Regular article

Prabhsimran Singh*, Karanjeet Singh Kahlon, Ravinder Singh Sawhney, Rajan Vohra and Sukhmanjit Kaur

Social media buzz created by #nanotechnology: insights from Twitter analytics

<https://doi.org/10.1515/ntrev-2018-0053>

Received May 25, 2018; accepted October 7, 2018; previously published online October 31, 2018

Abstract: The word “nanotechnology” has been exaggerated not only by media but also by scientist groups who have overstated the unforeseen benefits of nanotechnology to validate research funding. Even ecologists, who normally remain indulged in doom-and-gloom divinations, use this word to fuel their own motives. Such outcomes lead to widespread misinformation and an unaware public. This research work is a staunch effort to filter the Twitter-based public opinions related to this word. Our results clearly indicate more of positive sentiments attached to the subject of nanotechnology, as trust, anticipation and joy overweigh by many folds the anger, mistrust and anger related to nanotechnology.

Keywords: analytics; nanotechnology; sentiment analysis; social media; Twitter.

1 Introduction

There has been a lot of buzz recently about the word “nanotechnology” in various forms of media, be it print media, e-media or social media. Social media has seen an unparalleled growth as compared to other forms of media in recent years as it enables people from different nations having common interest to communicate on and discuss various topics [1]. Even scientists and researchers have become a

part of this virtual world, where they share their current research with the global audience. One such area of research where scientists from all around the world are contemplating to produce the novel applications is nanotechnology.

Nanotechnology is a technique where high circuit integration density can be realized on a single chip by scaling down the size of electronic devices. The scaling down of electronic devices is driving electronics into the realm of nanoelectronics. It is being professed that Moore’s law could cease to exist after 2020 [2]. Faster response and integration into small area are the major gains of molecular electronic devices when compared to its silicon counterpart [3]. Deoxyribonucleic acid (DNA)-based molecular wires are fast emerging as favorable candidates for molecular electronics. The self-replication property of DNA advocates its fitness for the design of alike molecular electronic devices. The research work of Bhat et al. [4] illustrated the choice of best electrode material in the three-dimensional (3D) nanostructure of adenine, which is one strand of DNA. The role of crystallographic orientation of electrodes has also been determined to see the transport properties through DNA [5]. Thus, over the years, various research works on conductivity through DNA have been carried, and these works can be helpful to produce an insight toward DNA-based molecular devices like photonic logic gates, memories and transistors.

Similarly, ever since the knowledge of mankind expanded, only two allotropic forms of carbon were known, namely, graphite and diamond, but the discovery of fullerenes by Harold W. Kroto and his team in 1985 [6] revolutionized the perception of scientists, and carbon emerged as wonder element of nanoage. The fullerenes, generally present in the form of spherical balls, can be constructed by pentagon and hexagon rings of N carbon atoms. However, only two isomers have been experimentally realized, C₆₀ [6] and C₂₀ [7] fullerenes.

The basic structure of such fullerene molecules is the thick planar sheet of carbon atoms generally arranged in honeycomb pattern, called graphene sheet. This graphene sheet was discovered in 2004 when Andre Geim and Kostya Novoselov used a specialized technique called

*Corresponding author: Prabhsimran Singh, Guru Nanak Dev University, Department of Computer Engineering and Technology, GT Road, Amritsar 143005, Punjab, India, e-mail: prabh_singh32@yahoo.com

Karanjeet Singh Kahlon: Guru Nanak Dev University, Department of Computer Science, GT Road, Amritsar, Punjab, India

Ravinder Singh Sawhney and Rajan Vohra: Guru Nanak Dev University, Department of Electronics Technology, Amritsar, Punjab, India

Sukhmanjit Kaur: Khalsa College of Management and Technology, Department of Computer Applications, Amritsar, Punjab, India

micromechanical cleavage and extracted a single sheet of graphene from a 3D graphite [8]. Such sheets can be molded into a number of isomers, namely fullerenes, carbon nanotubes, etc. Various contemplations have been made to understand its properties for multidisciplinary applications, be it medical [9], chemical, physical, electronic and other interdisciplinary fields [10].

The aim of this paper is to critically analyze the social media hype created by the word “nanotechnology” and related keywords by monitoring and applying latest data processing strategies on the Twitter traffic.

2 Literature review

Science and mass media have always shared a strong bond. Whether print media or social media, both have played a crucial role in mapping public opinion in regard to new technology. Earlier, it was newspapers and magazines that used to cover the latest trends in technology and tried to map public opinion towards these. But in the last decade things have changed and researchers have opted for social media in addition to the traditional print media.

This section is categorized into two parts: (a) scientific discussion in various media and (b) nanotechnology in media. The first part focuses on various media platforms used for communication about new technologies, while the later discusses various work carried out with regard to “nanotechnology” in mass media.

2.1 Scientific discussion in various medias

The earlier studies focused on print media [11, 12], with a core focus on accuracy and readability. These studies did not provide sufficient details, making it unsuitable for the public to form positive opinion about any such new technology. As a result of this, Friedman [13] termed print media as the “dirty mirror” of science, since it was creating a negative opinion among the public.

Researchers also analyzed television and film documentaries [14, 15] related to science and technology; however, these techniques suffered from various problems, especially lack of any generalized analysis model. With the emergence of Web 2.0, many researchers were attracted to websites and social media [16]. Unlike its previous predecessors, these provide a two-way communication mechanism, thus enabling the researchers to get a better insight about the various discussions being carried out with regard to new technologies.

Facebook and Twitter are the two most famously used social media platforms and are often considered as “conversational hubs” [17]. According to the reports of AOL and Nielsen online [18], social networking websites have become very popular as a source for information sharing. There is a considerable amount of studies where researchers have used Facebook [19–22] and Twitter [23, 24] as a platform to analyze public opinion regarding some entity. However, there have been very limited studies that use social media to represent or promote a new technology.

2.2 Nanotechnology in media

There are few studies on nanotechnology, but most of them analyzed printed media [25–32]. The scope of these studies was limited to US and European countries only, and the sole objective was to map the opinion of the public toward nanotechnology. The results of these studies showed that people in the US had positive opinions regarding nanotechnology. Similarly, the opinion of people in Europe toward nanotechnology was also highly positive, except in UK [27, 28]. The reason for few studies was the fact that people in the nanotechnology community were afraid that media coverage will be more risky instead of providing useful benefits [33, 34].

Apart from newspaper, a handful of work was done in other media also. This included evaluation of images of nanotechnology [35, 36]. Schummer [37] applied network analysis on Amazon.com data to identify the network of books related to nanotechnology. Veltri [17] and Runge et al. [38] took this research to a higher level by applying sentiment analysis on tweets generated on Twitter. However, the major limitation of these studies was that only sentiment analysis was applied despite the fact that there are a lot of other social media analysis techniques that could have been applied. So this paper draws inspiration from the work of Veltri [17] and Runge et al. [38] and aims to map the public opinion generated online (Twitter) using social media analytics.

3 Research methodology

To accomplish our objectives, we used a very simple yet realistic technique. This technique starts with data (tweets) collection from a famous social media website, i.e. Twitter. Tweets were collected in a time-specific manner starting from January 1, 2018, to January 31, 2018. Since the collected tweets contained a lot of unwanted material, they

were preprocessed. Once preprocessing was done, we applied various social media analytics technique ranging from tweet statistics, (#) hashtag analysis, geo-location analysis, and sentiment analysis. The detailed description of each task is explained in the upcoming sections.

4 Data collection

For collection of tweets in a trusted manner, we developed a system using ASP.NET [39] and further integrated tweetinvi API [40] to fetch tweets in json format from Twitter. Tweets were collected on a daily basis based on specific (#) hashtags. For selection of these hashtags, two independent expert teams (nanotechnology and allied fields) were constituted having three members each. Both teams gave keywords that were directly or indirectly related to nanotechnology, like “nanotechnology,” “nano,” “nanoscience” etc. These keywords were used as (#) hashtags to search nanotechnology-related tweets from Twitter.

An example of tweets fetched based upon these specific (#) hashtags is shown in Figure 1. The sample tweet shown in Figure 1 contains three hashtags (#graphenepower, #nano and #nanotechnologies) that matched the keywords given by the expert team.

A total of 6289 tweets were collected in 31 days starting from January 1, 2018, to January 31, 2018. The daily tweet collection is shown in Table 1. The collected tweets contained tweet message, tweet sender, date and time and location (country) from where the tweet originated. Note that the location of all the tweets was not available due to security reason and free API policy.

Figure 1: A sample tweet.

Table 1: Daily Tweet collection.

Date	Tweets collected	Date	Tweets collected
01-01-18	198	17-01-18	246
02-01-18	210	18-01-18	239
03-01-18	240	19-01-18	205
04-01-18	228	20-01-18	147
05-01-18	231	21-01-18	104
06-01-18	184	22-01-18	200
07-01-18	165	23-01-18	212
08-01-18	216	24-01-18	232
09-01-18	231	25-01-18	234
10-01-18	252	26-01-18	260
11-01-18	247	27-01-18	171
12-01-18	225	28-01-18	146
13-01-18	181	29-01-18	207
14-01-18	174	30-01-18	206
15-01-18	217	31-01-18	62
16-01-18	219		

5 Detecting irrelevant tweets

Since many keywords suggested by experts were ambiguous, i.e. they were related to multiple other entities apart from nanotechnology, this resulted in fetching of various irrelevant tweets that were not relevant to our context of analysis. Hence, it was necessary to remove them.

For this, the same expert teams (see Section 4) were asked to manually investigate the collected tweets. After manual investigation, it was identified that some tweets were not relevant to our context of analysis. Two authors performed the operation of removal of these irrelevant tweets. Examples of irrelevant and relevant tweets are shown in Figures 2 and 3, respectively. A total of 754 such irrelevant tweets were removed and we were left with 5535 relevant tweets.

Since on Twitter, a person can post tweets multiple times, this makes our collected data biased. This could

Figure 2: A sample tweet (irrelevant).

Figure 3: A sample tweet (relevant).

lead to a scenario where the results of our analysis could be diverted toward the opinion of people posting multiple tweets. So, in order to perform a fair analysis, we applied the same technique used by Singh et al. [41] for removing multiple tweets from the same person. This technique identifies all tweets that are from same users and marks them, leaving only the first tweet. This technique also helps to neutralize the effects of bots, which create unnecessary tweet traffic. After applying this, we were left with 3671 tweets. Note that this process is not a substitution of normalization [42, 43] or bot detection [44] but helps to perform a fair analysis.

6 Data preprocessing

Since the collected tweets contained a lot of noise and unwanted stuff, it was necessary to preprocess them

Table 2: Preprocessing results.

Original tweet	#Nanotech #nanotechnology for effective drug delivery https://t.co/dtFwkfQwdr https://t.co/EHaZ4q3690
Lower case conversion	#nanotech #nanotechnology for effective drug delivery https://t.co/dtFwkfQwdr https://t.co/ehaz4q3690
Web links removal	#nanotech #nanotechnology for effective drug delivery
Punctuation removal	nanotech nanotechnology for effective drug delivery
Stop words removal	nanotech nanotechnology effective drug delivery
Extra blank space removal	nanotech nanotechnology effective drug delivery

before applying any analysis operation as this unwanted stuff may lead to undesired results [45]. The preprocessing operation includes removal of punctuations, numbers, English stop words, web links and extra white spaces present in the tweets. The entire task of preprocessing was performed using R-language [46]. Table 2 shows the details of the preprocessing task.

7 Social media analytics

Social media analytics is an art of extracting important hidden information from user-generated content on social media and using this information for decision making [47, 48]. In this section, various social media analytics techniques are applied to extract important information regarding nanotechnology from the preprocessed tweets.

7.1 Tweet statistics

Tweet statistics [49] involves various quantitative statistics of tweets like number of tweets, number of users etc. The details of tweet statistics are shown in Table 3. A total of 5535 tweets were collected from 3671 users, averaging 1.18 tweets per user.

7.2 (#) Hashtag analysis

Hashtag analysis [50] deals with various hashtag statistics. A total of 14,366 hashtags were identified in 3671 tweets, out of which 2743 hashtags were unique. A total of 5386 tweets contained more than one hashtag. The hashtag with maximum occurrences was #nanotechnology (1733). The top five hashtags with most occurrences are shown in Figure 4.

Table 3: Tweet statistics

Total tweets	5535
Average tweets per day	178.5484
Max tweets (date)	236 (26-Jan-18)
Min tweets (date)	38 (31-Jan-18)
Unique senders	3671
Average tweets per sender	1.507

Figure 4: Top five (#) hashtags.

7.3 Geo-location analysis

This analysis takes into consideration the locations from where the tweet originated [51]. However, due to privacy reasons, only the location of those tweets is returned wherein privacy settings allow us to do so. Out of 3671 tweets, 514 were geo-location enabled. Out of these 514, maximum tweets originated from the US (141), closely followed by India (107). The result of the geo-location analysis is shown in Figure 5.

7.4 Sentiment analysis

Sentiment analysis is a text analysis technique that deals with the extraction of sentiment from a given piece of text [52, 53]. Sentiment analysis further involves two sub-operations: (a) polarity analysis [54] and (b) E-motion analysis [55].

Figure 5: Results of geo-location analysis.

- (a) **Polarity analysis:** This deals with identifying the polarity (i.e. positive or negative) of a given text. We used WEKA tool [56] to perform the polarity analysis. A classification model was built using a supervised machine learning algorithm, support vector machine (SVM) [57], to classify the given tweets into positive or negative tweets. The reason for choosing SVM over other algorithms was that multiple studies have concluded that the SVM gives best results in sentiment analysis [58, 59], since supervised machine learning involves training and then testing of the dataset. For training purposes, we have used IMDb [60] dataset consisting of 500 positive and 500 negative instances. The reason for choosing the IMDb dataset for training was that it is often considered one of the best and authenticated datasets for supervised machine learning [58]. Once training was completed, we tested the classifier on preprocessed tweets. The results of polarity analysis are shown in Figure 6, which indicates a highly positive polarity among tweet senders.
- (b) **E-motion analysis:** This deals with categorizing data based upon eight e-motions. E-motion analysis was performed using R-language. The results of the e-motion analysis are shown in Figure 7. These results clearly indicate that the tweets contained more positive words (anticipation + joy + surprise + trust).

Figure 6: Results of polarity analysis.

Figure 7: Results of E-motion analysis.

8 Discussion

Social media represents a virtual world where people around the world can have a two-way communication on various topics, including those related to science and technology. This paper aims to explore one such booming technology: nanotechnology. The results of our research are quite encouraging as the results show an overall positive attitude among people who are involved in this conversation. Most of the discussion focuses upon various applications of nanotechnology, be it in medical field for cancer detection or the various optical application of graphene. This was also a strong reason that graphene was one of the most commonly used hashtags (#) as depicted by our study.

However, there were few challenges that are needed to be addressed. The data collection period of 1 month was too short; had this analysis been covered over a period of 6 months or so, it would have delivered more useful results. Further, we can detect what events lead to polarization of public opinion. Another important challenge that was not addressed in this study was the normalization of tweets [42, 43]. Twitter has highly varying usage rates per person for different geographical regions. This depends on people's privacy concerns, available infrastructure, age of the population etc. Normalization of tweets can certainly help in answering some of these issues. Similarly, bot detection [44] remained another important challenge that was not addressed.

All these motivate us to further extend this study to a larger time frame, which can produce even better results by applying other social media analysis techniques like topic modeling and community analysis and addressing challenges that were not addressed in this study.

9 Conclusions

With the rise in social media users, social media analytics have become an important tool. In this paper, we used social media analytics to analyze the buzz created by nanotechnology on Twitter. Our results indicate that there is a lot of talking going on in Twitter regarding nanotechnology and in a positive sense, too. Our results clearly indicate that there is lot of positive sentiments attached to the subject nanotechnology as trust in the technology, anticipation about the outcome and joy about the availability of the predicted applications outweigh many folds the anger due to nanowaste, mistrust about the failures in achieving the target and anger of

wasting tons of taxpayers' money in projects related to nanotechnology.

However, tweets collected in a 1-month time period are not sufficient to analyze such a vast topic, and these results could be still improved by extending the tweet collection period. We can substantiate this research topic using a more suitable dataset by comparing nanotechnology with other booming technologies like artificial intelligence and internet of things.

References

- [1] Kapoor KK, Tamilmani K, Rana NP, Patil P, Dwivedi YK, Nerur S. Advances in social media research: past, present and future. *Inf. Syst. Front.* 2018, 20, 531–558.
- [2] Schaller RR. Moore's law: past, present and future. *IEEE Spectr.* 1997, 34, 52–59.
- [3] Tour JM, Kozaki M, Seminario JM. Molecular scale electronics: a synthetic/computational approach to digital computing. *J. Am. Chem. Soc.* 1998, 120, 8486–8493.
- [4] Bhat Y, Vohra R, Kaur M, Sawhney RS. Impact of different metallic electrodes on quantum transport through deoxyribonucleic acid. *J. Comput. Theor. Nanosci.* 2017, 14, 4137–4142.
- [5] Vohra R, Bhat Y, Kaur M, Sawhney RS. Scrutiny of electron transport properties of adenine molecule under dissimilar miller orientations. *J. Bionanosci.* 2017, 11, 363–369.
- [6] Kroto HW, Heath JR, O'Brien SC, Curl RF, Smalley RE. C₆₀: Buckminsterfullerene. *Nature* 1985, 318, 162.
- [7] Prinzbach H, Weiler A, Landenberger P, Wahl F, Wörth J, Scott LT, Gelmont M, Olevano D, Issendorff, BV. Gas-phase production and photoelectron spectroscopy of the smallest fullerene, C₂₀. *Nature*, 2000, 407, 60.
- [8] Novoselov KS, Geim AK, Morozov SV, Jiang D, Zhang Y, Dubonos SV, Grigorieva IV, Firsov AA. Electric field effect in atomically thin carbon films. *Science* 2004, 306, 666.
- [9] Kaur M, Sawhney RS, Engles D, Kaur RP. Design of fullerene-based biomarker for detection of lead impurities. *ICT Express* 2016, 2, 159–162.
- [10] Kaur M, Sawhney RS, Engles D. The density functional implementation of hybrid graphene devices stringed to C₂₀ fullerene. *J. Nanoelectron. Optoelectron.* 2017, 12, 1146–1153.
- [11] Dunwoody S, Scott BT. Scientists as mass media sources. *Journal. Q.* 1982, 59, 52–59.
- [12] Bader RG. How science news sections influence newspaper science coverage: a case study. *Journal. Q.* 1990, 67, 88–96.
- [13] Friedman SM. *TMI: The Media Story That Will Not Die. Bad Tidings: Communication and Catastrophe*. Lawrence Erlbaum: Hillsdale, 1989.
- [14] Gopfert W. Scheduled science: TV coverage of science, technology, medicine and social science and programming policies in Britain and Germany. *Public Underst. Sci.* 1996, 5, 361–374.
- [15] Jones RA. The Boffin: a stereotype of scientists in post-war British films (1945–1970). *Public Underst. Sci.* 1997, 6, 31–48.
- [16] Waldrop MM. *Science 2.0: Great New Tool, or Great Risk?* Scientific American, 2009. <https://www.scientificamerican.com/article/science-2-point-0-great-new-tool-or-great-risk/>.

- [17] Veltri GA. Microblogging and nanotweets: nanotechnology on twitter. *Public Underst. Sci.* 2013, 22, 832–849.
- [18] Pew Research. Global Publics Embrace Social Networking. 2010. Available at: <http://www.pewresearch.org/2010/12/15/global-publics-embrace-social-networking>. Accessed February 1, 2018.
- [19] Jain SH. Practicing medicine in the age of Facebook. *N. Engl. J. Med.* 2009, 361, 649–651.
- [20] Hawn C. Take two aspirin and tweet me in the morning: how Twitter, Facebook, and other social media are reshaping health care. *Health Aff.* 2009, 28, 361–368.
- [21] Waters RD, Burnett E, Lamm A, Lucas J. Engaging stakeholders through social networking: How nonprofit organizations are using Facebook. *Public Relat. Rev.* 2009, 35, 102–106.
- [22] Westling M. Expanding the public sphere: the impact of Facebook on political communication. *The New Vernacular* 2007, 28, 1–13.
- [23] Pang B, Lee L. Opinion mining and sentiment analysis. *Found. Trends® Inf. Ret.* 2008, 2, 1–135.
- [24] Marwick AE, Boyd D. I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media Soc.* 2011, 13, 114–133.
- [25] Lewenstein BV, Gorss J, Radin J. The salience of small: nanotechnology coverage in the American Press, 1986–2004. Paper presented at the International Communication Association, New York (2005, 26–30 May 2005).
- [26] Scheufele DA, Lewenstein BV. The public and nanotechnology: how citizens make sense of emerging technologies. *J. Nanopart. Res.* 2005, 7, 659–667.
- [27] Friedman SM, Egolf BP. Nanotechnology: risks and the media. *IEEE Technol. Society Mag.* 2005, 24, 5–11.
- [28] Gaskell G, Eyck TT, Jackson J, Veltri G. Imagining nanotechnology: cultural support for technological innovation in Europe and the United States. *Public Underst. Sci.* 2005, 14, 81–90.
- [29] Anderson A, Allan S, Petersen A, Wilkinson C. The framing of nanotechnologies in the British newspaper press. *Sci. Commun.* 2005, 27, 200–220.
- [30] Kjølberg KL. Representations of nanotechnology in Norwegian newspapers – implications for public participation. *Nanoethics* 2009, 3, 61–72.
- [31] Kjærgaard RS. Making a small country count: nanotechnology in Danish newspapers from 1996 to 2006. *Public Underst. Sci.* 2010, 19, 80–97.
- [32] Donk A, Metag J, Kohring M, Marcinkowski F. Framing emerging technologies: risk perceptions of nanotechnology in the German press. *Sci. Commun.* 2012, 34, 5–29.
- [33] Wood S, Jones R, Geldart A. The social and economic challenges of nanotechnology. Economic and Social Research Council, Swindon, 2003.
- [34] Lewenstein BV. What counts as a ‘social and ethical issue’ in nanotechnology? *HYLE – Int. J. Phil. Chem.* 2005, 11, 5–18.
- [35] Landau J, Groscurth CR, Wright L, Condit CM. Visualizing nanotechnology: the impact of visual images on lay American audience associations with nanotechnology. *Public Underst. Sci.* 2009, 18, 325–337.
- [36] Hanson VL. Amidst nanotechnology’s molecular landscapes: the changing trope of subvisible worlds. *Sci. Commun.* 2012, 34, 57–83.
- [37] Schummer J. Reading nano: the public interest in nanotechnology as reflected in purchase patterns of books. *Public Underst. Sci.* 2005, 14, 163–183.
- [38] Runge KK, Yeo SK, Cacciatore M, Scheufele DA, Brossard D, Xenos M, Anderson A, Choi DH, Kim J, Li N, Liang X. Tweeting nano: How public discourses about nanotechnology develop in social media environments. *J. Nanopart. Res.* 2013, 15, 1381.
- [39] Visual Studio 2012 [Online], Available at: <https://www.visualstudio.com/vs/older-downloads/>. Accessed: February 1, 2018.
- [40] Tweetinvi API [Online], Available at: <https://www.nuget.org/packages/TweetinviAPI/>. Accessed: February 1, 2018.
- [41] Singh P, Sawhney RS, Kahlon KS. Forecasting the 2016 US Presidential Elections Using Sentiment Analysis. In *Conference on e-Business, e-Services and e-Society*, Kar, AK, Ilavarasan, PV, Gupta, MP, Dwivedi, YK, Mäntymäki, M, Janssen, M, Simintiras, A, Al-Sharhan, S, Eds. Springer: Cham, 2017, pp. 412–423.
- [42] Thom D, Bosch H, Ertl T. Inverse document density: a smooth measure for location-dependent term irregularities. *Proceedings of COLING 2012*, 2012, 2603–2618.
- [43] Bornmann L, Haunschild R. How to normalize Twitter counts? A first attempt based on journals in the Twitter Index. *Scientometrics* 2016, 107, 1405–1422.
- [44] Chu Z, Gianvecchio S, Wang H, Jajodia S. Who is tweeting on Twitter: human, bot, or cyborg? In *Proceedings of the 26th Annual Computer Security Applications Conference*. ACM: Austin, TX, USA, 2010, pp. 21–30.
- [45] Haddi E, Liu X, Shi Y. The role of text pre-processing in sentiment analysis. *Procedia Comput. Sci.* 2013, 17, 26–32.
- [46] R-Language [Online], Available at: <https://www.r-project.org/about.html>. Accessed: February 1, 2018.
- [47] Stieglitz S, Dang-Xuan L. Social media and political communication: a social media analytics framework. *Social Network Analysis and Mining* 2013, 3, 1277–1291.
- [48] Chen S, Lin L, Yuan X. Social media visual analytics. *Comput. Graph. Forum* 2017, 36, 563–587.
- [49] Purohit H, Hampton A, Shalin VL, Sheth AP, Flach J, Bhatt S. What kind of #conversation is Twitter? Mining #psycholinguistic cues for emergency coordination. *Computers Human Behav.* 2013, 29, 2438–2447.
- [50] Chae BK. Insights from hashtag #supplychain and Twitter analytics: considering Twitter and Twitter data for supply chain practice and research. *Int. J. Prod. Eco.* 2015, 165, 247–259.
- [51] Singh P, Sawhney RS, Kahlon KS. Sentiment analysis of demonetization of 500 & 1000 rupee banknotes by Indian government. *ICT Express* 2018, 4, 124–129.
- [52] Liu B. Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies* 2012, 5, 1–167.
- [53] Agarwal A, Xie B, Vovsha I, Rambow O, Passonneau R. Sentiment analysis of twitter data. In *Proceedings of the Workshop on Languages in Social Media*. Association for Computational Linguistics: Portland, OR, USA, 2011, pp. 30–38.
- [54] Ou G, Chen W, Wang T, Wei Z, Binyang LI, Yang D, Wong KF. Exploiting community emotion for microblog event detection. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar, 2014, pp. 1159–1168.
- [55] Mohammad SM, Turney PD. Emotions evoked by common words and phrases: using Mechanical Turk to create an emotion lexicon. In *Proceedings of the NAACL HLT 2010*

Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. Association for Computational Linguistics, 2010, pp. 26–34.

- [56] Witten IH, Frank E, Hall MA, Pal CJ. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann: Burlington, MA, USA, 2016.
- [57] Soentpiet R. *Advances in Kernel Methods: Support Vector Learning*. MIT Press: Cambridge, MA, USA, 1999.
- [58] Srivastava R, Kumar H, Bhatia MP, Jain S. Analyzing Delhi assembly election 2015 using textual content of social network. In *Proceedings of the Sixth International Conference on Computer and Communication Technology 2015*. ACM: Allahabad, India, 2015, pp. 78–85.
- [59] Ye Q, Zhang Z, Law R. Sentiment classification of online reviews to travel destinations by supervised machine learning approaches. *Expert Sys. Appl.* 2009, 36, 6527–6535.
- [60] Maas AL, Daly RE, Pham PT, Huang D, Ng AY, Potts C. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies – Volume 1*. Association for Computational Linguistics: Portland, OR, USA, 2011, pp. 142–150.