

The Untold Story of USA Presidential Elections in 2016 - Insights from Twitter Analytics

Purva Grover^{1(✉)}, Arpan Kumar Kar¹, Yogesh K. Dwivedi², and Marijn Janssen³

¹ DMS, Indian Institute of Technology, Delhi, India
groverdpurva@gmail.com

² School of Business and Economics, Swansea University, Swansea, UK

³ Delft University of Technology, Delft, Netherlands

Abstract. Elections are the most critical events for any nation and paves the path for future growth and prosperity of the economy. Due to its high impact, a lot of discussions take place among all stakeholders in social media. In this study, we attempt to examine the discussions surrounding USA Election, 2016 in Twitter. Further we highlight some of the domains influencing the voter behaviour by applying the outcome of Twitter analytics to Newman and Sheth's model of Voter Choice. Through the analysis of 784,153 tweets from 287,838 users over 18 weeks, we present interesting findings on what may have affected the polarization of USA elections.

Keywords: Social media · Social media analytics · Twitter analytics · Information propagation · Public policy

1 Introduction

Every presidential election of United States of America (USA) is hugely significant for the country and as well for the world due to all the economic and trade relations USA has with other countries. United States presidential election of 2016 was held on Tuesday, November 8, 2016. The final two candidates for the presidential election of 2016 was Republican Donald Trump and Democrat Hillary Clinton. Although initially Hillary Clinton had higher visibility, Donald Trump won the 2016 election. According to Statista, out of 251 million voters in USA, there are around 67 million monthly active users in Twitter. Thus Twitter data can become a significant source of information for analyzing the impact of the election. Now days, people without meeting physically can create, share and exchange their thoughts, ideas, opinions, information, videos, images and other digital content through social media platforms like Twitter [28]. In Twitter anything tweeted by an user becomes available to others following the discussion.

The objective of this paper is to understand the impact of Twitter on the US Presidential Elections 2016. This research paper attempts to evaluate how the sentiments and topics evolving among the voters change over the period of time of the election and how there voting preferences was getting polarized over the period of election. For our study we had collected 784,153 tweets from 287,838 users on USA election over the 18 weeks,

starting from 13th of the August to 10th of December, 2016. We applied different social media analytics methods and Newman and Sheth's model of Voter Choice to get a better understanding of discussions and voting outcome.

2 Review of Literature

The first section in the review of literature highlights the importance of social media and links it to the current context. The second section, highlights some of the public policies related to social media which have been already explored in existing literature.

2.1 Importance of Social Media

Social media platforms are important for various sectors such as education [34], marketing [40], customer engagement [15], brand management [20], product and services promotions [30], recruitment [16], sales forecasting [3] and in evaluation of corporate agility [37] purposes. More and more people are joining these platforms and interacting within the virtual communities in specific interest domains and domain specific understanding may be developed by analyzing user generated content and understand market dynamics [19, 41]. Social media data (i.e. user generated content) had been extensively used for analyzing real life problems such as predicting flu trends [1], predicting electoral forecasting [5], engaging with voters [2], identifying social tensions [6], evaluating voting intentions [18] and measuring transition in organization behavior [22].

2.2 Social Media and Public Policy

Literature highlights that Twitter had been used by Chicago Department of Public Health for the campaigns of electronic cigarettes in public health policy [14]. Twitter was used for giving the early warning of the natural hazards to citizens as done by Indonesian government in 2012 [9]. Sentiments relating to "climate" had also been analyzed to understand social sensitivity towards the environment [10]. Literature indicates post on tobacco and its new products had been analyzed for policy purposes [29].

The evidences and potential of using Twitter to uncover unbiased information from user generated content was the driver for choosing Twitter data for our study.

3 Research Contribution

The contributions of this study is interdisciplinary and addresses both political science and social media literature. To develop a better understanding of the event of USA elections, some of our objectives and contributions are listed subsequently:

- What is the nature of discussions surrounding US elections?
- Which types of social discussions tend to affect outcome of elections?
- Are there indications of polarization of voting preferences during the entire period?

This study highlights a new mixed research methodology of developing insights out of the real time events and the discussion surrounding them in social media. The study lists down the four methodologies for analyzing the Twitter data such as descriptive, content, network and time-space analysis. We try to explain the insights derived out of Twitter analytics using the Newman and Sheth’s model of Voter Choice Behavior [43]. In particular, the focus of how polarization happened in voting choices in social media platform, is a unique contribution of the existing study.

4 Research Methodology

The methodology had been divided into the five phase such as phase 1 identifies the search terms to extract the data from Twitter. For this study, a list of election related search terms like “USA election”, “Hillary Clinton” and “Donald Trump” were identified based on listing in Twitter trends. Phase 2 of the study focuses on extracting data from Twitter. The unstructured data collected through the Twitter API using Python scripts was in JSON format. Phase 3 of the study helps in converting unstructured data to structured data, i.e. JSON to the structured excel format. The steps in phase 2 and 3 where repeated daily over the 18 weeks to extract the data from the Twitter. Phase 4 helps in digging the insights of the data through various Twitter analysis methodologies such as descriptive, content, network and time-space analysis. Table 1 illustrates an indicative list of methods for Twitter analytics. The Phase 5 explains the impact of the findings through the Newman model of voter behavior using seven concepts like issues and policies, social imagery, emotional feelings, candidate image, current events, personal events and epistemic issues. Figure 1 illustrates the flow of analysis based on Twitter analytics mapped to voter behavior model as adopted in this study.

Table 1. Overview of Twitter analytics methods

Descriptive analytics	Content analysis
Tweet statistics (Tweet, Reply, RT) [33]	Sentiment analysis [21]
User statistics (i.e. number of users) [23]	Polarity analysis [35]
URL analytics [39]	E-motion analysis [32]
Hashtags analysis [8]	Topic modelling [26]
@mentions analysis [36]	Lexical diversity [11]
Word cloud (most frequent words) [31]	
Reach metric [12]	
Network analysis	Space-time analysis
Friend-follower networks [13]	Time-trend analysis [27]
Network layout [17]	Time series comparisons [4]
Network diameter [9]	Geo-spatial analysis [42]
Centrality analysis [8]	Geo-location analysis [38]
Cluster detection [42]	Topic evolution [25]
Information flow networks [7]	

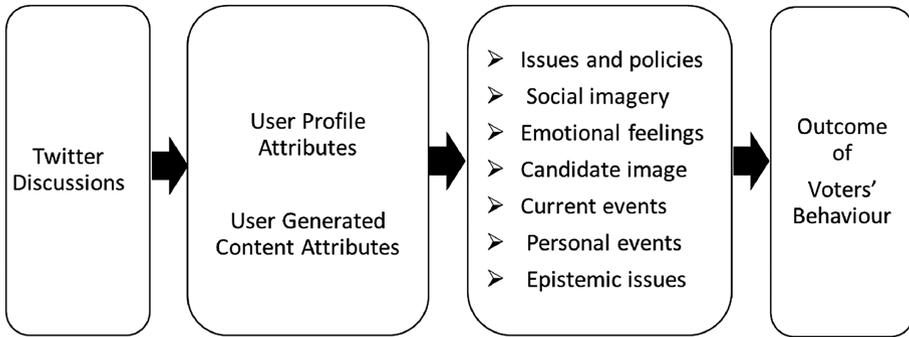


Fig. 1. Proposed model of analyzing voter behavior

Social media analytics can extract the crucial information from the user profiles, hashtags, groups, communities and search terms. Thus social media analysis can give us useful, non-biased user preferences without intruding the context. An indicative list of methods for Twitter analytics is illustrated in the Table 1.

Descriptive analysis focuses on descriptive statistics, such as the number of tweets and its types, number of unique users, hashtags, @mention and hyperlinks added in the tweets with frequency, word cloud and the reach metrics. Word clouds help us to visualize the popular words/topics tweets [31]. The “reach” metric can be used to measure the reach of the messages of the influencer [12]. Similarly reply and retweet feature in Twitter helps in assessing two way interaction and engagement [33]. The tweet can contain the hyperlinks as well to relevant resources [39]. The hashtags are used in the tweets so that the tweet opinion can be associated with a wider community of similar interest [8]. Similarly the @mentions analysis helps in identifying the influencers who had influenced the users to the extent that he/she wants to have a discussion with the influencer on the tweet topic [36].

Content analysis is used to extract the semantic intelligence from the text data. It leverages upon natural language processing (NLP) and text mining to retrieve the information from large amount of the text data. For example, sentiment analysis includes two types of the analysis such as polarity analysis and emotion analysis. Sentiment analysis is the process of computationally identifying and categorizing the opinions of the text [21]. For this study the sentiment analysis of the tweets were done using the R using *syuzhet*, *lubridate* and *dplyr* libraries. Polarity analysis is one of the highest used techniques for Twitter data analysis to measure the opinions of the user [35]. The e-motion analysis is one of the sentiment analysis techniques where user generated content is grouped into eight emotions categories such as anger, anticipation, disgust, fear, joy, sadness, surprise and trust. Similarly, topic modelling identifies the key themes among the tweets through mining of unstructured text [26]. Topic modelling was done in our study by using the *tm* and *topicmodels* libraries of R.

5 Findings and Interpretation

A descriptive overview of the Twitter activity of Clinton and Trump is presented in Table 2, which illustrates the degree of interaction both candidates had with the voters.

Table 2. Descriptive statistics of activity and engagement

	Retweet_count		Favorite_count	
	Clinton	Trump	Clinton	Trump
Total Tweets	2,400	1,227	2,400	1,227
Minimum activity/tweet	175	1,792	0	0
Maximum activity/tweet	665,370	345,548	1,197,489	634,112
Mean activity/tweet	4619.51	12,439.78	8,617.21	32,749.12
Std. Dev. of activity/tweet	16,190.92	14,256.63	31,359.86	37,376.37

We also tried to assess the possibility of voter’s polarization in terms of their preferences. For understanding the same, the election period was divided into the two phases of 60 days each. Phase 1 was considered from August 13, 2016 to October 11, 2016 and Phase 2 was considered from October 12, 2016 to December 10, 2016. For both the phases the tweets was segregated on the basis of Clinton and Trump. The sentiment analysis was applied on tweets for identifying the polarity. Table 3 illustrates the count for users in which sentiment transition had occurred during the election period for Trump and Clinton respectively. For Trump there was around 48.18% of polarization whereas for Clinton there was around 49.66% polarization.

Table 3. Impact assessment of polarization of preferences among voters

Highlighted cells indicate polarization from Phase 1 to Phase 2		Hillary Clinton		Donald Trump	
		Phase 2		Phase 2	
		Positive	Negative	Positive	Negative
Phase 1	Positive	11236	10250	476	309
	Negative	10944	10243	485	361

In the subsequent section, we attempt to explain based insights derived from “USA Election Twitter data” by applying Twitter analytics method through the Newman and Sheth’s model of voter choice, through seven distinct and separate cognitive domains which drives the voter’s behavior. These factors are issues and policies, social imagery, emotional feelings, candidate image, current events, personal events and epistemic issues [43]. Validation of insights from Twitter analytics, is done by exploring news and blog articles for confirmatory evidences.

5.1 Issues and Policies

This factor tries to address the economic policy, foreign policy and social policy raised by candidate during the election period and the leadership characteristics possess by the

candidate. Literature highlights the issues and policies are important component in influencing the voter behavior [43]. Voters will vote for candidate that will provide them with higher level of utility. Economy policy refers to the policies focusing on reducing inflation and budget balancing. Foreign policies include polices like increasing the defense spending. The tweets from both the presidential candidates Twitter screen where extracted and classified into four areas such as economy, foreign policy, social issues and leadership with the help of content analysis. The content analysis procedure was applied on the tweets by both the judges individually. There were 14,508 decision points (2400 tweets of Hillary Clinton, 1227 tweets of Donald Trump and four areas. Two independent judges agreed on 13,293 decisions and disagreed on 1,215 decisions with a coefficient of reliability of 91.62% which satisfies the thresholds of being over 85% [44]. Figure 2 illustrates the counts of the tweets posted by presidential candidates regarding the policies and issues.

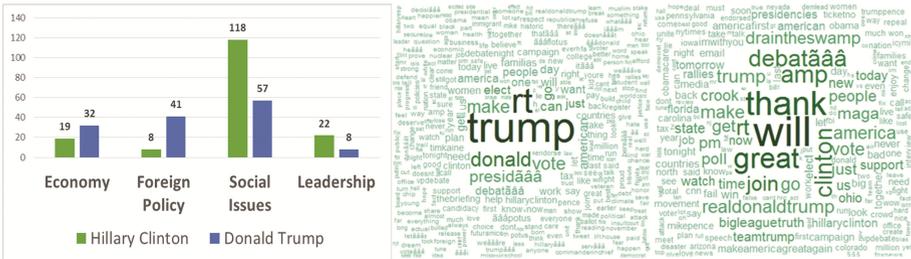


Fig. 2. Issues and policies raised by Clinton (left cloud) and Trump (right cloud)

There were around 167 tweets posted by Hillary Clinton regarding the policies and issues where as Donald Trump raised 138 tweets only. Clinton discussed various social issues surrounding the women and children related to equality, safety, empowerment and child care leave, disability, free education, career progression and mental stability. Clinton’s tweets were focusing more on social issues (and Trump’s policies!) whereas Trump was focusing more on economy and foreign policies like fighting against terrorism and crime, immigration, raising jobs and easing the business processes in USA.

5.2 Social Imagery

The factor refers to image of the candidate perceived by the voter in his/her mind. The candidate can have positive and negative stereotypes of the candidate depending on the various attributes such as demographic, socioeconomical, cultural, ethical, political and ideological dimensions. Figure 3 show the top 30 popular hashtags in the election period through which the social image of the candidate can be highlighted. Interestingly, Wiki-Leaks had released around 20,000 emails with almost 8,000 attachments of Democratic National Committee which indicated possibility of corruption in campaigns led by Clinton. Such discussions are indicated with hashtags like #podestaemails, #wikileaks, and #crookedhillary. However the popularity of #iamwithher was also one of the dominant among the hash tags, which indicate a huge amount support for Clinton.

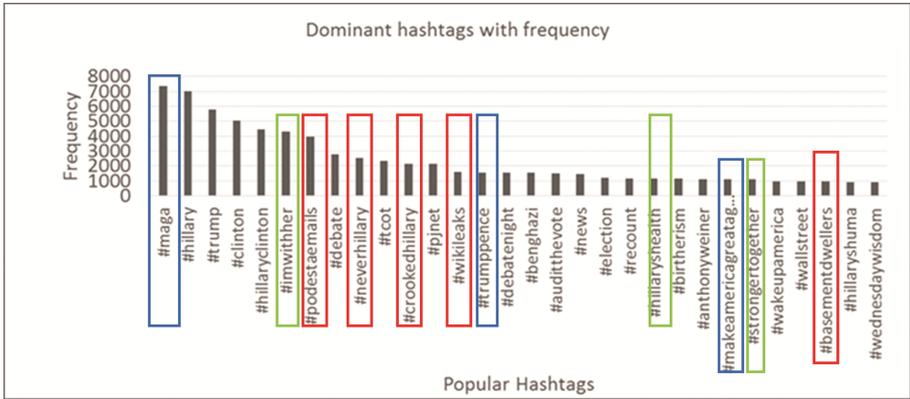


Fig. 3. Top 30 hashtags in election discussions and their dominant imagery in Tweets

The hashtags in green box indicates positive imagery of the Clinton, hashtags in red box indicates negative imagery of Clinton, the hashtag in blue box show positive imagery of Trump and no negative imagery appear among top 30 hashtags for Trump.

5.3 Emotional Feelings

Emotional feelings refer to the personal feelings possessed by the voter towards the candidate. A comparative analysis of all discussions surrounding the two candidates was conducted in terms of emotion analysis, as illustrated in Fig. 4. Higher visibility and presence among social discussions are likely to win an election through possible polarization [24]. In sheer volumes, discussions centered on Clinton surpassed all discussions surrounding Trump, in terms of all sentiments. This outcome is also comparable in the emotion comparison where the difference is highly contrasted for emotions like trust,

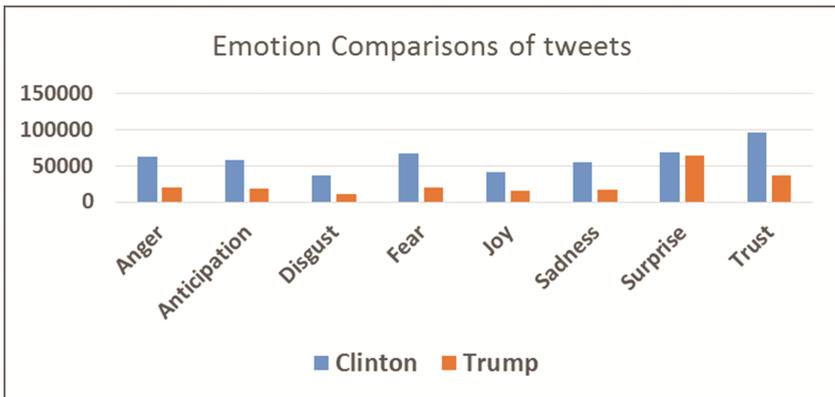


Fig. 4. Emotion analysis around Clinton and Trump

anger, anticipation, fear and disgust. In terms of surprise, however, count of tweets were somewhere comparative surrounding both the candidates.

5.4 Candidate Image

This factor refers to the salient personality traits of candidate image. However, in terms of percentage of tweets, polarity is somewhat similar. But given the difference of number of tweets, it is apparent that discussions surrounding Clinton, negative as well as more positive tweets, are more as compared to that of Trump.

Voters make up their opinion of vote on the basis of “candidate image” rather than referencing into election campaign issues, which result in interaction and engagement. Figure 5 illustrates the top 30 @mention along with their frequency over 18 weeks. Among 784,153 tweets there are 32,568 tweets which had @realdonaldtrump (around 4.15%) and 20,515 tweets had @hillaryclinton (around 2.61%). However the third popular mention was @wikileaks where a lot of debate was presented surrounding corruption of Clinton’s administration. This is indicative that the role of WikiLeaks may have been significant in deciding the outcome of the final result. Further dominant mentions were from news and journalism based sources (cnn, nytimes, reuters, foxnews). Further the role of opinion leaders like Linda Suhler and Mike Cernovich is also highlighted, who actively supported Trump, is also indicative in the outcome.

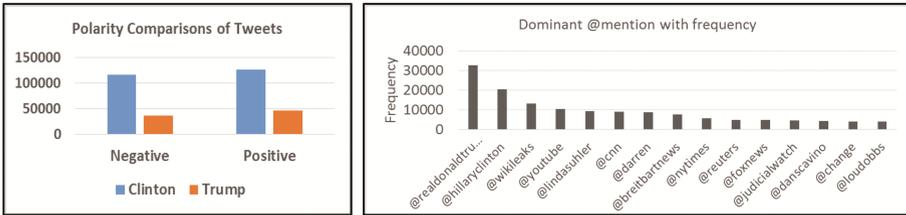


Fig. 5. Polarity analysis and top @mentions in USA election discussions

5.5 Current Events

This factor takes into the account all the events which had happened during the course of the election campaigning it includes both the domestic and international situations that would cause the voter to switch his/her voting preference. Since topic modeling is extremely computationally extensive, only the selective days when user sentiments in Twitter fluctuated significantly (i.e. mean tweet polarity $\pm 2 \times$ standard deviation), the tweets were analyzed. Then the topic identified from 18 days for creating the word cloud to identify the main concerns during the periods which enhanced user activity and resulted in major fluctuations of sentiments during the period of the elections. For topic modelling, each day top 15 topics were identified. Figure 6 illustrates the word cloud created based on the popularity of 15 topics across 18 days each, to visually present the dominance among emerged topics. Trump has 17.6 million followers on Twitter with 34,160 tweets whereas Hillary Clinton has 11.7 million followers with 9,838 tweets.

6 Concluding Discussion

Our study highlights some of the reasons which may have affected the outcome of USA elections. The study help us in understanding the possible reasons for polarization of voters among the Twitter users during the USA election. It helps us to identify the popular hashtags, @mention and the various domains influencing the voter's behavior on Twitter. However, the analysis of tweets highlights that the election outcome may have been strongly polarized by the presence of debates and opinion leaders. The study also helps us in examining the reactions of the users towards news evolving over the period of the elections. Despite Clinton having much more visibility in terms of interaction, the outcome of the election was effected by the nature of visibility and the resonance the voters had with her content. It appears that the campaigns of Clinton failed to gain popularity, though Trump's campaign gathered significant support, in terms of their presence in the descriptive analytics of hashtags, @mentions and word-cloud built of topics created. More than the campaigns and their outcome, Clinton also appeared to have spoken more about her competitor which was strongly contrasting for Trump who focused more on his policies and their outcome. Further, interestingly, as highlighted in Fig. 6, massive fluctuations in social activity happened when voters predominantly talked about Clinton, rather than any other topics.

However this study is still descriptive and may be further extended to explore the dynamics of verified and non-verified information which may be have been discussed at length in the USA elections, which may have polarized the outcome. The study also signifies in today's world Twitter handle plays the great role in the success of the election. The limitation of the study is if Twitter user gets influence by any other external events rather than Twitter discussion than that cannot be mapped. Further only if users contribute to the hashtag or topic directly, the discussion may be analyzed.

References

1. Achrekar, H., Gandhe, A., Lazarus, R., Yu, S.H., Liu, B.: Predicting flu trends using twitter data. In: IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 702–707 (2011)
2. Adams, A., McCorkindale, T.: Dialogue and transparency: a content analysis of how the 2012 presidential candidates used twitter. *Public Relat. Rev.* **39**(4), 357–359 (2013)
3. Asur, S., Huberman, B.A.: Predicting the future with social media. In: 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT), vol. 1, pp. 492–499 (2010)
4. Bollen, J., Mao, H., Zeng, X.: Twitter mood predicts the stock market. *J. Comput. Sci.* **2**(1), 1–8 (2011)
5. Burnap, P., Gibson, R., Sloan, L., Southern, R., Williams, M.: 140 characters to victory? Using Twitter to predict the UK 2015 General Election. *Electoral. Stud.* **41**, 230–233 (2016)
6. Burnap, P., Rana, O.F., Avis, N., Williams, M., Housley, W., Edwards, A., Sloan, L.: Detecting tension in online communities with computational Twitter analysis. *Technol. Forecast. Soc. Chang.* **95**, 96–108 (2015)

7. Cha, M., Benevenuto, F., Haddadi, H., Gummadi, K.: The world of connections and information flow in Twitter. *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.* **42**(4), 991–998 (2012)
8. Chae, B.K.: Insights from hashtag# supplychain and Twitter analytics: considering Twitter and Twitter data for supply chain practice and research. *Int. J. Prod. Econ.* **165**, 247–259 (2015)
9. Chatfield, A.T., Scholl, H.J.J., Brajawidagda, U.: Tsunami early warnings via Twitter in government: net-savvy citizens' co-production of time-critical public information services. *Gov. Inf. Q.* **30**(4), 377–386 (2013)
10. Cody, E.M., Reagan, A.J., Mitchell, L., Dodds, P.S., Danforth, C.M.: Climate change sentiment on twitter: an unsolicited public opinion poll. *PLoS One* **10**(8), e0136092 (2015)
11. Cohen, R., Ruths, D.: Classifying political orientation on Twitter: it's not easy!. In: *ICWSM* (2013)
12. Ganis, M., Kohirkar, A.: *Social Media Analytics: Techniques and Insights for Extracting Business Value Out of Social Media*. IBM Press, New York (2015)
13. Hale, S.A.: Global connectivity and multilinguals in the Twitter network. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 833–842. ACM (2014)
14. Harris, J.K., Moreland-Russell, S., Choucair, B., Mansour, R., Staub, M., Simmons, K.: Tweeting for and against public health policy: response to the Chicago Department of Public Health's electronic cigarette Twitter campaign. *J. Med. Internet Res.* **16**(10) (2014)
15. Heller Baird, C., Parasnis, G.: From social media to social customer relationship management. *Strategy Leadersh.* **39**(5), 30–37 (2011)
16. Henderson, A., Bowley, R.: Authentic dialogue? The role of "friendship" in a social media recruitment campaign. *J. Commun. Manage.* **14**(3), 237–257 (2010)
17. HerdaGdelen, A., Zuo, W., Gard-Murray, A., Bar-Yam, Y.: An exploration of social identity: the geography and politics of news-sharing communities in twitter. *Complexity* **19**(2), 10–20 (2013)
18. Ceron, A., Curini, L., Iacus, S.M., Porro, G.: Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens' political preferences with an application to Italy and France. *New Media Soc.* **16**(2), 340–358 (2014)
19. Joseph, N., Kar, A.K., Ilavarasan, V., Ganesh, S.: Review of discussions on Internet of Things (IoT): insights from Twitter analytics. *Forthcoming J. Glob. Inf. Manage.* **25**(2), 38–51 (2016)
20. Kim, A.J., Ko, E.: Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *J. Bus. Res.* **65**(10), 1480–1486 (2012)
21. Kolchyna, O., Souza, T.T., Treleaven, P., Aste, T.: Twitter sentiment analysis (2015)
22. Lakhiwal, A., Kar, A.K.: Insights from Twitter analytics: modeling social media personality dimensions and impact of breakthrough events. In: Dwivedi, Y.K., et al. (eds.) *I3E 2016*. LNCS, vol. 9844, pp. 533–544. Springer, Cham (2016). doi:[10.1007/978-3-319-45234-0_47](https://doi.org/10.1007/978-3-319-45234-0_47)
23. Lampos, V., Aletras, N., Preoŕiu-Pietro, D., Cohn, T.: Predicting and characterising user impact on Twitter. In: *14th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2014*, pp. 405–413 (2014)
24. Larsson, A.O., Moe, H.: Studying political microblogging: Twitter users in the 2010 Swedish election campaign. *New Media Soc.* **14**(5), 729–747 (2012)
25. Lau, J.H., Collier, N., Baldwin, T.: On-line trend analysis with topic models: #twitter trends detection topic model online. In: *COLING*, pp. 1519–1534 (2012)
26. Llewellyn, C., Grover, C., Alex, B., Oberlander, J., Tobin, R.: Extracting a topic specific dataset from a Twitter archive. In: Kapidakis, S., Mazurek, C., Werla, M. (eds.) *TPDL 2015*. LNCS, vol. 9316, pp. 364–367. Springer, Cham (2015). doi:[10.1007/978-3-319-24592-8_36](https://doi.org/10.1007/978-3-319-24592-8_36)

27. Mathioudakis, M., Koudas, N.: Twittermonitor: trend detection over the twitter stream. In: Proceedings of the 2010 ACM SIGMOD International Conference on Management of Data, pp. 1155–1158 (2010)
28. Munar, A.M., Jacobsen, J.K.S.: Motivations for sharing tourism experiences through social media. *Tour. Manag.* **43**, 46–54 (2014)
29. Myslín, M., Zhu, S.H., Chapman, W., Conway, M.: Using Twitter to examine smoking behavior and perceptions of emerging tobacco products. *J. Med. Internet Res.* **15**(8) (2013)
30. Neiger, B.L., Thackeray, R., Van Wagenen, S.A., Hanson, C.L., West, J.H., Barnes, M.D., Fagen, M.C.: Use of social media in health promotion purposes, key performance indicators, and evaluation metrics. *Health Promot. Pract.* **13**(2), 159–164 (2012)
31. Nooralahzadeh, F., Arunachalam, V., Chiru, C.G.: 2012 presidential elections on Twitter—an analysis of how the US and French election were reflected in tweets. In: 2013 19th International Conference on Control Systems and Computer Science, pp. 240–246. IEEE (2013)
32. Ou, G., Chen, W., Wang, T., Wei, Z., Li, B., Yang, D., Wong, K.F.: Exploiting community emotion for microblog event detection. In: EMNLP, pp. 1159–1168 (2014)
33. Purohit, H., Hampton, A., Shalin, V.L., Sheth, A.P., Flach, J., Bhatt, S.: What kind of #conversation is Twitter? Mining #psycholinguistic cues for emergency coordination. *Comput. Hum. Behav.* **29**(6), 2438–2447 (2013)
34. Reuben, R.: The use of social media in higher education for marketing and communications: a guide for professionals in higher education, 04-420 (2008)
35. Hassan, S., Miriam, F., Yulan, H., and Harith, A.: Evaluation datasets for Twitter sentiment analysis: a survey and a new dataset, the STS-Gold. In: 1st International Workshop on Emotion and Sentiment in Social and Expressive Media: Approaches and Perspectives from AI (ESSEM 2013), Turin, Italy (2013)
36. Shuai, X., Pepe, A., Bollen, J.: How the scientific community reacts to newly submitted preprints: article downloads, twitter mentions, and citations. *PloS One* **7**(11), e47523 (2012)
37. Singh, A.: Social media and corporate agility. *Glob. J. Flex. Syst. Manage.* **14**(4), 255–260 (2013)
38. Singh, V.K., Gao, M., Jain, R.: Situation detection and control using spatio-temporal analysis of microblogs. In: Proceedings of the 19th International Conference on World Wide Web, pp. 1181–1182. ACM (2010)
39. Tao, K., Hauff, C., Houben, G.J., Abel, F., Wachsmuth, G.: Facilitating Twitter data analytics: platform, language and functionality. In: 2014 IEEE International Conference on Big Data (Big Data), pp. 421–430. IEEE (2014)
40. Thackeray, R., Neiger, B.L., Hanson, C.L., McKenzie, J.F.: Enhancing promotional strategies within social marketing programs: use of Web 2.0 social media. *Health Promot. Pract.* **9**(4), 338–343 (2008)
41. Utsuro, T., Zhao, C., Xu, L., Li, J., Kawada, Y.: An empirical analysis on comparing market share with concerns on companies measured through search engine suggests. *Glob. J. Flex. Syst. Manage.* **18**, 3–19 (2016)
42. Walther, M., Kaisser, M.: Geo-spatial event detection in the Twitter stream. In: Serdyukov, P., Braslavski, P., Kuznetsov, S.O., Kamps, J., Rüger, S., Agichtein, E., Segalovich, I., Yilmaz, E. (eds.) ECIR 2013. LNCS, vol. 7814, pp. 356–367. Springer, Heidelberg (2013). doi:[10.1007/978-3-642-36973-5_30](https://doi.org/10.1007/978-3-642-36973-5_30)
43. Newman, B.I., Sheth, J.N.: A model of primary voter behavior. *J. Consum. Res.* **12**(2), 178–187 (1985)
44. Kassarian, H.H.: Content analysis in consumer research. *J. Consum. Res.* **4**(1), 8–18 (1977)