

A Survey on Classification of Rumors on Social Media Using Machine Learning

Ria Purohit^{1*}, Nidhi Ruthia², Chetan Agrawal³

^{1,2,3} Department of Computer Science, Radharaman Institute of Technology & Science, Bhopal, India

*Corresponding Author: ria16purohit@gmail.com

DOI: <https://doi.org/10.26438/ijcse/v8i4.136140> | Available online at: www.ijcseonline.org

Received: 2/Mar/2020, Accepted: 28/Apr/2020, Published: 30/Apr/2020

Abstract— Due to recent mobile technology advances, consumers have 24* 7 accesses to social networks. With regard to knowledge gaps, the dissemination of misinformation is closely linked, particularly when the data is published slowly, often as unverified data. A significant investigation is done in online social media, particularly micro-blogging websites, automatically detect rumors. Recent research on the follow-up of disinformation in social media has explored such terminology. This article will present an overview of social media rumor detection research including various types of rumor classification available in order to recognize the rumor and class text. In this survey paper we will also highlight the features of classification algorithms like Naïve Bayes, Support Vector Machine, Logistic Regression and K-Nearest Neighbor.

Keywords— Rumor detection, social networks, machine Learning, fake, NLP

I. INTRODUCTION

The online social networks have given people worldwide tremendous speed in accessing and sharing information [1]. In recent times online content has played a major role in influencing user choices and opinions [2]. The social media is the main source of information in a huge community of online users. Today, most people use social media to gather information and communicate with the world rather than traditional media. The distribution of information in social media is cheaper and takes much less time, as opposed to traditional media, e.g. TV and newspapers [3]. But such sites have not only allowed the online community to post

The dissemination of rumors has influenced the corporate community and rumors spread via social media play a major role in changing consumer regular purchasing decisions, which in turn affect company business growth. Rumor detection is therefore extremely important in social media [4]. Regardless of the reliability of this information, the design of the social networks has facilitated the rapid distribution of information in real time and created unparalleled challenges to ensure accuracy. Dissemination of misinformation is concerned in particular with breaking news where information is released increasingly and often as unverified information. Allport and Postman [5] have defined rumor as "conceptions on certain (or current) subjects, usually word by word of mouth, which go from person to person without any proof of reality.

Dunn and Allen also set out another definition [6] 'A rumor is a hypothesis provided in the absence of verifiable information regarding uncertain circumstances, because of such uncertainties, is significant for those who are concerned about their uncontrollable circumstances'. Rumor is defined by DiFonzo and Bordia [7] as "

uninformed, instrumentally relevant and circulated knowledge statements in uncertainty, danger or threats and helping to make sense and manage risk." This great number of rumors can have harmful results both for individuals and society over a short period of time. Twitter is one of the most popular social networks on the Web and is used to share information with other users. It was intended for any user to send up to 140 characters of text, called short tweets. The 'Twitter follow up' agreement allows users to easily disseminate information where each user can respond to message receipt with their 'follow-ups' by using the 'follow-ups' feature, which can easier to distribute information by making them his or her "followers," whereas other users follow the first user. This easy distributor of information can be used to disseminate gossip on the social network in Facebook. Over recent years, several researches have been conducted to address the problem of misinformation in the identification of social media.

The objective of this paper is to discuss about the different types of rumors and the various types of classification algorithm like Naïve Bayes, Support Vector Machine, Logistic Regression, etc. which can be used to classify rumors. This will also covers the various literatures that discussed the difficulties faced during rumor detection and classification.

In this article, first we already begin with introduction for this study, and in Section 2 we will then summarize the history of different studies on rumors with different types of rumors. Next, Section 3 discussion about the classification algorithm based on supervised learning system with several feature sets and then in Section 4 which defines the problem statement and in last section we

conclude the paper and some of future research objectives related to rumor analysis and classification.

II. LITERATURE SURVEY

Rezwanul et al. [8] build a practical classifier which can correctly and automatically identify the unknown tweet feeling. They suggested methods that can accurately identify the sign of emotion. There are two implemented methods: One is known as the SCA (sensitive classification algorithm) for K-nearest neighbor (KNN), and one is based on the SSVM. The calculations are also based on actual tweets. Zubiaga et al. [9] compared the new state-of-the-art rumor detection system with other baselines that can benefit from the sequential existence of Social Media messages using conditionally random fields. Unlike existing works, their classifier need not look at tweets which question the post's position to find it a rumor, but rather use the context learned during the case. The classification has increased precision and is reminder of the state of the art tweet-based classification and our best basis.

Etaiwi and Naymat [10] shown the effect on the accuracy of spam detection feedback from preprocessing measures was investigated. Diverse algorithms such as Support Vector Machine (SVM) and Naïve Bayes (NB) have been implemented. An analysis and compilation will be performed using a data set of branded hotel reviews. Efficiency is measured according to various measurement criteria like: precision, recall and accuracy.

Souris et al. [11] discussed the efficacy of machine learning techniques in the detection of companies that file false financial statements (FFS) and classify FFS-related factors. In this context, a series of experiments were carried out with representative algorithms of learning, trained in the recent period 2001-2002 with a data set of 164 Greek companies responsible for fraud and non-fraud. This study shows that a decision tree can effectively be used to classify FFS and highlights its significance.

Ben et al. [12] constructed text vectors from rumored contents using two separate representation codes, the word model bag and the neural network language model. They also contrasted the results with some state-of-the-art classification algorithms of two text representations in rumor detection. They have found that the best rating accuracy of a bag is over 90% of the experiments in 10,000 Sina Weibo posts and the best rating accuracy of the model's neural network language is over 60%. This says that terms of posts are more effective in gossip detection than semantic meaning vectors.

Majumdar and I. Bose [13] automatically provided Big Data framework for financial rumors for automated detection. They focus on the current research on information in databases and on fraudulent financial recognition. An exhaustive case study is presented on the Bombay Stock Exchange, the world's largest stock market. You underline the value of analytics as well as big-data technologies to identify financial speculation for carrying out such a task. They described a number of key factors leading to financial rumors being successfully confirmed.

They assumed that market regulators, stock exchanges and securities can use the system

Sebastian et al. [14] has taken into account the use of crowd signals for false news, and is driven by Facebook tools recently launched to identify users with fake news. By adding the flags of users, their goal is to pick a small newsgroup every single day, to send them to an expert (for example, through a third-party testing agency). It will also reduce the spread of misinformation by stopping the spread of false news throughout the network. It's there.

Hamidian and Diab [15] tried to tackle the rumor detection and Twitter beliefs investments issue. Their rumor definition is an unverifiable assertion that distributes misinformation or disinformation. They used the standard dataset to carry out a supervised rumor classification function. The rumor recall function up to 0.972 is extended by the use of the Latent vector (TLV) feature, which generates a 100 d vector representative for each message. In the gossip posters from 2010 to 2016, they also add the beliefs label and research the change of belief.

Nair et al. [16] has showed how the regression algorithm operates on the feeling analysis of film screenings and what regression algorithm for sentiment analysis is stronger. Random Forest, Ridge, Linear and ElasticNet are the regression algorithms they have introduced. The dataset we used for feelings analysis is based on movie reviews that are called IMDB dataset, while the square error and R squared error are the mean parameters that has been used for analyzing. The result is a very simple inference that regression analysis can be used as a benchmark for all other algorithms with the highest possible precision..

III. DEFINING AND CHARACTERIZING RUMORS

Classification of rumor is done in two ways one is new rumors and the other one is long standing rumors.

New rumors that generate from breaking news - Rumors that arise in the sense of breakup are usually rumors that were not previously observed. Rumors therefore have to be identified automatically and a system of rumor classification has to be capable of handling new and unknown rumors provided that the system's training data those vary from what will be observed later. When it is important to track and settle rumors at an early stage, a flood of papers must be processed in real time. The identity of a potential terrorist is a warning that a theory arises during breaking news. Another similar case of suspected terrorist may have been identified by a rumor classification system.

Long standing rumors - Over long periods of time, some rumors will spread without their truthfulness being known. Such rumors, despite or perhaps because of the difficulties in determining actual truth cause significant and continuing concern. That is the misconception this Barack Obama is Muslim, for starters. While this argument remains false, it seems that there is no evidence to degrade it to everyone's satisfactory satisfaction. A rumor classification system, as could be assumed a priori, may not be sufficient for rumor

classification. In addition, the program will use historical gossip discussions to identify current controversies.

Occurrences of rumors:

There were numerous studies on rumors and associated phenomena [17], from psychological studies to machine analyzes [18]. Traditionally, it was difficult to study people's reactions to rumors as this involves a reaction that is set in real time, as rumors have been hired.

Rumors on the Internet - A new phase in the study of naturalistic rumors has emerged [19] as the Internet is widely accepted and the creation of social networks that provide not only powerful new tools for the sharing of information, but also facilitate multi-member data collection. For example, Takayasu et al. [20] used the social media to investigate the dissemination of gossip circulated in Japan during the 2011 earthquake.

Rumors in social media - As a rumor review, in recent years social media have become a major source for collection of vast sets of data on rumors and because its broad user base and the ease of communication make it a fertile breeder for rumor. Research has found that Twitter uses the auto-correcting properties of crowdsourcing to uncover inaccurate information, as users share thoughts, conjectures and evidence. In the case of the 2010 Chile earthquake, for example, Castillo and other [21] found that the ratio of endorsing and dismissing false rumors was 1:1.

IV. MACHINE LEARNING

Today machine learning algorithms has played an important role in the field of rumor detection and classification. Most of the work done in this area uses natural language processing tools. In this section we will discuss about the different machine learning approaches for rumor detection and classification.

Depending on the specific use case, the design of a rumor classification system can vary slightly. We describe here a standard rumor classification system architecture that includes all the components required for a whole system. But, depending on the specifications, we point out in the following definitions that some of these components may be omitted. A classification system of rumors usually starts by deciding that a component information (i.e. rumor detection) is not verified and finishes by evaluating the approximate veracity value of that component information (i.e. veracity classification).

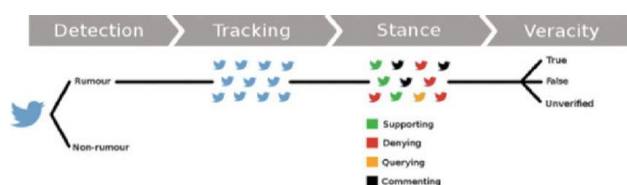


Figure 1. Architecture of a rumor classification system

Description of the classification components are as follows:

1. Rumor detection: A rumor classification system must first determine whether a piece of information is a rumor. Typically, a stream of social media postings may form part

of a rumor detection component, whereby a binary classifier needs to determine whether any message is a rumor or non-rumor. The output of this part is the stream of posts that mark every post as rumor or rumor. This part is useful in discovering new rumors, but when dealing with rumors identified a priori, it is not necessary.

2. Rumor tracking: If rumors are detected, either because the feature of the rumor detection is established a priori or because it is remembered, the rumor tracking function gathers posts that speak about rumor. This part tracks social media to identify posts that address rumors, while deleting irrelevant posts, using a rumor as an input that can define a post or a sentence. a collection of keywords. A series of postings addressing rumor is the production of these components.

3. Classification of stance: While the component of rumor tracking retrieves posts related to a rumor, the component of position classification decides how each item is truthful. With a set of items linked to the same theory as the input, it gives a mark for each object where labeling is selected from a commonly specified collection of stances. Each portion can be useful to assist the following component in the assessment of truthfulness. Furthermore, cases which are only based on expert evidence or checked by authoritative sources may be excluded if the public's attitude is not considered useful.

4. Classification of Veracity: The final factor of veracity classification seeks to determine the true meaning of rumors. It can use both the input of the posts obtained from the component gossip tracking and the position labels generated in the component for position classification. Additional data from other outlets such as news media or other blogs and databases can also be obtained. The components performance can only be the true value predicated, but can also include contexts such as URLs or other data sources that help end users determine the classifier's reliability by double-checking the sources.

Classification Algorithms

There are different types of supervised algorithm which can be used for classification of reviews. These algorithms classify the text using natural language processing (NLP) tool that will act as a preprocessing tool during classification. Let us discussed some of the machine learning algorithms which are as follows:

A. Naïve Bayes

It is based on the theorem of Naive Bayes, which says, by definition, that the relationship between dependent events can be defined with a $P(A)$ notation, read as the probability of event A since event B happened. The probability of A (i.e. depends on what happens to Event B) is called the conditional probability [22].

$$P(A = \text{target_class} | B = \text{word_freq}) =$$

B. K-Nearest Neighbour

The distance between 2 records in the dataset is calculated in this algorithm [23]. In our case the distance is generally measured as an Euclidean distance calculated over user dependent functions, as shown below.

$$Distance(u_i, u_j) = \sqrt{\sum_k^{features} (u_{ik} - u_{jk})^2}$$

C. Support Vector Machine

It is based on linear classification and it act as a binary classifier. Firstly It was introduced by HAvA Siegelmann and Vladimir Vapnik and he has shown its effectiveness mainly in the area of pattern recognition problem. Many times it has shown better classification than other classifiers mainly in case of small dataset. Let us discuss how it works, it segregate a pair of training vectors for two dissimilar groups $(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)$, where $x_i \in \mathbb{R}^d$ Represent vectors in d -dimensional attribute space and $y_i \in \{-1, +1\}$ is a group label [24].

D. Decision Tree

Decision tree is an algorithm based on a tree that solves regression and problems with classification. It is a one of the most widely used algorithm. The Decision Trees consist of decision nodes, branches and leaves. Decision

Tree determines the predictive value according to a number of issues and conditions [25]. For instance, this simple Decision Tree determining on whether an individual should play outside or not. This simple decision tree, for example, decides whether or not a person should play outside. The tree takes into consideration multiple weather variables and makes a decision or asks a different question provided each factor. Each time it is rainy, we play outside in this example. But if it rains, do we wonder whether or not it is windy? We're not going to play if we are windy. But without the storm, firmly tie those shoelaces, when they play outside.

Other than the above discussed algorithms there are some more algorithms available like Random forest, Logistic Regression, etc. All the classification algorithms have their own advantages and disadvantages. It totally depends on the type of dataset that which algorithm will perform better in terms of accuracy, precision, recall and F1 score.

Lets discuss about the strength and weakness of the classification algorithm:

Table 1. Performance comparison of classifiers

S.No.	Classifiers	Description	Strength	Weakness
1.	Support Vector Machines	This classifier use kernels, which measures the distance between two observations. The SVM algorithm then defines a decision limit which maximizes the distance between the closest members of different classes.	SVM can model non-linear boundaries for decisions, and a broad variety of kernels is required. These are also quite robust in high dimensions against overfitting	But, SVMs are more memory intensive, more difficult to settle because to pick the right kernel is very important and they don't scale to larger datasets.
2.	Naive Bayes	Naive Bayes (NB) is an extremely simple algorithm based on the likelihood and the number of people. Your model is essentially a table of probabilities that is actualized by your training data. You will simply "look" at the class probabilities in the "probability table" based on the feature values to predict a new observation. It's called "naive," as its central concept of conditional probability (that is, every input function is independent) is rarely true in the real world.	Although the assumption of conditional independence rarely applies, NB models do in practice surprisingly well and especially for the simplicity of their function. You can quickly deploy and scale with your dataset.	Due to their simple nature, NB models are often tampered with correctly trained models and modified according to the previous algorithms.
3.	Logistic Regression	The classification alternative to linear regression based on logistic function. Predictions are calculated by the logistic function to be 0 to 1 which means predictions can be interpreted as class probabilities. The models themselves still function "linear" so that when you have a linear separation of your classes	Outputs are well represented probabilistically, and the algorithm can be regularized to prevent overfitting. For new data using stochastic downward gradient, logistic models can be easily modified.	If multiple or non-linear decision limits exist, the logistic regression appears to be weak. You are not sufficiently versatile to handle complex relationships naturally.
4.	K-Nearest Neighbor	These nearest neighboring algorithms are instance-based, so every training observation can be saved. We then forecast new observations by searching for and consolidating their values for the most similar training observations.	This algorithm is very easy to implement and it works fine when dealing with small dataset.	Such algorithms are memory-intensive, poorly performed on high-dimensional data and require a significant distance function for similarity calculations.

The problem of rumor detection can be considered as a story x which is defined to mean of n pieces of related messages $M = \{m_1, m_2, \dots, m_n\}$. m_1 is a source message (post) initiating the message chain that might be a multi-branch tree structure. It has attributes, such as the text and the picture, for each message m_i .

Every message is also connected to a user who posted the message. The user has a range of attributes such as the name, definition, avatar image, tweets, etc. The task of rumor detection is then described as: Given a story x with its message M and a user set U , the task for rumor detection is to see if it's correct, wrong or unverified (or j).

V. CONCLUSION AND FUTURE SCOPE

In this survey paper the discussion is about the different types of rumors available for research. This paper is about the analysis of rumor and the different type of classification algorithms available that can be used further for the detection and classification of rumors. It also covers the past research which is done in the area of rumor classification through machine learning techniques. It also covers the steps that will be used during the rumor detection and classification through machine learning approach. In the future work we will take the real time dataset from twitter or Facebook and analysis will be done through above discussed machine learning algorithms. In future we will also implement some of the deep learning algorithms for rumor analysis and prediction. It might happen that they can perform better than machine learning algorithms especially in case of image and video analysis.

REFERENCES

- [1] K. Ali, H. Dong, A. Bouguettaya, A. Erradi, and R. Hadjidj, "Sentiment Analysis as a Service: A Social Media Based Sentiment Analysis Framework," in *Proceedings - 2017 IEEE 24th International Conference on Web Services, ICWS 2017*, 2017.
- [2] H. Ahmed, I. Traore, and S. Saad, "Detecting opinion spams and fake news using text classification," *Secur. Priv.*, 2018.
- [3] M. Granik and V. Mesyura, "Fake news detection using naive Bayes classifier," in *2017 IEEE 1st Ukraine Conference on Electrical and Computer Engineering, UKRCON 2017 - Proceedings*, 2017.
- [4] M. Z. Asghar, A. Khan, F. Khan, and F. M. Kundi, "RIFT: A Rule Induction Framework for Twitter Sentiment Analysis," *Arab. J. Sci. Eng.*, 2018.
- [5] G. W. Allport and L. Postman, "An analysis of rumor," *Public Opin. Q.*, 1946.
- [6] H. Dunn and C. Allen, "Rumors, urban legends and internet hoaxes," *Proc. Annu. Meet. ...*, 2005.
- [7] N. DiFonzo and P. Bordia, "Rumor, gossip and urban legends," *Diogenes*. 2007.
- [8] M. Rezwani, A. Ali, and A. Rahman, "Sentiment Analysis on Twitter Data using KNN and SVM," *Int. J. Adv. Comput. Sci. Appl.*, 2017.
- [9] A. Zubiaga, M. Liakata, and R. Procter, "Exploiting context for rumour detection in social media," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2017.
- [10] W. Etaiwi and G. Naymat, "The Impact of applying Different Preprocessing Steps on Review Spam Detection," in *Procedia Computer Science*, 2017.
- [11] S. Kotsiantis, E. Koumanakos, D. Tzelepis, and V. Tampakas, "Predicting fraudulent financial statements with machine learning techniques," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2006.
- [12] B. Ma, D. Lin, and D. Cao, "Content representation for microblog rumor detection," in *Advances in Intelligent Systems and Computing*, 2017.
- [13] A. Majumdar and I. Bose, "Detection of financial rumors using big data analytics: the case of the Bombay Stock Exchange," *J. Organ. Comput. Electron. Commer.*, 2018.
- [14] S. Tschitschek, A. Singla, M. Gomez Rodriguez, A. Merchant, and A. Krause, "Fake News Detection in Social Networks via Crowd Signals," 2018.
- [15] S. Hamidian and M. Diab, "Rumor Identification and Belief Investigation on Twitter," 2016.
- [16] Rajit Nair, Vaibhav Jain, Amit Bhagat, Ratish Agarwal, "An Efficient Approach for Sentiment Analysis Using Regression Analysis Technique," *International Journal of Computer Sciences and Engineering*, Vol.7, Issue.3, pp.161-165, 2019..
- [17] P. Donovan, "How idle is idle talk? One hundred years of rumor research," *Diogenes*. 2007.
- [18] V. Qazvinian, E. Rosengren, D. R. Radev, and Q. Mei, "Rumor has it: Identifying misinformation in microblogs," in *EMNLP 2011 - Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, 2011.
- [19] P. Bordia, "Studying verbal interaction on the Internet: The case of rumor transmission research," *Behav. Res. Methods, Instruments, Comput.*, 1996.
- [20] M. Takayasu, K. Sato, Y. Sano, K. Yamada, W. Miura, and H. Takayasu, "Rumor diffusion and convergence during the 3.11 Earthquake: A twitter case study," *PLoS One*, 2015.
- [21] C. Castillo, M. Mendoza, and B. Poblete, "Predicting information credibility in time-sensitive social media," *Internet Res.*, 2013.
- [22] K. Chai, H. T. Hn, and H. L. Cheiu, "Naive-Bayes Classification Algorithm," *Proc. 25th Annu. Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.*, 2002.
- [23] P. Cunningham and S. J. Delany, "K -Nearest Neighbour Classifiers," *Mult. Classif. Syst.*, 2007.
- [24] C. Cortes and V. Vapnik, "Support-Vector Networks," *Mach. Learn.*, 1995.
- [25] S. R. Safavian and D. Landgrebe, "A Survey of Decision Tree Classifier Methodology," *IEEE Trans. Syst. Man Cybern.*, 1991.

Authors



Ria Purohit is M.Tech Scholar from Radharaman Institute of Technology & Science, Bhopal. She has completed her BE from Radharam Engineering College in the year 2016. Her area of research is Machine Learning.



Nidhi Ruthia studied Master of Engineering in CSE at Sagar Institute of Research Technology and Science, Bhopal. She completed her Bachelor of Engineering from Sagar Institute of Research and Technology, Bhopal. Currently, working as Assistant Professor at Radharaman Institute of Technology and Science, Bhopal. Her area of interest in the field of Research is Data mining, Big data, Data Analytics and Artificial Intelligence



Chetan Agrawal Studied Master of Engineering in CSE at TRUBA Institute of Engineering & Information Technology Bhopal. He has studied his Bachelor of Engineering in CSE at BANSAL Institute of Science & Technology Bhopal. Currently He is working as Assistant professor in CSE department at RADHARAMAN Institute of Technology & Science Bhopal M.P. India. His research area of interest is Social Network Analysis, Data Analytics, Machine Learning, Cyber Security, Network Security, Wireless Networks, and Data Mining.