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# An Analytical Study of Rumoured Tweets by Using Twitter Data

***Shubham Sharma[1], Kunal Rathore[1], Shally Mittal[1], Dr. Sanjay Srivastava[2]***
*[1]UG Students, [2]Professor*
*[1,2]Department of Computer Science and Engineering,*
*MGM's College of Engineering and Technology,*
*Noida, UP, India*
***Email:*** *1509510079@coet.in*
***DOI:***

***Abstract***

*Earlier when the internet was not there, rumours were spread by word of mouth technique but in this era of technology where we have social networking sites like twitter, rumours can be spread easily and quickly and a situation of panic can arise. Twitter is an American online news and social networking service on which users finds the latest news and world events faster. It is used for communication, interaction withpeople, announcement of event etc. from breaking news to sports, politics and everyday interests, one can find this service very addictive and an easy way to gather information about a certain event. Businesses can also use it to build their own brands and for marketing. But the founders of twitter like jack Dorsey forgot one thing that every coin has two sides. While twitter is a great way to interact with the masses, it is also a home of spammers. Spamming is a very common thing on twitter. Spammers create twitter accounts to perform a variety of tasks like posting links with unrelated tweets and the speed at which these fake and malicious misinformation spread on twitter in a real-time emergencies always causing a huge flood of tweets on twitter. In this paper, we demonstrated an analytical study of those rumoured tweets by twitter data. Using some of the rumoured tweets posted during the Chennai flood in 2015 and some non-rumoured tweets, we trained a classifier. The ability to track rumours and predict their outcomes have many applications for journalists, emergency services, and thereforehelp in minimizing the impact of false and fake information on this twitter platform.*

***Keywords:*** *Chennai Flood Twitter, Rumour Detection, Social Networks.*

## INTRODUCTION

Social Media has become an important part of all of our lives. More than 2.6 billion people globally use social media today. This shows the impact of social media on humans is immense. The difference between twitter and other social networking services is its limited 140 characters but it does not affect its growth as it has around 340 million monthly active users today. This couldn't be possible without the rapid development of technology.

Nowadays, social networks available at all time provide the information which is spreading faster than ever. But the rumours spread from these social media network like twitter have been around as long as the internet and hoaxes. Twitter space can be quirky in terms of the reliability of the facts shown in the tweets. It's only takes a second to click that share button but how one can know what others are reading and sharing is true and which are false information. Some of the most common social media rumours hitting twitter today: fake celebrity deaths, chain mail rumours, falsities about the social network like Facebook, unnecessary social experiments etc. these rumours can easily confuse the people and it is difficult to trust the information spreading on twitter.

The major task in the scenario we chose (Chennai rains 2015) was the extraction of

tweets. The twitter APIs (Application programmer's interface) which are available are only useful for getting tweets of data as old as a week. There are some tools which help us extracting old tweets but are all paid. So we developed our own system for the extraction of tweets.

## RELATED WORK

Rumour can be defined as "an unofficial interesting story or piece of news that might be true or invented, and quickly spreads from person to person." It can also be defined as "acurrently circulating story or report of uncertain or doubtful truth." But when put differently, rumours may be seen as a form of collective sense-making to a community attempting to understand ambiguous or uncertain situations when official information is lacking. But rumours may negatively affect the individuals, groups of people depending on the topic, its details etc. rumours often carry some truth and counter-rumours confirming that specific part of the rumour that is true may be sufficient to neutralize its impact. The rise of social media like twitter to share information means that as an unfortunate side- effect, people have also used this platform to spread rumours and other forms of misinformation. This phenomenon needs a research attention.

Shubham attempted to model the diffusion of the rumour tweets found in the dataset. He found some characteristics on twitter by using the model; however, they did not mentioned how to detect rumour.
Kunal investigated rumour tweets focusing on the content of retweeted tweets. While he found that some features in the form of content of rumour tweet, he did not mention how to detect rumour tweets either.

Shally tried to detect flood related dataset from twitter. This work focused on a single kind of event, namely only flood. The major difference between this work and ours is that any event can be rumours. We cannot prepare unexpected type of event in advance.

## DATA COLLECTION

To access confirmed rumours while creating a training data which is appropriate is definitely a critical challenge. Rumours as we know are a tiny portion of the total social media content. Also, we need access to rumours that are confirmed to be true or false by trustworthy sources. We choose **UCL library** for our datasets on this project as it provides access to a wide range of databases. Databases can also be accessed via explore. We crawled and collected more than 1.4 million tweets using #chennairains, #chennaifloods and #chennairainshelp hashtags to crowd-source assistance and help each other through this natural disaster posted during November-December 2015. Record is given below:

***Table 1:*** *Example of Collected Rumours and Truths*

| Date | Events | Veracity |
|---|---|---|
| 1-15 | Actor created a team for food parcel pickup and delivery | Truth |
| 2-14 | Crocodiles escaping from the madras crocodile bank trust | Rumour |

Since the prediction is based on event level, we also need to collect all relevant tweets for each story. Instead of using Twitter's search API which limits its result to one week, we submitted eachquery directly to twitter's search interface to get full history and used a web scraper to download all matched tweets automatically.

To collect additional true stories, we sent Twitter's free data stream to our event detection system for which pre-processing is done and after that clustering algorithm is used that groups tweets of the same

stories or events, very close to the outcomes of twitter monitor.

## METHODOLOGY

This section explains the methodology we used to automatically detect rumours on Twitter and find the origin. The methodology has been broadly classified in to the following sections: data, feature extraction, classification, and reduction of features and identification of the origin.

### Data

To automatically detect rumours and train a classifier with the available tweets which have been verified as rumours, as well as tweets which are not rumours, we downloaded tweets from the Twitter Streaming API using Python. The tweets which didn't contain any rumours, such as conversation tweets, tweets about news, tweets containing the user's opinions, etc. were downloaded from the Twitter API. In total, 260 instances correspond to "Rumour" class and 246 instances correspond to "Non-Rumour" class, achieving a data balanceequivalent to 50 / 47.3. We were unable to download a larger dataset as Twitter doesn't allow downloading of tweets which are more than 7 days old. In order to overcome this limitation, in the next phase of training, we used a dataset containing 260 rumoured tweets and 1040 non-rumoured tweets. Using the SMOTE technique available in Weka tool, the number of rumoured instances was increased to 1045 instances, achieving a data balance equal to 50/49.76.

### Feature Extraction

After going through previous Literature, we identified the features which are necessary to classify whether a given tweet is a rumour or not. Thus, we selected 20 features based on tweet content and user accounts, as shown in Table 2. To analyze the sentiment of the given tweet, sentiment dictionary produced by Theresa Wilson, Janyce Wiebe, and Paul Hoffmann at the University of Pittsburgh which is freely available was used. The Wilson et al. database has more than 600 citations in Google Scholar. Since the Wislon et al. list combines negative and positive polarity words in one list, and includes both words; it was cleaned up a bit and two files: one containing positive words and the other containing negative words were used. The files contain 2231 positive words and 3906 negative words, respectively. We wrote a python code in order to extract the previously identified features and perform the feature extraction. The tweets had to be pre-processed before the features could be extracted. To analyse the sentiment of the tweet and count the number of positive and negative words present, we performed sentiment analysis. The tweets downloaded were provided as the input to the code. The tweets were first pre-processed to remove all punctuation marks and all upper case words were converted in to lower case. The feature values were obtained as the output. The algorithm is as depictedbelow:

**Input:** The data file downloaded from the Twitter API
**Output:** Feature values

**Algorithm:**
1) For each line in the file, perform the following steps:

1. Count the number of exclamation marks, question marks, hashtags, ampersands, url links, happy and sad smileys present in the tweet and append each of them to their respective lists. ii. Find the total word count and the fraction of upper case words present.
2. Pre-process the tweets to remove punctuation marks and convert the whole tweet to lowercase.
3. Find the total number of positive and negative words present and find the sentiment of the tweet.
4. Extract account-based features such the friends, followers, statuses and favourites count and the other features such as whether the account contains a description, a default profile image and

whether the account is verified. 2) Output the feature values.

***Table 2:*** *Features Extracted*

| |
|---|
| Tweet length |
| Total word count |
| The number of positive words present |
| The number of negative words present |
| The sentiment of the tweet |
| The number of exclamation marks |
| The fraction of upper case letters |
| The number of question marks present |
| The number of hashtags present |
| The number of ampersands present |
| The number of url links present |
| The number of happy smileys present |
| The number of sad smileys present |
| Whether the profile image is a default one |
| Whether the account is verified |
| The followers count |
| The statuses count |
| Whether a description for the account is present |
| The friends count |
| The favourite count |

**Classification**

A classifier is called supervised if it is built based on training corpora containing the correct label for each input. We trained a J48 classifier to perform the classification of tweets based on the extracted features. Twitter API only allows downloading of tweets which are 7 days old. Due to this restriction, we could not download a large set of tweets containing rumours. As a classifier is better able to classify when trained using a large dataset, we synthetically generated the feature values for rumoured tweets. We resample the dataset by applying the Synthetic Minority Oversampling Technique (SMOTE).

**Reduction of the Features**

To identify the contribution of each of the features extracted towards the correct classification of the tweets, we performed feature reduction. The output of the feature reduction algorithm helped in analyzing the important features and eliminating the ones which don't contribute to the classification process. E. Identification of the origin Once a tweet has been predicted as a rumour, the following steps are to be taken in order to identify the source of that tweet i.e. identify the user who first posted the tweet containing the rumour. To perform this task, we propose the following algorithm:

**Input**: Tweet which has been predicted as a rumour; the file containing the dataset.
**Output:** The rumoured tweet and the username of the account which first posted the rumoured tweet.

**Algorithm**

1. Search for the hashtags included in thetweet.
2. Eliminate the stop words: conjunctions, prepositions, adverbs andpronouns.
3. Search for meaningful words: nouns, verbs, adjectives, proper nouns, namesof places, people and call them the searchterms.
4. Using these search terms, search the tweets to find whether these terms or hashtags are included in thetext.
5. If the search terms or hashtags are included,then compare the time of posting of that tweet to the min_time,

if it is lesser than min_timethen

1. Make min_time equal to the time of posting of thattweet.
2. Make origin_user equal to the username who posted that tweet.
3. Stop searching when you obtain a large number of tweets which don't match the search terms or hashtags.
4. Output the tweet and origin_user variable andstop.

Twitter API has a restriction of not allowing the download of the tweets which were posted more than 7 days earlier. From the time we started working on this project, no tweets containing rumours, which caused an impact were spread. The rumoured tweets posted during the London riots in 2011 were searched using the Twitter Search, which provides only 100 tweets per search. As a result, we were not able to obtain a complete set of tweets containing rumours, containing the very first tweets posted. Moreover, most of the user accounts which previously posted rumoured tweets have been blocked now. Due to the unavailability of the dataset, we were not able to test our proposed solution.

## RESULTS AND ANALYSIS

### Training

To predict whether a given Tweet is a rumour or not, we tried a number of learning algorithms with best results achieved by a J48 decision tree. For training process, we performed a 10-fold cross validation with 10 iterations. The summary of the classifier is shown in Table 3. Table 4 contains the detailed accuracy by class and Table 5 provides the Confusion Matrix. The Confusion Matrix shows that 228 of the rumoured tweets have been correctly classified as Rumour and 32 of the rumoured tweets have been wrongly classified as Non-Rumour. Similarly, 34 of the nonrumoured tweets have been wrongly classified as Rumour and 212 of the nonrumoured tweets have been correctly classified asNon-Rumour.

### Analysis of Synthetically GeneratedData

The percentage of correctly classified instances considerably increased and the summary, detailed accuracy by class and the confusion matrix of the classifier are as given in the Table 6, 7 and 8 respectively. The Confusion Matrix shows that 989 of the rumoured tweets have been correctly classified as Rumour and 54 of the rumoured tweets have been wrongly classified as Non-Rumour. Similarly, 66 of the non-rumoured tweets have been wrongly classified as Rumour and 979 of the nonrumoured tweets have been correctly classified as Non-Rumour.

***Table 3:*** *Summary for Training Set*

| | |
|---|---|
| Correctly Classified Instances | 86.9565% (440) |
| Root mean squared error | 0.3436 |
| Relative absolute error | 30.4828% |
| Root relative squared error | 68.7527% |
| Total Number of Instances | 506 |

***Table 4:*** *Detailed Accuracy by Class for Training Set*

| Precision | Recall | F-Measure | Class |
|---|---|---|---|
| 0.87 | 0.877 | 0.874 | Rumour |
| 0.869 | 0.86 | 0.865 | Non-Rumour |
| 0.87 | 0.87 | 0.87 | Weighted Avg. |

***Table 5:*** *Confusion Matrix for Training Set.Å Classified as*

| a | b |
|---|---|
| 228 | 32 Rumour |
| 34 | 212 Non-Rumour |

**Feature Reduction**

To determine the features which do not contribute to the classification, Information Gain Attribute Evaluator with Ranker search method, on the whole training set was used. The following features contributed the least for the classification process:

1. The friendscount
2. The followerscount
3. The favouritecount
4. Whether the profile image is a defaultone
5. The number of happy smileyspresent
6. Whether a description for the account is present
7. The number of sad smileyspresent
8. Whether the account is verified

The percentage of correctly classified instances increased to 87.9% after removing these attributes. The summary of the classifier, the detailed accuracy by class and the Confusion Matrix are provided in Tables 9, 10 and 11 respectively.

***Table 6:*** *Summary for Synthetically Generated Training Set*

| | |
|---|---|
| Correctly Classified Instances | 94.2446% (1965) |
| Root mean squared error | 0.2303 |
| Relative absolute error | 13.0713% |
| Root relative squared error | 46.0635% |
| Total Number of Instances | 2085 |

***Table 7:*** *Detailed Accuracy by Class for Synthetically Generated Training Set*

| Precision | Recall | F-Measure | Class |
|---|---|---|---|
| 0.937 | 0.948 | 0.943 | Rumour |
| 0.948 | 0.937 | 0.942 | Non-Rumour |
| 0.943 | 0.942 | 0.942 | Weighted Avg. |

***Table 8:*** *Confusion Matrix for Synthetically Generated TrainingClassified as*

| a | b | |
|---|---|---|
| 986 | 54 | Rumour |
| 66 | 979 | Non-Rumour |

***Table 9:*** *Summary for Reduced Feature Set.*

| | |
|---|---|
| Correctly Classified Instances | 87.9447% (445) |
| Root mean squared error | 0.3289 |
| Relative absolute error | 29.2581% |
| Root relative squared error | 65.7968% |
| Total Number of Instances | 506 |

***Table 10:*** *Detailed Accuracy by Class for Reduced Feature Set*

| Precision | Recall | F-Measure | Class |
|---|---|---|---|
| 0.869 | 0.869 | 0.881 | Rumour |
| 0.866 | 0.89 | 0.878 | Non-Rumour |
| 0.88 | 0.879 | 0.879 | Weighted Avg. |

***Table 11:*** *Confusion Matrix for Reduced Feature SetClassified as*

| a | b | |
|---|---|---|
| 226 | 34 | Rumour |
| 27 | 219 | Non-Rumour |

## DISCUSSION

The experimental results show that the tweet-based features are very important in the classification process. The user-based features other than the status count don't contribute towards the correct classification of the tweets. This might be because the dataset used by us to train the classifier is populated by retweets and contains very few original tweets. But, this dataset is obtained from a real-life event and the situation might hold true for other such events as well. In a situation where rumours are spread on Twitter, in has been noticed that the person who intends to spread false rumours, posts a rumoured tweet and other genuine users who believe the tweet to be true, retweet the same. We showed that, in cases of crisis, people often retweet and propagate tweets containing fake images that they find in Twitter search or trending topics, irrespective of whether they follow the user or not. Here, we have established that the same holds true for tweets containing rumours as well. According to us, the status count of the users might be playing an important role because the casual users who are active on Twitter generally tend to naïvely retweet new information or news. So, according to our experimental results, a user who has a high status count, indicating that the user is very active, is likely to retweet a rumoured tweet.

## CONCLUSION AND FUTURE WORK

The huge impact social media such as Twitter have on today's day-to-day activities and the rapid speed with which the tweets propagate make it critical to provide tools to automatically detect the spread of rumoured tweets. In our work, we collected certain tweets containing false information which were posted during the Chennai flood which took place in the year 2015. We identified the features necessary to automatically detect rumours and were able to train a J48 classifier to detect rumours. Our classifier was able to correctly classify the tweets with high accuracy. We showed that with a larger dataset, we can obtain better results. By performing the feature reduction, we showed that the tweet-based features are more important for the detection of rumours and user-based features play considerably a smaller part as the account details of casual users who naïvely retweet the tweet containing the rumour. We proposed an algorithm to find the origin of the tweets. Once the account information of the users who first posted the tweets containing the rumours is obtained, they can help better understand the role of user-based features in the detection of rumoured tweets.

However, there is much work to be pursued in this area. Future work includes

Clustering of tweets into various clusters such as rumour, news, conversation, spam,etc. This would help to better understand the tweets and differentiatethem.

Obtain the complete data set containing the very first tweets which were posted and test the working of our algorithm to identify the origin.

Develop a complete tool which would continuously stream the tweets from Twitter and automatically detect rumours in real time. If rumour is detected, then the tool needs to automatically find the origin of the rumours and output the usernames

who started posting the rumouredtweets.

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