JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

# Detection of Rumor Microblogs from Social Network Sites using Bayes Algorithm

**Abdul Rahiman[1], Syed Abdul Sattar[2]**
[1]Research Scholar, Dept. of Computer Science, Rayalaseema University, Kurnool, A.P, India.
[2]Dept. of Computer Science, Nawab Shah Alam Khan College of Engineering & Technology, Hyderabad, India

**Abstract**

In recent days majority of the people receive information through online social networks. These networks help the people/users to communicate and transfer information freely irrespective of geographical locations. The flip side of these networks is a misinformation would also spread very fast, which causes noteworthy damage in society. This issue has attracted most of the researchers which aims to detect or stop the unverified post on social media.

Many techniques ware applied to find the veracity of information in social networks. In this paper we propose a novel model called RD System to find the rumor content in social networks. This model uses a set of pre-defined rules and Nave Bayes algorithm to find the posted information veracity. Our proposed system achieved substantial good results when compared with ICDM model.

**Keywords:** Rumor Detection, RD System, Social Networks, ICDM model.

## 1. Introduction

Nowadays most of the people are connected to each other by different networks like Social network, Internet, Technological network etc. This leads to elevate the amount of information propagation and diffusion rapidly among the networks. Nowadays, anyone, at any place can post information in these networks. Dissemination of information in social networks may be in the form of good information or deceptive information. Deceptive information will have substantial concerns on people status, economy, and politics and even on countries security; because this will create confusion or misunderstanding among the information receivers [1]. Discriminating such deceptive information from social networks is a challenging task. Detecting such a deceptive information from social networks has been attracted the interest of majority of researchers and industry professions.

A rumor can be defined as a statement or a story which is consciously false or whose truthfulness is not verified when it is broadcasted in the social networks [2]. Identification of rumors at their early stage of broadcasting can significantly decrease the damage in society [3]. One of the basic conventional rumor detection models was designed in 1965 called DK [4].

In order to improve the creditability of social networks and minimize the damaging effects of false information prompt detection and control on social networks is necessary [5]. Most of the previous studies in social networks are unable to find the new rumor words. In our proposed system we applied pre – defined logical rules and Bayes algorithm to detect rumors from social networks.

## 2. Literature Review

A very title work has been done in identifying the rumors at its early stage. The first method to identify the rumor was proposed by Zhao et al [6] which identifies the "signal tweets" and that are grouped into different clusters. Those clusters are ranked using certain likelihood of post; using the rank of cluster a rumor can be identified. To detect rumor from twitter [26] has considered two features namely, 1) linguistic features to represent writing system and 2) sensational news headlines features. [7] proposed reinforcement model of learning to detect the rumor dynamically depending on responses.

The main purpose of designing rumor detection model is to find information posted in social networks is rumor or not. Jing Ma et al [8] proposed a model which categorizes the dissemination as tree to evaluate likeliness among the trees to decide whether the information is rumor or not. Nivetha et al [9] developed two-step process to find the rumor in social networks. In the first step injecting perceiving nodes to report the receipt data and step two to identify rumor post by applying the GSSS algorithm. Ma et al. [10] applied various RNN methods to the repost orders. K. Wu et al [11] applied the hybrid kernel SVM cataloguing to recognize rumor, which joints the CA – LPT and the random walk graph kernel. Yu et al. [12] adopted the CNN model on the repost classification to find the interactions with high features. Ruchansky et al. [13] combines three features: the article script, user reactions on the script, and the source user who was stimulating the post/message.

## 3. PROPOSED RUMOR DETECTION SYSTEM FRAMEWORK

Rumor messages in social networks leads to social disaster. Multi lingual rumor are also failed to detect by existing Rumor Detection models. Note: Many of the Rumor Detection models specifically built to surveillance rumor words in a specific situation or context in Social Networking Sites. The propagation of rumor messages in various social networking sites is depicted in the below picture.

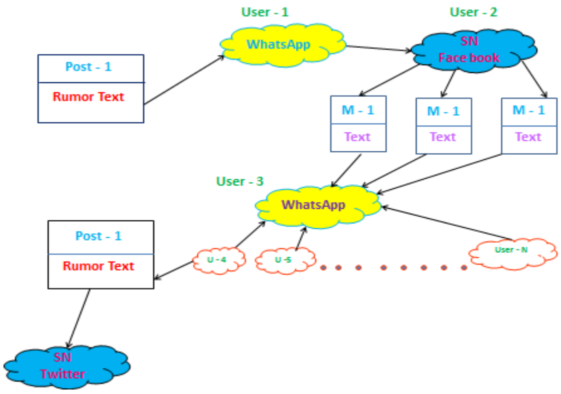


Fig 1: Rumor spreading scenario in social networks

As shown in above fig.1, the information will propagate from one user to another user in the social media. The information may be sent to N number of his/her friends by a single user. If the information comprises any rumor content, such content spreads in social networks and causes damage in society. To void this we must stop the post/ information at an early stage.

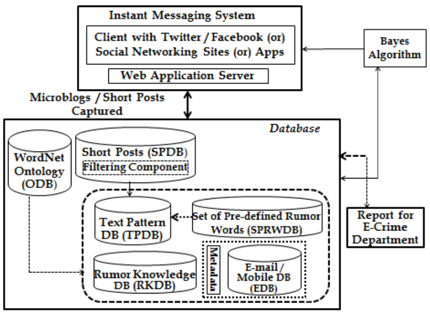


Fig. 2 Rumor Detection System

The domain the rumor word which it is belongs to can be predicted by the probabilistic learning method OBIE [14]. Different database tables namely SPDB, TPDB, ODB, SPRWDB, RKDB, EDB and Metadata were used in the design of Rumor Detection System (RDS) shown in Fig. 2. In this RDS, the online messages/posts which were communicated among the user/friends (chat mates) are stored in SPDB (Short Posts database). ODB (Ontology Database) is a lexical database that identifies terms, Synonyms, Concepts, Taxonomy (concept hierarchy), relations, Axioms and Rules [15] [16].

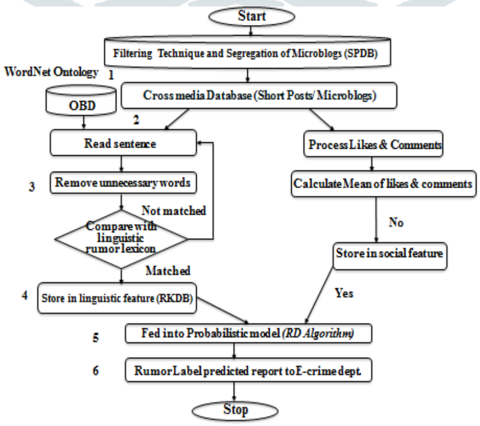


Fig 3: Rumor Detection System Flowchart

The steps involved in pseudo code algorithm for rumor detection is shown in Fig. 3, are illustrated as follows:

1. The first step is to capture the short posts or microblogs sent between users of Social Networks (SN). These messages are saved in the database.
    a) In this step a single text post is taken. This text message is transformed to plain text removing stop-words (such as articles, preposition).
    b) Next, we will check social interface to calculate number of comments and like.
2. a) This is main step in which it will compare plain text with linguistic rumor lexicon ( Table 1) to find out number of rumor words present in text and store result into RKDB.

b) In this step, we calculate the mean value of comments and likes and stored it in feature set table.

$$M_{L,C} = \frac{\text{Total No. of Likes + Comments}}{2} \quad \text{.......} \ (1)$$

3. a) All the textual features are fed into the probabilistic model to predict whether a post is a rumor or non-rumor. It uses maximum likelihood estimates for the detection.

b) Social feature is fed into social model (EIDB) and compared with threshold value.

4. In the last step results are displayed to user if and only if user posts satisfies all the threshold values then only his/her posts will tagged as rumor and if the user is rumoured then will send recommendation to user regarding rumor management.

Table 1**:** Depicts set of knowledge based pre-defined logical rules internally supported with WordNet Ontology for Linguistic rumor lexicon

| RULE 1 (Pre-defined Knowledge based rules) | |
|---|---|
| Type of rumor (Domain) | words to be detected in a given context |
| Political rumor → | Self-assured, nuptial, earned, embarrass, prominent |
| Share Market rumor → | Falling down, harshly, quickly, strikes, anguish |
| Decease rumor → | Health services intrude, indemnity, trouble, peculiar, brutal |
| Anticipatory rumor → | Excited, considering frontward, heedful, apprehensive, intolerant |
| RULE 2 | |
| Social Interaction (Mean Value) | No. of likes, dislikes and comments |
| RULE 3(threshold value) | |
| The user-defined threshold value will be checked for stem words that may fit in to several domains, using precision & Mean Values. (RD algorithm) | |

## 4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

### *4. 1. Evaluation method for data sets*

Precision metric is used as given in Equation (1) [17] for evaluation of tweets in RDS. The rumor words extracted are based on two factors, the number of actual words available in the pre-defined database i.e. *SPRWDB* with respect to rumor domain, to that of the number of extracted rumor words from tweet chat session:

$$Precision\ (P) = \frac{\text{Correctly Extracted}}{\text{Total Extracted Correctly}} \quad \text{..................} \ (1)$$

### *4.2. Preparation of data sets*

Rumor related datasets in social media are not freely accessible due to restriction of privacy policies of FISA Act. Many of the rumor detection strategies tested their developed frameworks for detection of rumor from data collected through their local databases from social networking sites which includes Twitter, Facebook, Instagram, WhatsApp and other social media applications [18,19,20, 21-25]. To test our RDS architecture, we have used pre-defined rules that have rumor related words totaling of 50 words. Further, each of these words is supported with WordNet ontology that had created synonyms for the existing pre-defined words.

### *4.3.* Tested using RDS and ICDM

The real chatting session is intentionally conducted and the experimental results are demonstrated for the conversation happened between the two users, as shown in Table 2.

**Room: dread**
**Identity:Ameen**
Samiya : Did you hear that flight 101 has been missing since yesterday?
Ameen : I have been watching the news too.
Samiya : It left from Dallas airport and it was supposed to have landed this morning.
Ameen : the air traffic control said they lost all contact with it.
Samiya : There were around 300 passengers along with the crew. I wonder what might have happened.
Ameen : it could have been a hijack or even worse.
Samiya : :(

| | profile_name text | room_name text | message text | time_stamp timestamp without time zone | category text | ip_adress text |
|---|---|---|---|---|---|---|
| 12 | Ameen | test | fierce | 2019-08-22 15:52:00.821 | Wedge_Rumors | 192.168.1.5 |
| 13 | Ameen | test | vicious | 2019-08-22 16:33:24.569 | Wedge_Rumors | 192.168.1.5 |
| 14 | Ameen | test | vicious | 2019-08-22 17:05:11.649 | Wedge_Rumors | 192.168.1.5 |
| 15 | Ameen | test | Test | 2019-08-23 10:39:40.142 | Anticipatory_Rumors | 192.168.1.5 |
| 16 | Ameen | test | Today | 2019-08-23 10:39:48.53 | Anticipatory_Rumors | 192.168.1.5 |
| 17 | Ameen | Today | fighting | 2019-08-23 10:47:05.729 | Wedge_Rumors | 192.168.1.5 |
| 18 | Ameen | Today | visualization | 2019-08-23 10:47:26.997 | Wish_Rumors | 192.168.1.5 |
| 19 | Ameen | Today | :) | 2019-08-23 10:48:44.874 | Wish_Rumors | 192.168.1.5 |
| 20 | Ameen | test | great | 2019-08-23 11:17:40.558 | Wish_Rumors | 192.168.1.5 |
| 21 | Ameen | test | :) | 2019-08-23 11:17:45.667 | Wish_Rumors | 192.168.1.5 |
| 22 | Ameen | test | hijack | 2019-08-23 12:43:57.953 | Dread_Rumors | 192.168.1.5 |
| 23 | Samiya | test | Did you hear that flight 101 has been missing since yesterday? | 2019-08-23 12:51:51.993 | Dread_Rumors | 192.168.1.5 |
| 24 | Samiya | test | It left from Dallas airport and it was supposed to have landed this morning | 2019-08-23 12:52:34.553 | Dread_Rumors | 192.168.1.5 |
| 25 | Ameen | test | the air traffic control said they lost all contact with it | 2019-08-23 12:52:53.865 | Dread_Rumors | 192.168.1.5 |
| 26 | Ameen | test | it could have been a hijack or even worse | 2019-08-23 12:53:38.411 | Dread_Rumors | 192.168.1.5 |
| 27 | Samiya | dread | Did you hear that flight 101 has been missing since yesterday? | 2019-08-23 13:18:49.082 | Dread_Rumors | 192.168.1.5 |
| 28 | Samiya | dread | It left from Dallas airport and it was supposed to have landed this morning. | 2019-08-23 13:19:14.506 | Dread_Rumors | 192.168.1.5 |
| 29 | Ameen | dread | the air traffic control said they lost all contact with it. | 2019-08-23 13:19:27.635 | Dread_Rumors | 192.168.1.5 |
| 30 | Ameen | dread | it could have been a hijack or even worse. | 2019-08-23 13:19:54.956 | Dread_Rumors | 192.168.1.5 |
| 31 | Samiya | dread | :( | 2019-08-23 13:20:48.97 | Wish_Rumors | 192.168.1.5 |

Fig. 4 Real Tweet, constitutes of Linguistic rumor lexicon words

Table 2: Depicts the domain of "***Share Market*"** *rumor* words communicated between the users.

| **Domain of Rumor** | **User 1** | **User 2** |
|---|---|---|
| **Share Market** | "Do you know the reason for the downfall of share market rapidly?"<br><br>"It might be due to recent Russian strikes on Ukraine" | "Why it is falling so harshly?" "Was there any outbreak?"<br><br>" It can anguish the shareholder" |
| **Rumor words to be detected:** | downfall, rapidly, harshly, outbreak, strikes, anguish | |

The chatting session, is tested using RD algorithm, the rumored words stored in pre- defined database are mapped with microblogs, if it matches it stores those rumored posts separately into its log. The accuracy rate obtained by ICDM is 70%, whereas 93% with RDS model as shown in Figure 5.

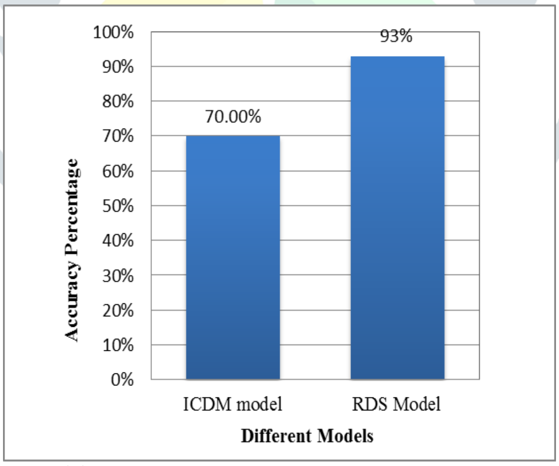


Fig. 5 Comparisons of ICDM with proposed RDS Model

## 5. CONCLUSION AND FUTURE WORK

Most of the earlier rumor detection systems consider only text part of the posts. However it is necessary to take into consideration social interaction as popular posts tend to grab more attention quickly. With the popularity of social media, people are used to sharing their daily activities and interacting with friends on social media platforms. Social media data are being considered more in the rumor detection systems as it is inexpensive, transparent and provides primary access to new opportunities. Thus, many researchers are focusing on leveraging social media interactions to improve effectiveness of social media analysis of rumor detection. The proposed strategy is to utilize these social media interactions content to detect rumours by employing a Rumor Detection System (RDS) model. Detecting user's rumor levels from user's social media content will improve the rumor detection performance efficiently. The proposed RDS strategy detects rumours by employing the probabilistic model. In RDS model an additional feature (social interactions) are added which is not used earlier, except ICDM which has used only one feature of pre-defined rules that to only textual words are considered. Experimental results show that proposed model can improve the detection performance and achieved 93 percent of accuracy when compared to ICDM model shown in Table 3.

| Parameter / Models | Text | Support for Social Interaction | Pre-defined rules | Report generation for e-crime dept. | Ontology support | Accuracy |
|---|---|---|---|---|---|---|
| ICDM | ✓ | × | ✓ | × | × | 0.70 |
| RDS model | ✓ | ✓ | ✓ | ✓ | ✓ | 0.93 |

Table 3: Comparison of efficiency & effectiveness using different model

## References


1. Karlova NA, Fisher KE, Plz RT. A Social Diffusion model of Misinformation and disinformation for understanding human information behavior. Inform Res. 2013; 18(1):1–17.
2. DiFonzo N, Bordia P (2007) Rumor psychology: social and organizational approaches, vol 1. American Psychological Association,
3. Ma J, Gao W, Wong K-F (2018a) Detect rumor and stance jointly by neural multi-task learning. In: Companion of the the web conference 2018 on the web conference 2018, pp 585–593
4. D. J.Daley andD. G.Kendall, "Epidemics and rumours," *Nature*, vol. 204, no. 4963, p. 1118, 1964.
5. M. Bharti, R. Kumar, S. Saxena, and H. Jindal, "Optimal resource selection framework for internet-of-things," *Computers & Electrical Engineering*, vol. 86, p. 106693, 2020.
6. Zhao, Z., Resnick, P., & Mei, Q. (2015). Enquiring minds: Early detection of rumors in social media from enquiry posts. Proceedings of the 24th international conference onworld wide web. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee1395–1405.
7. Kaimin Zhou, Chang Shu, Binyang Li, and Jey Han Lau. 2019. Early rumour detection. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1614–1623.
8. Ma J.,Gao W., Wong K.: "Detect Rumors in Microblog Posts Using Propagation Structure via Kernel Learning", the ACL, pp. 708–717, 2017.
9. NivethaS., Priyadharshini R. et al: "Detecting Root of the Rumor in Social Network Using GSSS", International Research Journal of Engineering and Technology, 2017.
10. S.Nivetha, R.Priyadharshini, P.Balakumar, K.Kapilavail, "Detecting root of the rumor in social network using GSSS", International Research Journal of Engineering and Technology (IRJET).
11. Ruixia Zhang 1 and Deyu Li," Identifying Influential Rumor Spreader in Social Network", Discrete Dynamics in Nature and Society 2019:1-10 · May 2019.
12. YuF., LiuQ., WuS., WangL., and TanT.: "A convolutional approach for misinformation identification," in Proceedings of IJCAI, 2017.
13. RuchanskyN., SeoS., and LiuY.: "CSI: A hybrid deep model for fake news detection," in Proceedings of 7 ACM on Conference on IKM, pp. 797–806, 2017.
14. Rehana Moin, Zahoor-ur-Rehman, Khalid Mahmood," Framework for Rumor Detection in Social Media", International Journal of Advanced Computer Science And Application (IJACSA), 2018.
15. RuchanskyN., SeoS., and LiuY.: "CSI: A hybrid deep model for fake news detection," in Proceedings of 7 ACM on Conference on IKM, pp. 797–806, 2017.
16. Mohammed Mahmood Ali, Mohammad S. Qaseem, Ateeq ur Rahman, "Rumour Detection Models & Tools for Social Networking Sites", International Journal of Engineering & Advanced Technology (IJEAT), Vol. 9, issue 2, 2019 Published on December 30, 2019.
17. Massimo Ostillia, Eiko Yonekic, Ian X. Y. Leungc, Jose F. F. Mendesa, Pietro Li´oc, Jon Crowcroft, "Statistical mechanics of rumor spreading in network communities", International Conference on Computational Science, ICCS 2010.
18. J. Gottfried and E. Shearer, "News use across social media platforms2016," Pew Research Center, 2016.
19. Mohammed Mahmood Ali, Mohammad S. Qaseem, Ateeq ur Rahman, "Rumour Detection Models & Tools for Social Networking Sites", International Journal of Engineering & Advanced Technology (IJEAT), Vol. 9, issue 2, 2019 Published on December 30, 2019.
20. P. Suthanthira Devi, S. Karthika, "Veracity Analysis of Rumors in Social Media",International Conference on Computer, Communication, and Signal Processing (ICCCSP),2018.
21. A.M. Meligy, H. M. Ibrahim and M. F. Torky," Recognizing and Stopping Rumors Patterns in Social Networks", Indian Journal of Science and Technology, Vol 10(28), July 2017.
22. S.Nivetha, R.Priyadharshini, P.Balakumar, K.Kapilavail, "Detecting root of the rumor in social network using GSSS", International Research Journal of Engineering and Technology (IRJET).
23. Ruixia Zhang 1 and Deyu Li," Identifying Influential Rumor Spreader in Social Network", Discrete Dynamics in Nature and Society 2019:1-10 · May 2019.
24. Anjan Pal, Alton Y.K. Chua, and Dion H. Goh," Rumor Analysis &Visualization System", Proceedings of the International MultiConference of Engineers and Computer Scientists 2019 IMECS 2019, Hong Kong, , March 13-15, 2019.

25. Laijun Zhao, Xiaoli Wang, Jiajia Wang, Xiaoyan Qiu, Wanlin Xie," Rumor-Propagation Model with Consideration of Refutation Mechanism in Homogeneous Social Networks", semantic scholar 2014.

26. Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. 2017. Fake news detection on social media:A data mining perspective. ACM SIGKDD ExplorationsNewsletter, 19(1):22–36.