# Retweetability Analysis and Prediction during Hurricane Sandy

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**ABSTRACT**

Twitter is a very important source for obtaining information, especially during events such as natural disasters. Users can spread information in Twitter either by crafting new posts, which are called "tweets," or by using retweet mechanism to re-post the previously created tweets. During natural disasters, identifying how likely a tweet is to be highly retweeted is very important since it can help promote the spread of good information in a network such as Twitter, as well as it can help stop the spread of misinformation, when corroborated with approaches that identify trustworthy information or misinformation, respectively. In this paper, we present an analysis on retweeted tweets to determine several aspects affecting retweetability. We then extract features from tweets' content and user account information and perform experiments to develop models that automatically predict the retweetability of a tweet in the context of the Hurricane Sandy.

**Keywords**

Twitter, Retweetability Analysis, Retweetability Prediction, Hurricane Sandy, disaster events.

## INTRODUCTION

In response to increased online public engagement and the emergence of digital volunteers, emergency responders have sought to better understand how they too can use online media to communicate with the public and collect intelligence (Denef, Bayerl, and Kaptein 2013; Latonero and Shklovski 2011; Hughes and Palen 2012; Sutton et al. 2014; St. Denis, Palen, and Anderson 2014). Many emergency decision makers see the data produced through crowdsourcing as ubiquitous, rapid and accessible - with the potential to contribute to situational awareness (Vieweg et al. 2010). As public social media use in crisis increased, emergency responders started to take notice of the way citizens engaged with social media and the information exchanges that took place there (Hughes and Tapia, 2015). Consequently, responders began to consider if social media might be a useful tool for their practice. Research revealed that social media could be used to distribute information quickly to a wide-spread audience (Kodrich and Laituri 2011) and to engage more directly in a two-way conversation with members of the public (Hughes and Palen 2012). However, incorporating the products of digital volunteer activity into professional emergency practice has proved to be challenging due to issues with credibility, liability, training, and organizational process and procedure (Hughes and Palen 2012; Tapia et al. 2011).

The information that the public produced looked to be useful, as researchers showed that it could contribute to situational awareness during a crisis event (Cameron et al. 2012; Ireson 2009). Vieweg et al. (2010) found that retweeted tweets are likely to contain information that contributes to situational awareness and are actionable compared with non-retweeted tweets. In addition to the information which creates awareness to the responders, people also post information related to relief efforts (such as offering shelters, donations, and food) during the disasters, for which the target consumers are the victims who need aid. However, retweeting such useful information is influenced by several factors including the aspects of a user who posted the information and the content present in it. We particularly focus on identifying factors that affect retweetability of a tweet during mass emergencies. This could be used in a real-time system to promote important tweets that convey useful information as well as to flag tweets that contain misinformation, but have a high chance of being retweeted.

Emergency managers see the potential of social media as a means of engaging the public quickly and widely during a crisis. We believe that the retweeting function inside Twitter is a means for these emergency managers to influence the speed and spread of messages. If we can identify elements of a message, which make it more likely to be retweeted during a crisis, we can better inform emergency managers on how to reach the widest audience in the fastest way.

The contributions of this paper are as follows: (i) we present an analysis on retweeted tweets during Hurricane Sandy to determine several aspects affecting the retweetability; (ii) we extract features from tweets' content and user account information and use them in conjunction with machine learning classifiers to predict the tweets' retweetability during the hurricane; and (iii) we show that the classifiers trained on these features outperform those trained using the "bag of words" approach.

## BACKGROUND

In Twitter, users are able to create tweets, i.e. posts that must not exceed 140 characters, and can share any public tweets in the network. This process of sharing a tweet is called "Retweeting." When users share tweets, all of the users' followers will be able to see it. Several research groups have demonstrated that emergency managers and responders see the value of social media for crisis communication (Hughes and Palen, 2012). In addition, there have been several studies of emergency managers and responders who have used social media to get the word out during a crisis (Denef, Bayerl and Kaptein, 2013; Hughes et al. 2014; St. Denis et al. 2014; Sutton et al. 2012). More directly, there have been several research efforts to understand how emergency managers and responders have tried to influence the public's information or behavior via social media during crises (Hughes and Chauhan, 2015; Sutton et al. 2014). Recent research around disasters has started to investigate automated machine learning approaches that can reliably be used by emergency managers and responders in crisis events (Li et al., 2015; Caragea et al., 2014; Imran et al., 2013; Caragea et al., 2011). With the aforementioned research efforts, and with the limitation of only 140 characters per message, there is still a strong agency for developing predefined terse messages to be used during a given crisis (Sutton et al. 2014; Sutton et al. 2015).

Much work is done on how information is propagated through a network. For example, Sutton et al. (2012) studied the effect of centrality on the dissemination of information, and how this feature allows a certain organization to broker said information. Kwak et al. (2010) conducted a quantitative study on Twitter data to find how information is diffused in the network. They suggested that the number of followers a user has and the number of times that a user's tweet is retweeted are different measures of popularity. Olteanu et al. (2015) have studied the propagation of information in crisis situations using statistical analysis and have shown that different disasters contain similar tweets, and human-induced disasters are more similar to each other than to natural disasters. Also, it was verified that tweets containing keywords related to a disaster and tweets by local media and emergency agencies are very important sources of information. Starbird and Palen (2010) studied the information propagation in Twitter during Red River floods and Oklahoma Fires and found that people are more likely to use the retweet function to pass on crisis related information than other types of information during a crisis event. Pervin et al. (2014) studied the factors affecting the retweetability using Japan Earthquake Twitter data and observed that network features such as the type of user sharing the information are very crucial for the propagation of information. Furthermore, there have been several studies recently, which directly studied the propagation of rumors and misinformation through social media. For example, Mendoza et al. (2010) found that immediately after the Chilean earthquake of 2010 there was significant evidence of the propagation of false statements on Twitter. Using only a small set of cases, their results indicate that unverifiable information tended to be questioned much more than confirmed information. Castillo et al. (2011) analyzed information credibility in microblogs (i.e., information "offering reasonable grounds for being believed"). In contrast to these works, we use machine learning techniques to predict the retweetability of a tweet, i.e., how likely a tweet is to be retweeted.

There are several works that are similar to our work. Zaman et al. (2010) developed a probabilistic model to predict a retweet given the tweet content, tweeter and retweeter. They found that features such as the name, number of retweet-followers and number of retweet following of the author of a given tweet are important. Suh et al. (2010) found that the context of a tweet author (such as age, followers, and friends) influenced the retweetability. They also stated that tweets with URLs and hashtags were more likely to be retweeted. The authors developed a Generalized Linear Model to predict the retweetability. Petrović et al. (2011) addressed the problem of predicting retweetability in Twitter and have shown that social features, i.e., features related to the author of the tweet such as number of followers, friends, statuses, favorites, the number of times that a user was listed and if the user is verified, play an important role in increasing the accuracy of the prediction. Uysal and Croft (2011) have proposed methods to rank tweets using retweet behavior in order to bring more important tweets forward and also determined the audience of tweets by ranking users based on their likelihood of retweeting the tweets. Starbird and Palen (2012) have performed statistical analysis on 2011 Egyptian uprising and showed that information diffusion is mostly due to the retweets. Jenders et al. (2013) also focused on predicting retweetability of tweets. However, in contrast to Jenders et al. (2013), we designed features based on actual numbers in tweets, such as phone numbers, measuring units, dates which are useful during disasters. It is worth noting that all the above works are not focused on how the retweetability prediction would look like in a disaster scenario, whereas in our work, we specifically focused on data (tweets) from a disaster event.

## DATASET

We collected Twitter data posted during the Hurricane Sandy between October 26 and November 11, using the Twitter Streaming API[1]. Specifically, we collected 12.9 million (M) total tweets with 5.1M unique users. Out of the 12.9M tweets, 7.1M are initial tweets (or direct posts) and 5.8M are retweets (derivative posts). Out of the 7.1M initial tweets, only about 1.1M tweets are retweeted, whereas the remaining tweets are never retweeted.

A post in Twitter (or a tweet) is a short message of up to 140 characters, posted by a user. A post may be direct or derivative. A direct post refers to a post that is published for the first time (by a user), whereas a derivative post refers to a re-post of a post from another user. In Twitter terminology, the former is called “tweeting” and the latter is called “retweeting.” Retweeted messages have a common pattern as: “RT @A: message x”, which specifies that the post is a retweet (“RT”) or re-post of message x that was originally posted by user A (“@A”). A user A is called a follower of a user B if user A “follows” (or receives updates from) user B (but not vice-versa). If both users “follow” each other, then they are called friends. We believe that both relations “followers” and “friends” are important since they help pass the information in the network.

## DATA ANALYSIS

In this section, we provide a description and analysis of our set of tweets and study how information is spread in the network via retweeting. Figure 1 (left plot) shows the distribution by day of the 12.9M collected tweets in our dataset by day. We can observe a burst after two days from the beginning of the event.

The delay can be explained by the hurricane progressive nature, i.e., it was forecasted a few days prior to the strike and the pace in postings picked up as it hit the coast from the Atlantic Ocean. As can be seen from the figure, the number of tweets per day decreases as time elapses.

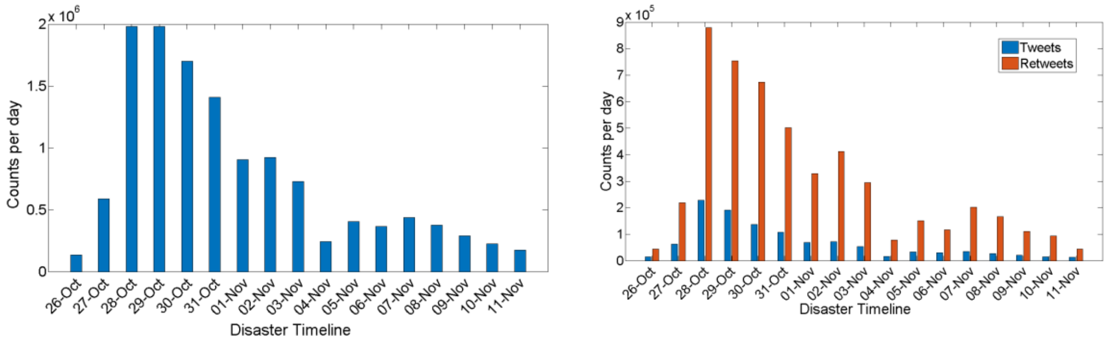


**Figure 1. The distribution of total posts per day (left) and distribution of retweeted tweets and their retweets (right) during Hurricane Sandy.**

An analysis of the 1.1M direct tweets and their retweets reveals a similar trend. Specifically, from the entire dataset, we remove the tweets that are not retweeted and separate the tweets (direct posts) from the retweets. Figure 1 (right plot) shows the number of tweets (direct posts) that are retweeted and their retweets by day. The trend is analogous to the plot in Figure 1 (left plot), where we can observe a decrease in the number of tweets and retweets as the days elapse. We can also observe that the number of retweets is much higher than the number of tweets every day, showing that information is substantially spread in the network.

[1] https://dev.twitter.com/streaming/overview

Table 1 shows statistics of the 1.1M tweets: the average, the maximum and minimum values of the retweet count and tweets' life span, and the number of tweets that are alive for less than one hour. For example, the number of tweets that are alive for less than one hour is very large, accounting for about 82.5% of the 1.1M tweets. The maximum number of retweets of a tweet in our dataset is 34,411, and the maximum life span is ≈386 hours.

| | |
|---|---|
| Maximum retweets of a tweet. | 34,411 |
| Minimum retweets of a tweet. | 1 |
| Maximum life span of a tweet. | ≈386 hrs. |
| The average life span. | 5.05 hrs. |
| The average number of retweets. | 4.49 |
| Quickly died tweets (< 1 hr.) | 929,370 |

**Table 1. Statistics of the 1.1M tweets and their retweets.**

### Retweetability vs. Number of Followers/Friends

Among the retweeted tweets (i.e., the 1.1M tweets), we study how the number of followers or friends[2] of a user would affect the retweetability. Intuitively, we expect that a user with more followers or friends would have a better chance of having his/her tweets retweeted more often. For this analysis, we divided the 1.1M direct tweets into five categories (see Table 2) based on their retweet count.

| Category | #Direct tweets | #Retweets |
|---|---|---|
| 1. Retweeted >100 times (Category 1) | 4,560 | 1,816,676 |
| 2. Retweeted >50 & <=100 times (Category 2) | 5,226 | 362,107 |
| 3. Retweeted >20 & <=50 times (Category 3) | 15,574 | 483,679 |
| 4. Retweeted >1 & <=20 times (Category 4) | 434,654 | 1,740,840 |
| 5. Retweeted Only Once (Category 5) | 665,437 | 665,437 |

**Table 2. The distribution of total number of direct tweets and their retweets into five categories.**

Table 2 shows, for each category, from 1 to 5: the number of direct tweets split by category (out of 1.1M), and the sum of the retweets count of all direct tweets (in a category). We can see that the number of direct tweets that are retweeted only once (last row in the table) is significantly higher than the number of tweets that are retweeted more than 100 times (first row), and, as we go from Category 1 to Category 5, the number of direct tweets keeps increasing. The total number of retweets in Category 1 is very high compared with the other categories and has a ratio of ≈398 retweets per each tweet. Category 4 has the next highest number of retweets, but has a very low ratio of ≈4 retweets per each tweet.

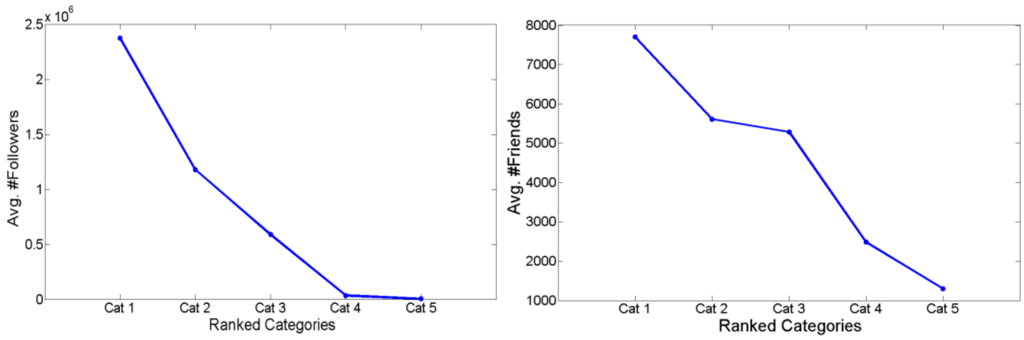


**Figure 2. Distribution of average followers (left) and average friends (right) among tweets from the five categories.**

We record the average number of followers and the average number of friends of the unique users in each category. In Figure 2 (left side), we plot the distribution of the average number of followers on Y-axis to the ranked categories on X-axis. Similarly, in Figure 2 (right side), we plot the distribution of the average number of friends. We observe that the trend in both plots is in decreasing order. As can be seen from the figures, Category 1 has the highest average number of followers and friends, whereas Category 5 has the lowest corresponding averages.

### Popularity Analysis among Users

We further analyze the popularity of users in terms of two measures: (1) the retweets count of their tweets, and

[2] Throughout the paper, we refer to the followers (or friends) of a tweet as the followers (or friends) of the user who posted the tweet.

(2) the number of other users who participate in retweeting their tweets i.e. the retweeters. Generally, both of these measures are important for the fast spreading of information in a network.

| Source Type | User id | Retweets | Retweeters | isVerified |
|---|---|---|---|---|
| Celeb | justinbieber | 137,599 | 66,452 | true |
| Politician | GovChristie | 38,177 | 26,752 | true |
| News Media | cnnbrk | 34,359 | 25,235 | true |
| News Media | HuffingtonPost | 34,019 | 22,398 | true |
| anonymous | FillWerrell | 32,984 | 32,665 | false |

**Table 3. Top 5 users during Sandy with total retweets in this disaster and total retweeters of their tweets.**

For this analysis, from all of our 1.1M retweeted tweets, we extracted the unique users who posted these initial tweets and found that the number of unique users is 487,026. We ranked these users based on the retweets count of their tweets and observed that most of the top ranked users are related to news media, celebrities (such as actors and musicians), politicians, and a small fraction is related to regular or anonymous users. The inspection of the top ranked users also revealed that, for these top ranked users, there is a significant number of other users who participated in retweeting their tweets. Table 3 shows the top 5 ranked users, along with their retweets count, retweeters count and the verifiability of the user account.

For users' credibility, we used the "verified account" attribute from Twitter which helps in establishing the authenticity of a user. In this aspect, we found an interesting pattern. From the users list ranked based on the number of retweets, we selected the top 1000 and the last 1000 users and found that the accounts of the users with more number of retweets and retweeters are verified. Figure 3 shows the top 1000 and the last 1000 ranked users on X-axis and their verification status on Y-axis, which takes 1 if an account is verified and 0 otherwise. The figure shows that, as we descend to the users with less number of retweets, the verification status is faded off. In the figure, the first half of the X-axis represents the users of top 1000 tweets with high retweets, where the density of blue bars is very high and the second half is for the users of the last 1000 tweets with only one retweet, where we see only a few blue bars. We found that in Sandy there are around 584 verified users in the

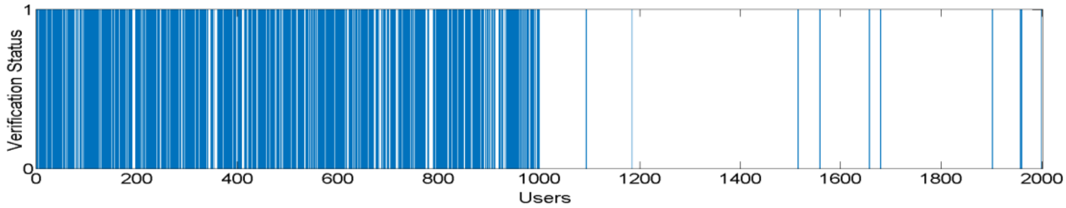


**Figure 3. The distribution of users based on the verification status for top 1000 and last 1000 authors extracted for Sandy.**

first 1000 users and only 11 verified users in the last 1000 users. Next, we present details of our retweetability classification task and show how factors that we discovered in the above analysis can be used in automatically predicting retweetability of a tweet.

## FEATURE EXTRACTION FOR RETWEETABILITY PREDICTION

We describe our features that we use as input to machine learning algorithms. We divide them into tweet content features and user details features.

### Tweet-content Features

These features, shown in *italic*, are: *Contains Hashtag? :* Hashtags are extremely relevant for the context of natural disasters because tweets from the same topic will likely contain the same hashtags. A user in search for information about a disaster may search for hashtags related to the particular disaster. We assign 1 if a hashtag is present in the tweet, and 0 otherwise. *Number of Hashtags:* Not only it is important to verify the presence of a hashtag in a tweet, but also the number of hashtags may be important for retweetability. The more hashtags a tweet has, the more people can see it, thus increasing the chance of it being retweeted. The value of this feature is the number of hashtags. *One-word and multiple sentences:* OpenNLP[3] Java Libraries were used to check whether the tweet contains a one-word sentence or multiple sentences. We assign a feature value of 1 for the

[3] https://opennlp.apache.org/

presence of one-word sentences, otherwise 0. Similarly for the presence of multiple sentences. *Presence of URL:* URLs from news sources are important and are more likely to be shared because they provide a complete background about a natural disaster. The feature value is 1 for the URL presence, and 0 otherwise. *Is a Reply?* A reply of a tweet usually indicates a conversation between users and is of more personal nature. We assign 1 if the tweet is a reply, otherwise 0. *Length of a tweet:* If a tweet is very short, it might not contain useful information. In contrast, a longer tweet might contain useful information, and the chance of sharing a longer tweet may be higher. *Phone Numbers:* Tweets that contain phone numbers are likely to be shared by users because the phone number might be an emergency number or a donation number. We assign feature value 1 for the presence and 0 otherwise. *Measuring Units:* In the case of natural disasters, there are a lot of measurements involved, such as wind speed, flood depth. This information may be important for users involved in the disaster, and they may want to share it with other users. *Date or Time:* A disaster could last for days. Hence, dates may be important so that users can keep track of the progression of a disaster. From the above features, we believe that the phone numbers, measuring units, date or time features are more informative and are unique, because they have the necessary vital information during disasters such as the magnitude of the disasters expressed in units (wind speed, water levels etc.), phone numbers to inform or seek aid from the responders.

In addition to the above feature, we extracted features that are derived based on certain word presences in the tweets. We manually parsed several random subset of tweets in our set and went through several online resources to construct the dictionaries for each of these features: *Emoticons*[4]*:* Emoticons are used in social networks to express emotions. We check for their presence and assign 1 for the presence or 0 otherwise. *Usswords:* A tweet containing a cussword indicates an informal way of expression, which may indicate no sign of helpful information. We assign 1 for the presence of cusswords and 0 otherwise. *Keywords:* We manually went through the tweets and selected a set of keywords such as “donate”, “txt” or “pm” that exist in tweets. If a tweet contains a certain keyword, users will likely evaluate the tweet as useful for the natural disaster and will retweet this tweet. *Abbreviations:* Users commonly use abbreviations on Twitter, due to 140 characters limit. Abbreviations are a common way of expression, e.g. “LOL” which means “Laughing Out Loudly”. We assign 1 for the presence of abbreviations, and 0 otherwise. If a tweet contains abbreviations, it might be viewed as more informal. We have selected most prevalent abbreviations found in the tweets such as lol, lmfao, lmao, roflmao, etc., from slang lookup table available in the data folder of SentiStrength project[5].

### User Details Features

*Number of Friends:* Friends are defined as all of the followers that a given user follows. Tweets of a user with more friends, will likely be more retweeted. *Number of followers:* If a user has a big number of followers, his/her tweets will gain more visibility in the network. Since more people are visualizing the tweets, the probability of a tweet being retweeted increases. *Number of favorites:* A user with high favorites count indicates that other people like his/her tweets in general, so a tweet created by this user may be retweeted. *Number of lists a user belongs to:* If a user is listed in multiple lists, he is connected and engaged with multiple communities. Consequently, the information that he posts is more likely to be seen by more people. Therefore, tweets made by this user may have a higher probability of being shared. *Verification:* A verified user is usually a celebrity or a media source. These users tend to post credible information, and this information is usually retweeted. *Status Count:* This represents the number of statuses (tweets) posted by a user since the inception of the account. More statuses indicate active user, implying that there might be a chance of sharing his/her information. *Account age:* If a user exists for a longer period of time in the network, he could potentially reach more people. Thus, information posted by this user would likely be retweeted.

## EXPERIMENTS AND RESULTS

In this section, we describe our experimental setup and the results obtained using machine learning approaches. Our goal is to predict how likely a tweet is to be retweeted. We constructed labeled datasets as follows: if a tweet was retweeted more than $k$ times, then the tweet was labeled as positive, otherwise it was labeled as negative. For example, for a retweet threshold value $k$=1, we labeled a tweet as positive if the tweet was retweeted more than one time (the tweet has more than one retweet), and as negative otherwise. Since we are interested in predicting tweets that are likely to be highly retweeted in Twitter during disaster events, it is reasonable to label a tweet as negative, if the tweet is retweeted very few times. In experiments, we used various values of $k$, i.e., 0, 1, 2, 5, 20, 50, 75, 90 and 100, and show results for $k$ = 0, 1, 5, and 20. After the generation

[4] https://en.wikipedia.org/wiki/List_of_emoticons
[5] http://sentistrength.wlv.ac.uk/

of the labeled datasets, we performed experiments with the following feature types (discussed in the Feature Extraction section): Tweet content features (TC), User details features (U) and Bag-of-words (BOW). For evaluation, we performed experiments using five disjoint train and test random splits and averaged the results. Examples in each split are randomly sampled from our 1.1M of initial (direct) tweets. The ratio of positive to negative class is 1:1 for the training set and 1:3 for the test set. We report the average of the metrics: precision, recall, and F-measure. We use Naïve Bayes and Support Vector Machine (SVM) classifiers to perform our experiments, of which Naïve Bayes performs better than SVM. We only show results for Naïve Bayes.

Initially, we started using each of the feature types individually and then formulated several combinations from them. However, not all of the combinations perform well on both the classes. We selected the following feature sets - TC, TC+U, TC+U+BOW, and BOW, which have good performance on both the classes and compare their performance in Tables 4 and 5 using the Naïve Bayes classifier. We show results for several thresholds *k*. The results show that the performance is significantly improved when the threshold is increased, e.g., the F-measure in Table 4 increases from 0.575 (for threshold *k*=0) to 0.74 (for threshold *k*=5) for the TC+U feature set.

**Results Comparison on Feature Types:** Overall, the feature set TC+U gives the best performance for retweet threshold *k*=20. Comparing the results of Table 4, we can see that the conjunction of user details features with tweet content features improved the classifiers' performance. This suggests that the user details and tweet content features are collaboratively assisting each other in boosting the classifier's performance. In Table 5, when we combine TC+U with BOW, the classifier performance has dropped and using only BOW is performing better than TC+U+BOW, but not better than TC+U.

| **Feature Set=** | **TC** | | | **TC+U** | | |
|---|---|---|---|---|---|---|
| **RT Threshold** | **Precision** | **Recall** | **F-Measure** | **Precision** | **Recall** | **F-Measure** |
| Threshold_0 | 0.698 | 0.561 | 0.589 | 0.595 | 0.559 | 0.575 |
| Threshold_1 | 0.656 | 0.564 | 0.592 | 0.68 | 0.733 | 0.688 |
| Threshold_5 | 0.702 | 0.614 | 0.639 | 0.744 | 0.771 | 0.74 |
| Threshold_20 | 0.725 | 0.636 | 0.66 | **0.786** | **0.801** | **0.781** |

**Table 4. Performance of Naive Bayes for various retweet thresholds using TC and TC+U**

| **Feature Set=** | **TC+U+BOW** | | | **Only BOW** | | |
|---|---|---|---|---|---|---|
| **RT Threshold** | **Precision** | **Recall** | **F-Measure** | **Precision** | **Recall** | **F-Measure** |
| Threshold_0 | 0.684 | 0.569 | 0.598 | 0.665 | 0.545 | 0.576 |
| Threshold_1 | 0.688 | 0.737 | 0.694 | 0.659 | 0.597 | 0.62 |
| Threshold_5 | 0.716 | 0.653 | 0.673 | 0.706 | 0.663 | 0.679 |
| Threshold_20 | 0.746 | 0.677 | 0.697 | 0.742 | 0.695 | 0.711 |

**Table 5. Performance of Naive Bayes for various retweet thresholds using TC+U+BOW and only BOW.**

**Results Comparison on Retweet Threshold (*k*):** As we can see from the tables, it is observed that the performance of the classifiers is increasing with the increase in the retweet threshold value. In the above two tables, we reported the results for only 0, 1, 5 and 20, for which a significant improvement is detected with an increase in the threshold. After the threshold 20, the performance is consistent with the increase of the threshold and it starts degrading for threshold *k*=100.

## CONCLUSION AND FUTURE WORK

In this paper, we studied the problem of predicting the retweetability of a tweet in the context of disaster events. We used the tweets posted during the Hurricane Sandy in 2012 as a case study. The strongest contribution of the paper is the design and exploration of features for training machine learning classifiers that can predict how likely a tweet is to be highly retweeted in Twitter. We developed models that automatically predict the retweetability of a tweet and found that classifiers trained on tweets' content features and user details features together outperform those trained using the "bag of words" approach.

The results of our experiments using different threshold values for labeling a tweet as highly retweetable show improved performance for classifiers trained using the combination of tweet content features and user details features over classifiers that are trained on each feature type independently. Our approach, when corroborated with approaches that identify trustworthy and misinformation in Twitter has the potential to help promoting good information as well as to stop the spread of misinformation, by flagging the tweets accordingly to their information content. Interesting directions for future work include predicting the number of retweets for a tweet. It would be interesting to explore how emotional divergence (having diversified emotions in a single message) affects the retweetability of a tweet. We expect that our approach would generalize well to other datasets, yet further experimentation needs to be conducted in future to further validate our findings.

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