"RULING OF AI BURDEN FINDING SORTING FOR S/W VIBRANT RELATIONSHIP"

¹Name of 1st RAJANBHAI PATEL

¹Designation of 1st Assistant Professor ¹Name of Department of 1st Faculty of Computer Science & Applications ¹Name of organization of 1st Gokul Global University, Sidhpur, Patan, Gujarat – India

Abstract

These networks help the people/users to communicate and transfer information freely irrespective of geographical locations.

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.

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]. 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].

Literature Review

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.

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.

PROPOSED RUMOR DETECTION SYSTEM FRAMEWORK

Rumor messages in social networksleads 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.



Rumor spreading scenario in social networks

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. 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.

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

- a) 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.

IMPLEMENTATION AND EXPERIMENTAL RESULTS

Evaluation method for data sets

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*) = Correctly Extracted / Total Extracted Correctly

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

| Room: dread |
|---|
| dentity:Ameen |
| amiya : Did you hear that flight 101 has been missing since yesterday? |
| Ameen : I have been watching the news too. |
| iamiya : 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. |
| jamiya : 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. |
| amiya : :(|

| | profile_name text | room_name text | monsage text | time_stamp timestamp without time zone | category text | ip_adress text |
|----|----------------------|-------------------|--|---|---------------------|-------------------|
| | NICCI | 1000 | 100.04 | BATS-OG-BE TALOTIASIARO | AGAAG WINCES | 12611001110 |
| 12 | Ances | 1005 | fieroe | 2019-08-22 18:82:00.821 | Wedge_Runces | 192.148.1.8 |
| 13 | Zaeen. | 2445 | vicious | 2019-08-22 14:33:24.869 | Wedge_Runnes | 192.148.1.5 |
| 14 | Aperts . | THAT | vicious | 2019-08-22 17:05:11.449 | Wedge_Roscen | 192.148.1.5 |
| 15 | Apeen | Test | Teat | 2019-08-23 10:39:40.142 | katicipatory_Runces | 192.140.1.5 |
| 16 | America | test | Today | 2019-08-23 10:39:48.53 | Asticipatory_Rumors | 192.160.1.5 |
| 37 | Aneen. | Today | fighting | 2019-08-23 10:47:05.729 | Wedge_Runces | 192.165.1.5 |
| 38 | Anees. | Today | visualization | 2019-08-23 10:47:26.997 | Wish_Rumocs | 192.165.1.5 |
| 19 | Ances | Today | 0 | 2019-08-23 10:48:44.874 | Wish_Rumocs | 192.145.1.5 |
| 30 | Aneen. | 5445 | great | 2019-08-23 11:17:40.888 | Wish Russes | 192.148.1.8 |
| 31 | Asees. | Teat | 13 | 2019-08-23 11:17:45.447 | Wish Rance | 192.148.1.5 |
| 32 | Asees | Test | hijack | 2019-08-23 12:43:57.953 | Doead_Runce | 192.140.1.5 |
| 23 | Santya | Test | Did you hear that flight 101 has been missing since yesterday? | 2019-00-23 12:51:51.993 | Doesd_Runce | 192.140.1.5 |
| 24 | Santya | test | It left from Dallas airport and it was supposed to have landed this morning | 2019-08-23 12:52:34.553 | Dreed_Rance | 192.165.1.5 |
| 25 | Aneen. | test | the air traffic control said they lost all contact with it | 2019-08-23 12:52:53.865 | Doeed_Rance | 192.165.1.5 |
| 26 | Ances. | test | it could have been a hijack or even worse | 2019-08-23 12:83:38.411 | Decod_Rance | 192.165.1.5 |
| 27 | Saniya | dread | Did you hear that flight 101 has been missing since yesterday? | 2019-08-23 13:18:49.082 | Deeped_Runnes | 192.148.1.8 |
| 38 | Santys | dread | It left from Dallas airport and it was supposed to have landed this morning. | 2019-08-23 13:19:14.806 | Doead_Runces | 192.148.1.5 |
| 29 | Jacob. | dread | the air traffic control said they lost all contact with it. | 2019-08-23 13:19:27.635 | Doead_Runce | 192.148.1.5 |
| 30 | Apeen | dread | it could have been a hijack or even worse. | 2019-00-23 13:19:54.956 | Doead_Runce | 192.140.1.5 |
| 31 | Saniya | dread | 11 | 2019-08-23 15:20:40.97 | Wish_Runce | 192.160.1.5 |

Real Tweet, constitutes of Linguistic rumor lexicon words

The accuracy rate obtained by ICDM is 70%, whereas 93% with RDS model as shown



CONCLUSION AND FUTURE WORK

However it is necessary to take into consideration social interaction as popular posts tend to grab more attention quickly. 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. In RDS model an additional feature (social interactions) are added which is not used earlier, except ICDM which has used only one feature of predefined 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.

| 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 |

Comparison of efficiency & effectiveness using different model

References

 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.
DiFonzo N, Bordia P (2007) Rumor psychology: social and organizational approaches, vol 1. American

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 (2017a) Detect rumor and stance jointly by neural multi-task learning. In: Companion of the the web conference 2016 on the web conference 2017, pp 585–593

4. D. J.Daley and D. 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, 2017.

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. 2017. Early rumour detection. In Proceedings of the 2017 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 2017:1-10 · May 2017.

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), 2017.

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, 2017 Published on December 30, 2017.

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.

J. Gottfried and E. Shearer, "News use across social media platforms2016," Pew Research Center, 2016.
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, 2017 Published on December 30, 2017.

20. P. Suthanthira Devi, S. Karthika, "Veracity Analysis of Rumors in Social Media", International Conference on Computer, Communication, and Signal Processing (ICCCSP), 2017.

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 2017:1-10 · May 2017.

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 2017 IMECS 2017, Hong Kong, , March 13-15, 2017.

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