Demystifying automatic rumour detection in social networks: A review

Osheen Sharma¹, Sachin Ahuja² and PreetKamal³

¹²Chitkara University Institute of Engineering & Technology, Chitkara University, Punjab, India,
³GGDSD College, Chandigarh, India

Email-osheensharma12@gmail.com, 2 sachin.ahuja@chitkara.edu.in, 3 preetkamal2904@yahoo.co.in

Abstract. The increase in the connectivity and availability of network has subsequently increased the use of social media. Social Media has emerged as the most readily accessible and fastest platform for updates related to events happening worldwide. The increase in the use of social media has also increased the misuse of resources for spreading unverified information generally termed as a rumour. The biggest problem in social media is the speed at which the information spreads without verifying its credibility. There has been lot of research for detection and prevention of rumours over social media. This paper focuses on presenting the present state of the art in automatic rumour detection in social networks. The paper highlights the prominent researches done in detecting these rumours in social network over the last 5 years. This paper shows both manual and automatic approaches that can be used. Also various tools have been identified which were developed for rumour detection in social media platforms. This paper shows the different available approaches that are being used and can be used in future with improvement.

Keywords: rumour, rumour detection, fake news detection, social network, misinformation, social media, social network analysis.

1. Introduction

Social media plays an imperative role in modern life from last few years. There is massive increase in the number of users on social media [31]. Social Media is imparting information to large audience in the form of news [42], general posts, information related to social issues [8], blogs, tweets, etc. without any hesitation and restriction and for connecting directly to group of people for the sake of their personal or official interests and to create some new associations.

Social media has been a major attraction from last two decades. Social media is a medium to share information and communication in various fields such as marketing, journalism [26, 34], and public relation [46] as well as for general people [1]. In present time, social media has become one of the important tools used in journalism for publishing news and articles [2] and also a medium for people with different interest to read most up-to-date news and articles [1]. Social network is an association of social interactions and personal relationships. Social Network Analysis (SNA) is a tool for modeling,
visualizing and analyzing the communication between the individuals within a group or an organization.

Social network is an exceptionally useful platform to share useful information related to various subjects, topics, events and individuals. Besides being extremely useful absentia of systematic efforts by platforms to examine the posts or any content being shared on social media it has become very easy source of sharing false information [14]. This false information is termed as a rumour or fake news regarding any person, event, subject, etc. This rumour requires extra effort to be identified and rectified.

To control the spread of rumours it is required to collect and to analyze the collected data from numerous people that are using the same platform [25, 19]. A detection system to identify these rumours should be built which can categorize the rumour in terms of true or false [47]. In order to build a detection system for rumours prevailing in social networks one should know how to analyze the posts or the content on social network.

1.1. Defining Rumour
According to various studies on rumours, there are different definitions quoted on it. Liang et al. and few more have defined rumours as misinformation or information which is deemed false [13, 10]. DiFonzo et al. (2007) have termed it as “unverified and instrumentally relevant information statements in circulation” [27]. According to Zubiaga et al. (2018) rumour can be well defined as “an item of circulating information whose veracity status is yet to be verified at the time of posting” [50]. Here the veracity status, categorize the rumour as true, partially true, entirely false or unresolved.

1.2. How Rumours are generated?
The chain of rumour starts when unverified information having no certainty of facts is circulated over a network. The information starts spreading very speedily on social network. The moment a statement is posted, social media instantly grasps it and the process of circulation gets started.

There are various reasons why people spread rumours:
- To gain attention
- To manipulate public opinion
- Political intend
- Rush to convey information
- To generate advertising revenue
- To gain financial profit
- Just for fun
- To blend in with a group sharing stories
- Malicious actors will also seed and propagate false narrative

A well intended spread rumour can be a threat to the society which can lead to fatal results such as riot or turmoil.

1.3. Need of Rumour Detection
Over the time information related to latest development and current affairs on social media spreads very fast and easily by numerous users on it, professional as well as public [16,6]. The way and speed the information spreads, it changes the reaction and situation towards the reality and affects people’s life in many ways. Public opinion on social media has been found very influential in all aspects be it politics [28] or any firm’s reputation [18] or even in health sectors by giving positive and negative opinions on different health programs [37]. This is because they trust the information available and spreading on social media and consider that all information circulated on social media is true. There
are many incidents quoted below which shows that the user hardly puts any effort on checking whether the information is true or is it a rumour being spread. They never try to verify it from a trusted source be it an official website or account, a verified news channel or any other medium which can help them in verifying the information. Unintentionally this makes them a part of the group spreading rumours.

There are several such incidents that can be quoted which show the negative and extreme impact of rumour on society. Like, in 2013 a news agency tweeted a news that created a huge panic in the USA which stated that there has been an explosion in the white house which has left the President of US Barack Obama injured, millions of people believed it till White House Press Secretary Jay Carney said ”The President is fine” [33]. The rumour got finally stopped when the Associated Press tweeted that their account was hacked. Luckily, this rumour was cleared early and quickly whereas in a similar incident when a rumour stating Barack Obama was injured during Boston Marathon, it consumed a lot of time and money of US government to recover. Some more incidents related to spreading of rumours are as follows

The Indian Express in 2018 reported that in the last one year 27 people were killed in 15 cases of mob lynching across nine different states. All these mob lynching were the result of rumours that got spread in these areas regarding child-kidnappers. This report included states like Jharkhand (7 killed), Tamil Nadu (1 killed), Karnataka (1 killed), Telangana (1 killed), Assam (2 killed), West Bengal (2 killed), Chhattisgarh (1 killed), Tripura (3 killed), Maharashtra (9 killed) [36].

They also claimed that in three months across country 20 people died due to lynching in the same year. These lynching cases were the result of rumours on child-lifters. All the victims were innocent people, who got trapped in the area with people provoked by rumour.

Rumour or fake news is a common problem in social network. Rumours are nothing but spreading of wrong information about a particular subject using a network. Rumour detection aims to classify information as rumour or non-rumour. The main aim of detecting a rumour is to predict the truth value or veracity status of the rumour. The major effects of rumours on the society were identified as follows:

- Can hamper public opinion about an issue
- Hurt the sentiments of an individual or group
- Spread misinformation with negative intention

1.4. Analyzing Rumour
There are several methods that can be identified on the basis of previous researches which can help in detecting rumours. According to research done by [30], they identified and concluded that Content based text and media are the methods that can help in rumour detection. Similarly, Ferrara et al. (2016) identified User activity tracking [9] and Tacchini et al. (2017) identified Followers and Friends Network as one of the methods that can be useful for rumour detection [43].

Sentiment analysis is one of the methods to analyze the content being shared on social network. Sentiment analysis is the strategy of arranging the perspectives of multiple users communicated over a specific article in the form of posts, blogs, tweets, comments, or any other social content. A large number of researchers using sentiment analysis have tried generating statistical reference from social networks [22].
With the advancement in technological tools, it became significant to know the common interests and disinterests related to any business, products or any common matter. Finding the feeling behind the posts using web-based networking, media helps the user to relate the perspective and react accordingly. Sentiment analysis helps in understanding the attitude and behavior of the user by analyzing their tone on the basis of opinion, sentiment and subjectivity in text. Sentiments can help in predicting stock market [32], opinions posted by investors [15] and effect of public opinion on selling and purchasing of goods and establishing the brand value [21].

The classification done on textual information available on social network and the network structure of social media platform is the base of research for the sentiment analysis.

1.5. Datasets
There are various studies that conducted thorough research in rumour detection and developed techniques for rumour detection. The first and foremost part of any technique is to identify datasets that can prove useful in application of developed technique.

Some publicly available datasets are listed below:

1.5.1. BuzzFeedNews. This dataset contains samples from nine news agencies of a week around 2016 U.S. election i.e. from September 19 to 23 and September 26 and 27. It comprises sample of news published in facebook. After some modifications in the dataset, it contains 1,627 articles– out of which 826 were from mainstream, 356 were left-wing, and 545 right-wing articles. The claim is that all the facts in this dataset have been checked and verified by 5 BuzzFeed journalists [24].

1.5.2. LIAR. The dataset is collected from PolitiFact using its API. PolitiFact is a fact checking website which checks and verifies the data related to US presidential elections. This dataset comprising of data from news releases, interviews, speeches, campaigns etc [44].

1.5.3. BS Detector. This dataset contains results from BS detector, a browser extension used by BS detector for checking veracity of news. The search includes verifying the data from all the web links available on a website to find the source.

1.5.4. PHEME. This dataset includes data related to breaking news or click baits. The dataset includes data from Twitter only. It is a repository of rumours and non rumours [12].

1.5.5. The FakeNews Net dataset. This dataset collection comprises of all kinds of social context including user reactions and comments. It is a repository of 24000 data points [17].

1.5.6. Weibo. This dataset is a collection from Sina Weibo, a Chinese authoritative news source. It contains data from 2012-2016. The dataset comprises of data checked by official rumour debunking system of Weibo [49].
1.5.7. **Twitter.** This data has a collection of text and images from Twitter. In addition, it also contains information such as user reactions and other context information [7].

Not just these, there are many other publically available datasets that can be used for rumour detection and as well as for analyzing social network data in many ways. These datasets discussed above are considered to be some of the available benchmark datasets used in rumour detection by researchers.

2. Related Work

There are many researchers who have used sentiment and semantic analysis for rumour detection along with some set features. Suchita Jain et al. (2016), used sentiment and semantic analysis approach to detect rumours on twitter in real time [41]. They divided the user accounts into two major categories- verified News Channel accounts and general public accounts. According to them the News Channel accounts provide more authentic and correct information as compared to the general accounts. On the other hand, Mao et al. (2016) concluded the study by showing that the sentiment orientation in social sites is the most effective in rumour detection [23]. They collectively used the previous shallow statistical features and deep feature together with sentiment orientation to detect rumours, which enhanced the accuracy of detection and F1 score (3.9% and 4.6% respectively). Similarly, Sivasangari et al. (2018), proposed a VADER sentiment analysis which calculated the sentiment category and the strength of each and every text using the rule based heuristics method [40]. They found out the sentiment lexicon score value for the scraped dataset using VADER to separate a rumour from genuine content with increased accuracy.

Another approach used by some researchers is Support Vector Machine along with sentiment analysis for detection of rumours. Like, Li (2016), tried to formulate a sentiment based hybrid kernel SVM 240 (SHSVM) classifier for rumour detection [20]. For analyzing the sentiment tendency of comments on social network they used a dictionary of emotions. This dictionary was used to get an idea of characteristics of emotion in a particular comment that can be used in the analysis. Qiao Zhang et al. (2017) used shallow and implicit features proposed by them for rumour detection [35]. They used supervised learning method i.e. SVM (Support Vector Machine), Random forest etc. for classifying the shallow features. The reason for using any of such method is that that in many cases, the shallow features cannot distinguish between a rumour and a normal message whereas, Ajao et al. (2019), proposed an algorithm of novel sentiment aware for fake news detection [29]. They considered the hypothesis that the emotional words used are an advantage in sentiment aware rumour detection. There algorithm showed improvement over state-of-the-art algorithm (considering no sentiments) on a benchmark dataset. The State-of-art approach was presented by Zubiaga et al. (2017) used the context from earlier posts related with a particular event to determine if a tweet is a rumour or not [3].

Both Zhiwei Jin et al. (2017) and Bhutani et al. (2019) tried using multiple approaches and compared the results to get a final and best possible result along with the best suitable approach for their research [48] [4]. On one side Zhiwei Jin et al. (2017), proposed an algorithm to detect rumours spreads in political events specifically in 2016 U.S. presidential election. They used word matching method i.e. TF-IDF, BM25, Word2Vec and Doc2Vec to detect rumour tweets with the verified rumour articles related to two presidential candidates i.e. Hillary Clinton and Donald Trump. They analyzed the tweets done by the accounts that follow the candidates [48]. Whereas Bhutani et al. (2019) focused on improving the accuracy of fake news detection using sentiments [4]. The results of the approach using three different datasets were tested and compared to other text processing techniques which showed the improvement in detection accuracy.

According to some studies, researchers have also tried to develop a specialized tool for rumour detection based on different techniques and using the already available approaches. Shu et al. (2019)
proposed a FakeNewsTracker tool for fake news detection with the help of deep learning-based solution [39]. For detection the technique used features such as linguistic and social engagement which helped in better detection. The tool also provides a better visualization feature for interpreting the results. Yan Zhang et al. (2017), used the most popular micro blogging site in china i.e. Sina Weibo which uses autoencoders for the detection of rumours [45]. For rumour detection, various self-adapting thresholds were used by them, calculated by using properties of different and recent Weibo set. They tried to find out how the performance of the detection approach can be affected by the hidden layers of autoencoder. Likewise, Ghanem et al. (2019), believes emotions play a major role in misleading readers [11]. They worked on the theory that a rumour or a fake content have unusual patterns of emotion. Based on their work they proposed an emotionally-infused model (EIM) using LSTM neural network model to detect false news.

Few researchers tried some different approaches for the same purpose and showed there are more ways of detecting the rumours other than the common and most used ones. Chang et al. (2016) used clustering-based approach for detecting rumours [5]. They focused on the detecting rumours on Twitter related to the politics. They analyzed the tweets related to two candidates Hillary Clinton in August 2015 and Barak Obama in September 2015, and identified different users as suspicious users. These users were tagged as suspicious by their history of posting false news on Twitter. The researchers tried finding the best combination for best possible results by comparing different parameters but concluded by saying that there is no definite way of finding, as there are many different combinations of parameters available to test. However, the author concluded that the method needs improvement as manually labelling clusters as rumours is a difficult task. Sahana V P et al. (2015), worked not only on detecting the rumours automatically but also on identifying the source from where the rumour is being spread for which they proposed an algorithm [38]. For detection they used some rumour and non-rumour tweets associated with London Riots-2011 and applied Weka classification tool for detection and achieved the Best accuracy by using J48 classification algorithm.

3. Methodology
Most of the approaches studied in the literature for rumour detection aims at labelling the particular information as rumour/non rumour or true/false. The approaches mostly used machine learning and deep learning and achieved improved accuracy. Some of the researchers also used data mining techniques.

Li WY (2016) [20], Zang et. al. (2017) [45] and Chang et. al. (2016) [5] used Support Vector Machines (SVM) method for classification. SVM is one of the most widely used methods for rumour detection. SVM is a machine learning supervised approach which is extensively used and highly recommended approach for solving tasks in information engineering. Among all the other supervised machine learning approaches, performance of SVM has been outstanding for deception detection in text, obtaining decent accuracy.

Another used approach for rumour detection is decision tree as used by Sahana V P et.al. (2015)[38]. In this approach, data with algorithms such as J48 is used and a decision tree is generated. In order to determine the class, a decision tree performs a recursive split on feature values. This approach is simpler than other machine learning approaches, with competitive performance results. J48 decision is an effective approach used for rumour detection.

Some researchers have used unsupervised approaches such as clustering. Clustering is the approach in which set of nodes which has similar content is determined. A cluster of such similar content is created and the clusters are linked on the basis of some selected factors. In many applications, linkage and content can be combined together for the purposes of classification. Chang et.al used clustering-based approach and analyzed tweets related to US elections [5]. They collected tweets related to two
candidates i.e. Hillary Clinton and Brack Obama and made clusters of the collected data on the basis of similarity factor. However, the authors conclude by saying that the method needs improvement as manually labelling clusters as rumours is a difficult task.

Another model proposed by Yan Zhang et al. (2017) is autoencoder [45]. Autoencoder follows Deep learning approach. This method minimizes the reconstruction error between encoding and decoding layers i.e. the input data and its reconstruction. This minimization helps in finding the features for performing the task of rumour detection.

Recently, the use of data mining techniques in social network analysis has increased rapidly. Data mining is another approach which has been extensively used in rumour detection as it makes easy to analyze the large amounts of data. Data mining is all about finding out patterns and associations in a large dataset. Sentiment and semantic analysis along with data mining techniques has been used by many researchers. Sentiment analysis helps in understanding the attitude and behaviour of the users by analyzing their tone on the basis of opinion, sentiment and subjectivity in text. Semantic analysis helps in finding the similarity score of context between the tweets. Suchita Jain et al. (2016), Mao et al. (2016) and Sivasangari et al. (2018) used sentiment and semantic analysis for detecting rumours [41][23][40]. On one side where Sivasangari et al. (2018) used VADER for the detection process [40], Mao et al. (2016) used the shallow and deep features for the same [23] whereas Suchita Jain et al. (2016) divided the tweets into two categories one of the tweets from verified news channel accounts and other of general public accounts [41].

Few of the researchers developed some specialized tools which were based on the approaches discussed above. They just blended the features and characteristics of some traditional approaches and tried developing a new model which can be used for rumour detection. As Shu et al. (2019) [39] proposed FakeNewsTracker tool, likewise Ghanem et al. (2019) [11] proposed an emotionally-infused model (EIM).

The literature studied related to rumour detection highlighted several different approaches as explained in this section. All the techniques and approaches provide a range of accuracy. The performance of each approach used by various researchers has been discussed in the next section.

**Table 1.** There are various techniques that can be used for rumour detection on social media network like Clustering, Support Vector Machine (SVM), Sentiment and semantic analysis etc. The researchers have used different available techniques as explained above. Table 1 shows the different techniques used by all the researchers for rumour detection. The table also highlights the models designed for the purpose like Social Article Fusion (SAF) model and Auto encoder.

| Title | Technique / Approach used |
|-------|---------------------------|
| Automatic detection of Rumoured Tweets and finding its Origin (2015) [27] | J48 decision tree Classifier |
Towards Automated Real-Time Detection of Misinformation on Twitter. (2016) [11]
Research on detecting microblog rumors based on deep features and ensemble classifier. (2016) [20]
Isolating Rumors Using Sentiment Analysis [23]

Research on Microblog Rumors Detection Pattern Based on Sentiment Analysis[22]
Automatic Detection of Rumor on Social Network. [13]
Sentiment Aware Fake News Detection on Online Social Networks (2019) [24]

Extreme User and Political Rumor Detection on Twitter.[14]
Detection and Analysis of 2016 US Presidential Election Related Rumors on Twitter. [12]
Fake News Detection Using Sentiment Analysis(2019)[28]
Detecting Rumors on Online Social Networks Using Multi-layer Auto encoder. [25]
An Emotional Analysis of False Information in Social Media and News Articles. [21]
FakeNewsTracker: a tool for fake news collection, detection and visualization. [29]

4. Analysis and Results
The analysis shows the performance of each approach observed by the researchers. As explained above there are multiple approaches that have been used for rumour detection. This section describes the performance in terms of accuracy obtained by each approach. The section shows the best accuracy obtained by an approach. The accuracy has been converted into percentage so as to give a clearer picture. The analysis of the literature shows that the maximum accuracy has been obtained by the Emotional-Infused LSTM neural network model proposed by Ghanem et al. (2019) [11] which is 96.31%. After this the best accuracy has been obtained by J48 decision tree classifier approach i.e. 93.7% using Synthetically generated training set proposed by SahanaV P et al. (2015) [38]. The best accuracy obtained by sentiment and semantic analysis approach and SVM is also decent i.e. 90% and 89% respectively [40] and [29]. Likewise the accuracy obtained by autoencoder proposed by Zhang et al., (2017) is also reasonable. The best accuracy provided by autoencoder is 88% [45].

The accuracy obtained by others is not that up to the mark as the accuracy ranges between 70-80% which is quit less and not that efficient for any rumour detection model. The approaches providing less
accuracy than the above mentioned includes clustering, Lexicon matching, TF-IDF and BM25 and also Social Article Fusion (SAF) model used by researchers [48] [39].

Table 2. Shows the analysis of the results obtained from all the papers reviewed. The table shows the use of techniques identified in Table 1. As explained in Table 1 multiple researchers have used same technique and provided different results and accuracy. Accuracy is a major factor in rumour detection. Table 2 highlights the highest accuracy obtained by a technique used for rumour detection.

| Technique/ Approach used                                      | Accuracy       |
|---------------------------------------------------------------|----------------|
| Emotionally-Infused LSTM neural network [11]                  | 96.31%         |
| J48 decision tree Classifier [38]                            | 93.7%          |
| (Synthetically generated training set)                        |                |
|sentiment and semantic analysis [40]                          | 90%            |
| Support vector machine [29]                                   | 89%            |
| Auto encoder (Artificial Neural Network) [45]                 | 88%            |
| Clustering [5]                                                | 80%            |
| TF-IDF and BM25, Word2Vec and Doc2Vec, Lexicon matching [48]  | 79.9% (BM25)   |
| Social Article Fusion (SAF) model [39]                       | 74.20%         |

5. Conclusion
After studying the different research papers on rumour detection, a conclusive study shows that there are multiple ways and methods for detecting rumours. In our today’s digital lives, rumours have become an integral part. These rumours have very adverse effect on the society. In this paper, a review of the approaches used by different researchers has been listed. The researchers have used different classification techniques to detect rumours such as, Support Vector Machine (SVM), VADER, Weka, LSTM neural networks model. Some used methods like TF-IDF, BM25, Word2Vec and Doc2Vec for rumour detection while others used approaches like Clustering and deep learning. This paper shows the use of semantic and sentimental analysis in rumour detection with different classification techniques, models and methods.

The review shows there are various techniques that are used for rumour detection. Table 1 shows the different techniques used by each researcher in rumour detection. It has been highlighted that sentiment and semantic analysis and Support vector machine (SVM) is the most commonly used
technique by the researcher, see Table1. Both the techniques provide a decent accuracy of 89% and 90% respectively in the best cases whereas Emotionally-Infused LSTM neural network provides an accuracy of 96% which is better than the other two commonly used techniques. The Emotionally-Infused network was based on emotions. While selecting a technique it is necessary to select the features and basis on which the detection is to be done. The researchers have used different set of classifiers and features. Each combination results in different accuracy rate.

The paper describes different approaches to tackle one of the major problems of social network i.e. the rumour problem. Some approaches giving good results are focusing on a particular case or used with set features; the accuracy of such approach will be justified only if it will produce an equal result in other cases too. Further research is required to find out the applicability of the approaches in different phenomena. In future, rumours can be detected by using some traditional approaches already being used along with some newly developed algorithms or tools. The algorithm or tool can be based on a modified set of statements depending on the features of concern.

References

[1] Hermida A 2010 Twittering the news: The emergence of ambient journalism Journal. Pract. 4, 3 (2010) pp 297–308
[2] Zubiaga A, Aker A, Bontcheva K, Liakata M, and Procter R 2018 Detection and Resolution of Rumours in Social Media: A Survey ACM Comput. Surv. 51, 2, Article 32, (2018)
[3] Zubiaga A, Liakata M, and Procter R 2017 Exploiting context for rumour detection in social media International Conference on Social Informatics Springer pp 109–123
[4] Bhutani, Rastogi N, Sehgal P and Purwar 2019 A Fake News Detection Using Sentiment Analysis Twelfth International Conference on Contemporary Computing (IC3) (India: Noida) pp 1-5
[5] Chang, Zhang Y, Szabo C, and Sheng Q 2016 Extreme User and Political Rumor Detection on Twitter 12th International Conference on ADMA (Australia: Gold Coast, QLD) pp. 751-763
[6] Fuchs C 2013 Social Media: A Critical Introduction Sage
[7] Boididou C, Andreadou K, Papadopoulos S, DangNguyen D, Boato G, Riegler M and Kompatsiaris Y 2015 Verifying Multimedia Use at MediaEval MediaEval
[8] Lazer D, Pentland A, Adamic L, Aral S, Barabasi A, Brewer D, Christakis N, Contractor N, Fowler J and Gutmann M 2009 Life in the network The coming age of computational social science. Science pp 323, 5915 (2009), 721
[9] Ferrara, Varol O, Davis C, Menczer F and Flammini A 2016 The rise of social bots Communications of the ACM vol. 59 no. 7 pp. 96–104
[10] Liang G, He W, Xu C, Chen L and Zeng J 2015 Rumor identification in microblogging systems based on users behavior IEEE Trans. Computat. Soc. Syst. 2, 3 pp 99–108
[11] Ghanem B, Rosso P and Rangel F 2019 An Emotional Analysis of False Information in Social Media and News Articles arXiv preprint arXiv:1908.09951. 1225, (2019)
[12] Greenhill, Kelly M, and Ben Oppenheim 2017 Rumor Has It: The Adoption of Unverified Information in Conflict Zones International Studies Quarterly 61(3) pp 660–76
[13] Guoyong Cai, Hao Wu, and Rui Lv 2014 Rumors detection in chinese via crowd responses. E/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM’14) IEEE pp 912–917
[14] Webb H, Burnap P, Procter R, Rana O, Stahl B, Williams M, Housley W, Edwards A, and Jirotka M 2016 Digital wildfires: Propagation, verification, registration, and responsible innovation ACM Trans. Inform. Syst. 34, 3(2016)
[15] Chen H, De P, Jeffrey Hu Y and Hwang B 2014 Wisdom of crowds: The value of stock opinions transmitted through social media Rev. Financial Stud. 27, 5 pp 1367–1403
[16] Dijek J 2013 The Culture of Connectivity: A Critical History of Social Media Oxford University Press (2013)
[17] Shu K, Mahudeswaran D, Wang S, Lee D and Liu H 2018 FakeNewsNet: A Data Repository with News Content, Social Context and Dynamic Information for Studying Fake News on Social Media arXiv:1809.01286 (2018)

[18] Sung K and Lee M 2015 Do online comments influence the public’s attitudes toward an organization? Effects of online comments based on individuals prior attitudes. J. Psychol 149, 4 pp 325–338 (2015)

[19] Derczynski L and Bontcheva K 2016 Pheme: Veracity in digital social networks UMAP Workshops (2016).

[20] Li WY Research on Microblog Rumors Detection Pattern Based on Sentiment Analysis Chongqing University (2016)

[21] Lee L, Hutton L and Shu S 2015 The role of social media in the capital market: Evidence from consumer product recalls J. Account. Res. 53, 2 (2015) pp 367–404

[22] Anjaria M and Guddeti R 2014 Influence Factor Based Opinion Mining of Twitter Data Using Supervised Learning Sixth International Conference on Communication Systems and Networks (COMSNETS) IEEE

[23] Mao ES, Chen G, Liu X and Wang B 2016 Research on detecting microblog rumors based on deep features and ensemble classifier Application Research of Computers 33(11) pp3369–3373

[24] Potthast M, Kiesel J, Reinartz K, Bevendorff J, and Stein B 2017 A stylometric inquiry into hyperpartisan and fake news arXiv preprint arXiv:1702.05638, 2017.

[25] Lukasik M, Srijith P, Vu D, Bontcheva K, Zubiaga A and Cohn T 2016 Hawkes processes for continuous time sequence classification: An application to rumour stance classification in Twitter 54th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics, pp 393–398

[26] Diakopoulos N, Choudhury M and Naaman M 2012 Finding and assessing social media information sources in the context of journalism SIGCHI Conference on Human Factors in Computing Systems. ACM pp 2451–2460

[27] DiFonzo N and Bordia P 2007 Rumor, gossip and urban legends Diogenes 54, 1 pp 19–35

[28] Anstead N and Loughlin B 2015 Socialmedia analysis and public opinion: The 2010 UK general election J. Comput.-Med. Commun. 20, 2 (2015) pp 204–220

[29] Ajao O, Bhowmik D and Zargari S 2019 Sentiment Aware Fake News Detection on Online Social Networks ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (United Kingdom: Brighton) pp. 2507-2511

[30] Ajao O, Bhowmik D and Zargari S 2018 Fake news identification on twitter with hybrid cnn and rnn models 9th Int’l Conference on Social Media & Society. Copenhagen (2018).

[31] Jain P and Katkar V 2015 Sentiments analysis of twitter data using data mining International Conference on Information Processing (ICIP) pp. 807-810. Pune

[32] Azar P and Lo A 2016 The wisdom of twitter crowds: Predicting stock market reactions to fomc meetings via twitter feeds The Journal of Portfolio Management 42, 5 (2016) pp 123–134

[33] Domm P 2013 False Rumor of Explosion at White House Causes Stocks to Briefly Plunge; AP Confirms Its twitter Feed Was Hacked April 23, 2013 from URL https://www.cnbc.com/id/100646197

[34] Tolmie P, Procter R, Rouncefield M, Liakata M and Zubiaga A 2018 Microblog analysis as a programme of work ACM Transactions on Social Computing 1, 1 Article 2, 40. DOI: https://doi.org/10.1145/3162956

[35] Qiao Zhang, Shuiyuan Zhang, Jian Dong, Jinhua Xiong, and Xueqi Cheng.: Automatic Detection of Rumor on Social Network, In: Springer International Publishing Switzerland 2015, pp. 14-24, Springer, (2017).

[36] Rajput R, Saha A, Kumari S, Janyala S, Johnson TA, Janardhanan A, Pandey P and Ghose D 2018 Murderous mob — 9 states, 27 killings, one year: And a pattern to the lynching July 15 2018 from URL https://indianexpress.com/article/india/murderous-mob-lynching-incidents-
[37] Shi R, Messaris P and Cappella J 2014 Effects of online comments on smokers’ perception of antismoking public service announcements J. Comput.-Med. Commun. 19, 4 (2014) pp 975–990

[38] Sahana V P, Pias A, Shastri R and Mandloi S 2015 Automatic detection of Rumoured Tweets and finding its Origin Intl. Conference on Computing and Network Communications (CoCoNet’15) IEEE pp 607-612

[39] Shu, K, Mahudeswaran D, and Liu H 2019 FakeNewsTracker: a tool for fake news collection, detection, and visualization Computational and Mathematical Organization Theory. 25 (1) pp 60–71

[40] Sivasangari V, Mohan AK, Suthendran K and Sethumadhavan M Isolating 2018 Rumors Using Sentiment Analysis Journal of Cyber Security and Mobility 7(1) pp 181–200

[41] Jain S, Sharma V and Kaushal R 2016 Towards Automated Real-Time Detection of Misinformation on Twitter, Intl. Conference on Advances in Computing, Communications and Informatics (ICACCI) IEEE pp 2025-2020

[42] Phuvipadawat S and Murata T 2010 Breaking news detection and tracking in Twitter IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT’10), Vol. 3. IEEE pp 120–123

[43] Tacchini, Ballarin G, Vedova M, Moret S and Alfaro L 2017 Some like it hoax: Automated fake news detection in social networks arXiv preprint arXiv:1704.07506 (2017).

[44] Wang W 2017 liar, liar pants on fire: A new benchmark dataset for fake news detection arXiv preprint arXiv:1705.00648 2017.

[45] Yan Zhang, Weiling Chen, Chai Kiat Yeo, Chiew Tong Lau and Bu Sung Lee 2017 Detecting Rumors on Online Social NetworksUsing Multi-layer Autoencoder IEEE Technology & Engineering Management Conference (TEMSCON) IEEE pp. 1-5

[46] Zafarani, R., Abbasi, M.A and Liu, H 2014 Social Media Mining: An Introduction Cambridge University Press, Cambridge (2014)

[47] Zhao Z, Resnick P and Mei Q 2015 Enquiring minds: Early detection of rumors in social media from enquiry posts Proceedings of the 24th International Conference on World Wide Web ACM pp 1395–1405

[48] Zhiwei Jin, Juan Cao, Han Guo, Yongdong Zhang, and Jiebo Luo 2017 Multimodal Fusion with Recurrent Neural Networks for Rumor Detection on Microblogs 25th ACM international conference on Multimedia (MM ’17) ACM (USA: New York) pp 795-816. DOI: https://doi.org/10.1145/3123266.3123454

[49] Zhiwei Jin, Juan Cao, Han Guo, Yongdong Zhang, Yu Wang, and Jiebo Luo 2017 Detection and Analysis of 2016 US Presidential Election Related Rumors on Twitter Springer International Publishing AG 2017 Springer pp. 230–239

[50] Zubiaga, A. Aker, K. Bontcheva, M. Liakata and R. Procter 2018 Detection and resolution of rumours in social media: a survey ACM Comput. Surv. 51 (2) pp 32:1–32:36