of important dates

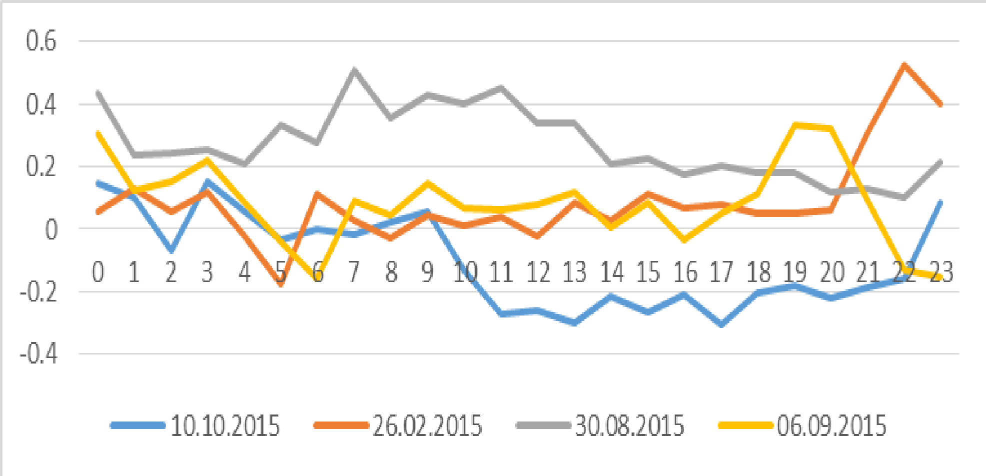

Figure 2 shows the distribution of hourly average polarities of the tweets in those days. Before analyzing the exploratory findings that show "how we react for important events in social media", the hours of those chosen events are given in Table 7.

Table 7. Hours of chosen events

Date	Event	Time
26.02.2015	Beşiktaş GC won against Liverpool. It was a record winning day of most crowded match of Turkish Football history with 63 thousand fans.	20:00 - 21:45
30.08.2015	Victory Day (Feast of Independence War winning day)	Whole day
06.09.2015	Dağlıca Attack by Terrorists - 16 soldiers were died.	15:30 - 17:40
10.10.2015	Ankara "Emek Meeting" Suicide Bombing on Central Railway Station – 103 civilians were killed and 400 were injured.	10:04

By combining the results shown in Figure 1, Figure 2 and Table 7, following findings can be concluded:

- General tendency of publishing tweet decrease in night time and has a "prime time" impact between 18:00 – 24:00 (Figure 1).
- The reaction of positive events, which begins in a given time (Beşiktaş GC match), in social media is immediate. Both the tweets count and positive polarity increase start at the beginning of football match (nearly at 20:00). Then, it has the highest value at the end of the match (nearly at 21:45). Lastly, the impact decreases after the end time, in other words, it does not stay in popular. This can be concluded as "sudden impact-sudden fall" effect.
- Positive events that stay whole day (e.g. Victory Day) have day long impact, but mostly in the middle of the day in terms of publishing tweets count. Also, the positive polarity rate of the tweets on these days have same tendency as tweet count, by having peak values in the middle of the day time. This can be called as "normal distribution" effect.
- Negative events that goes in a given time interval (Dağlıca Bombing), appears in social media approximately half an hour after the end (at 18:00 for this event) with a tweet

publishing bomb. On the other hand, the negativity of the tweets appears after 1 and a half hour (at 19:00). When the tweets published in that time interval are checked, the reason for this time shift between tweets count and polarity can be found as: users first ask for the events in social media and those tweets are neutral (tweet bombing phase and increase on tweet count). But, after proving the event, people start to act negative and polarity decreases suddenly. This can be called “hear, ask, prove, react” effect.

- The negative events which occurs at once (Ankara “Emek Meeting” Suicide Bombing), have immediate reaction on social media in both tweet publishing ratio and negative polarity concerns. Since this event is highly negative on society, the effect of it appears in social media most sudden way. And the effects of this kind of events are biggest and remain on social media most. This can be called as “one shot-long stay” effect.

CONCLUSION AND DISCUSSION

The main aim of this study is to design a sentiment analysis to find an answer for the question “how people react on social media for the important events?”

To answer this main research question, firstly, a list of events (134) in Turkey in 2015 and first quarter of 2016 was taken from Wikipedia (2016b, 2016c). 50 non-social events from that list was dropped and the remaining 84 events in the list were categorized as feasts, financial events, foreign events, military events, political events, tragic events, sports events and terror events.

As second step, the sentiments of the society were aimed to be calculated. At this point, for generalizable results, a brief judgement sampling methodology was developed. At first step of sampling, approximately 127 thousand users of Turkey were accessed on Twitter via following trend topics and the tweets published on those trending hashtags. By this way, it is aimed to access most active users. Then, by novel filtering options, the resultant dataset was prepared with 5000 users. Afterwards, more than 5 million tweets of those chosen users, which were published in 2015 and in first quarter of 2016, were collected with related Twitter API. For the sentiment analysis a literally significant Turkish dictionary was used with its more than 3500 words and polarities. For the polarity calculation, a software was developed and used for this study.

As the first findings of the study, number of average tweets of users is “2829” for 15 months which means 1 publish in two days. Average number of friends (Twitter calls the ones you follow as “friend”) is 916 in users’ dataset, and also average number of followers is 1953. The average number of favorite tweets for the users is 2816 which means Twitter users most like clicking on “Favorite” button for their friends. Lastly, average Twitter age of the users is approximately 4 years in the dataset.

After sentiment analysis was done on tweets in dataset, all 546 days in chosen time interval had a happiness polarity. In order to classify those dates as “extraordinary” and “ordinary”, a threshold value was calculated by “one standard deviation away from mean” execution. Then 89 days were found as extraordinary with sentiment analysis results. Then, the found dates were compared with 84 social event dates, and the accuracy of the sentiment analysis was found 69.05%. When the category accuracies were checked, the Feasts and Tragic Events categories were found as %100 accurate. This means the social event dates in those categories were perfectly detected by social media sentiment analysis. At the same time, the weakest accuracies were found in Political and Financial Events categories.

Lastly, the reaction analysis results concluded four main reaction types for negative and positive events. “Sudden impact-sudden fall” effect on social media occurs upon positive events which go in a time interval (not one shot). “Normal distribution” effect on social media occurs with positive day-long events. The effect of this kind of events start in the morning, go up to top in the noon and end at the evening. “Hear, ask, prove, react” effect type events are negative and have a time interval of occurring. At last, “one shot-long stay” effect events are negative and occur at one time and have immediate effect on society and social media.

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