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Intelligent Twitter Spam Detection: A Hybrid Approach

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Abstract. Over the years there has been a large upheaval in the social networking arena. Twitter being one of the most widely-used social networks in the world has always been a key target for intruders. Privacy concerns, stealing of important information and leakage of key credentials to spammers has been on the rise. In this paper, we have developed an Intelligent Twitter Spam Detection System which gives the precise details about spam profiles by identifying and detecting twitter spam. The system is a Hybrid approach as opposed to single-tier, single-classifier approaches which takes into account some unique feature sets before analyzing the tweets and also checks the links with Google Safe Browsing API for added security. This in turn leads to better tweet classification and improved as well as intelligent twitter spam detection.

Keywords: Twitter, Spam, Machine Learning, Google Safe Browsing, Hybrid Classifiers.

1 Introduction and Related Work

Twitter is a free Micro-blogging service that allows users to post messages, called tweets, up to 140 characters in length. Its value is in its ease of sharing and accessing user-generated content, including opinions, news, and trending topics. Thus, Twitter provides an opportunity to generate large traffic and revenue, especially since it has hundreds of millions of users.

Twitter users have different levels of awareness with respect to security threats hidden in social networking sites. For example, a previous study has showed that 45% of users on a social networking site readily click on links posted by any friend in their friend lists' accounts, even though they may not know that person in real life. Thus, spammers are attracted to use Twitter as a tool to send unsolicited messages to legitimate users, post malicious links, and hijack trending topics.

However, these opportunities make Twitter a prime target of spammers. It is easy for humans to distinguish spammers from actual users, but the existence of spammers wastes user time and attention, puts users at risk in accessing malicious and dangerous content, and devalues Twitter's services and the overall online social network. Some of the related work in the domain of spam detection is highlighted below:

The features extracted from each Twitter account for purpose of spam detection can be categorized into:

- (i) User-based features
- (ii) Content- based features.

User-based features are based on a user's relationships e.g. those whom a user follow (referred to as friends), and those who follow a user (referred to as followers) or user behaviors e.g. the time periods and the frequencies when a user tweets.

For content-based features, we use some obvious features. The average length of a tweet. Additional content-based features are described in subsequent subsections [4].

Based on the above identified features, we proceed to use traditional classifiers to help detect spammers. In this work, several classic classification algorithms such as Random Forest, Naïve Bayesian, Support Vector Machines, and K nearest neighbors are compared. The Random Forest classifier is known to be effective in giving estimates of what variables are important in the classification. This classifier also has methods for balancing error in class population unbalanced data sets. The naïve Bayesian classifier is based on the well-known Bayes theorem. The big assumption of the naïve Bayesian classifier is that the features are conditionally independent although research shows that it is surprisingly effective in practice without the unrealistic independence assumption[5-8].

2 Problem Statement and Solution Approach

In Twitter Spammer Detection we introduce features which exploit the behavioral-entropy, profile characteristics, spam analysis for spammer's detection in tweets. We take a supervised approach to the problem, but leverage existing hashtags in the Twitter data for building training data. Twitter is one such popular network where the short message communication (called tweets) has enticed a large number of users. Spammer tweets pose either as advertisements, scams and help perpetrate phishing attacks or the spread of malware through the embedded URLs.[9-10] In this system, we fetch twitters tweets for a particular hashtag. Each hashtag may have 1000s of comments and new comments are added every minute, in order to handle so many tweets we are using twiter4j API and perform preprocessing by removing quotes, hash symbols and spam analysis through URL, Number of Unique Mentions (NuMn), Unsolicited Mentions (UIMn), Duplicate Domain Names (DuDn) techniques and google safe browsing API.

3 System Modelling and Architecture

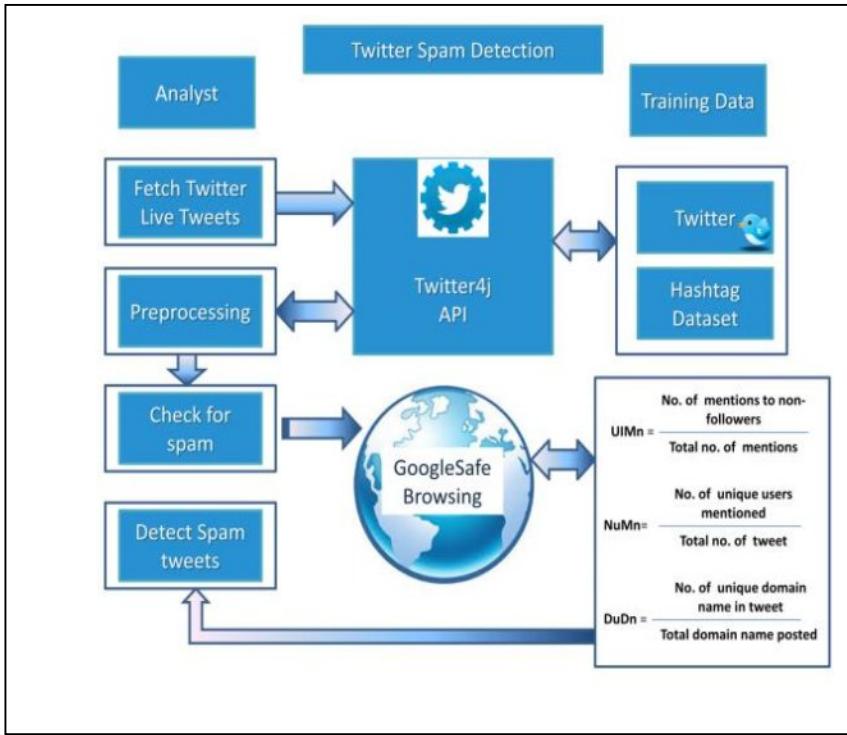


Fig 1.
System Architecture
The above system architecture gives an overview of the

Intelligent Twitter Spam Detection System which consists of unique feature vectors having features such as UIMn, NuMn, DuDn and comparison with Google Safe Browsing lists for detection and cross identification of URLs in Spam Tweets.

4 Algorithm and Tweet Analysis

4.1. Integrate the System with Twitter

The system will integrate with twitter and able to read the tweets for particular hash tags.

4.2. #HashTagging data set

To create the hash tagged data set, we first filter out duplicate tweets, non-English tweets, and tweets that do not contain #hashTags. From the remaining set (about 4 million), we investigate the distribution of #hashTags and identify what we hope will be the sets of frequent #hashTags that are indicative of positive, negative and neutral messages. These #hashTags are used to select the tweets that will be used for development and training.

4.3. Pre-Processing

The first pre-processing technique is remove @ which means it scans the whole document of input dataset and after comparing it with @ it deletes @ from every available comment with @. The next step of pre-processing is remove URL where the whole input document gets scanned and compared with http:\\... and the comments having URL are deleted. Further we move on to stop word removal being the next step in data pre-processing. Stop word removal exactly means that from the whole statement after scanning it removes the words like and, is, the, etc and only keeps noun and adjective. Tokenization and Normalization are carried out thereafter. Porter Stemmer Algorithm is used thereafter. The Porter stemming algorithm (or ‘Porter stemmer’) is a process for removing the commoner morphological and inflectional endings from words in English. Its main use is as part of a term normalization process that is usually done when setting up Information Retrieval systems.

4. Analysis of Tweets

In this phase we are filtering the tweets on the basis of some criterion Checking that is tweets contains URL or not, if it contains then we are passing that URL to Google Safe Browsing API & getting the spam result from Google Safe Browsing API. Furthermore we are checking that is the tweet contains any spam keyword. We have a list spam keyword which are banned by worldwide social networking organization. The Basic criteria to declare a tweet is spam or not is if a tweet contains both a SPAM URL as well as SPAM WORDS. The steps in the analysis of tweets are as under:

- a. Calculating the duplicate tweet count
- b. No of Unique Mentions
- c. Duplicate domain names
- d. Variance in tweet intervals
- e. Unsolicited mentions
- f. AFINN dictionary for finding word and their sense
- g. Finding negative annotations in the sentence and reverse the weight.
- h. Detecting spam tweets.
- i. Detecting spam accounts.
- j. Blocking the spam accounts
- k. Finally, positive, negative or neutral count for that particular #hashTag will be calculated.

4.4 Feature Sets:

- a. Calculating the duplicate tweet count
- b. No of Unique Mentions
- c. Duplicate domain names
- d. Variance in tweet intervals
- e. Unsolicited mentions

On the basis of the above constraints we will block/suspend the account

5 Implementation and Results

In the implementation part of Intelligent Twitter Spam Detection using a Hybrid Approach, we used Twitter 4J API, Google Safe Browsing Toolkit, A combination of classifiers including NB and SVM and unique feature sets that provide an intelligent spam detection solution. The system consists of 6 tabs which were designed in NetBeans using JavaSwing for the front end part. The Twitter Spammer tab consists of buttons that Fetch Live Tweets and Recent Twitter Feed related to the trending hashtags. The tweets are then stored on a local dataset which are then loaded for further analysis. Thereafter pre-processing takes place and the tweets are sent to the next stage for implementation of classification algorithms using the Hybrid Approach. A decision is made based on the code that runs on the filtered tweets using the aforementioned feature vectors and the tweets are classified as SPAM. Furthermore there is a provision for showing Trends-Wise Analysis for a particular hashtag in the next stage after which the final stage shows the suspended twitter accounts which were labelled as SPAM by the system. The analysis for this research was conducted by mining 10,782 tweets comprising of 72 hashtags that were trending on twitter. The system was able to classify 2,466 tweets as SPAM while the others were found legitimate. After cross-checking with Google Safe Browsing it was found that 2,153 tweets did contain a malicious URL that re-directed the user to suspicious websites. This affirmed that the accuracy of the said system stands at **87.30%** with this multi-tier approach which is greater than systems which use a single-classifier and non-hybrid approaches. The snapshots of the system at various stages are as follows:

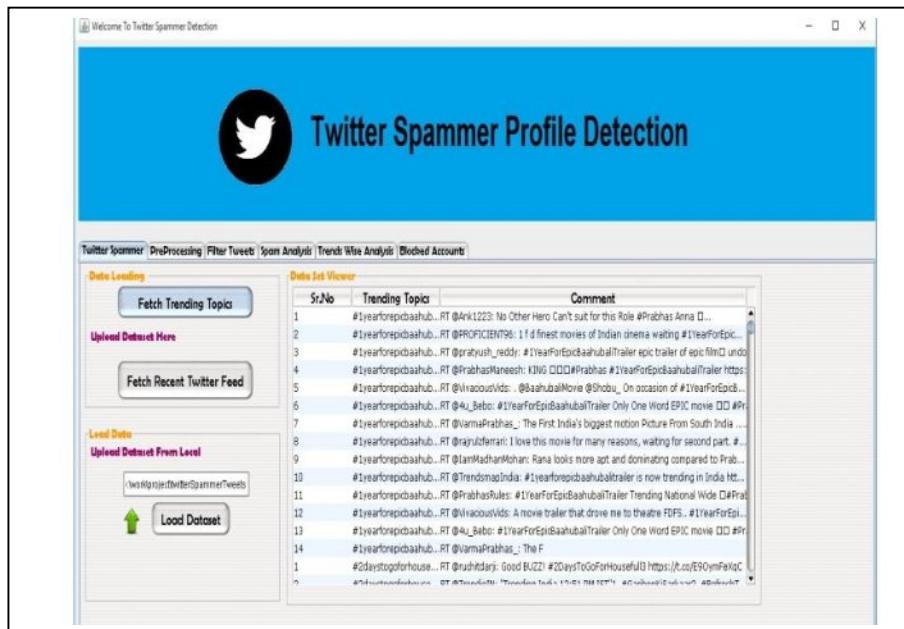


Fig 2. Phase 1: Fetching of Tweets and Trends

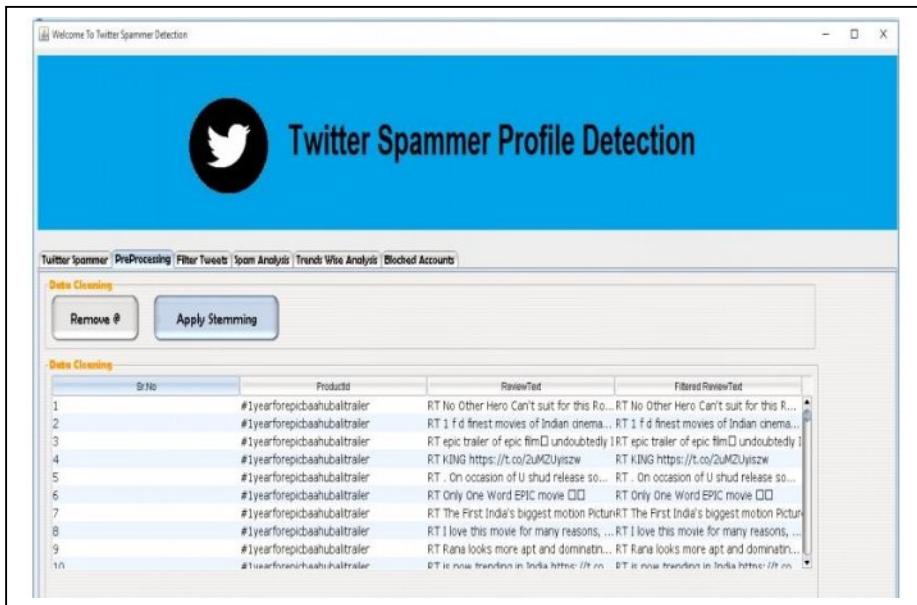


Fig 3. Phase 2: Preprocessing

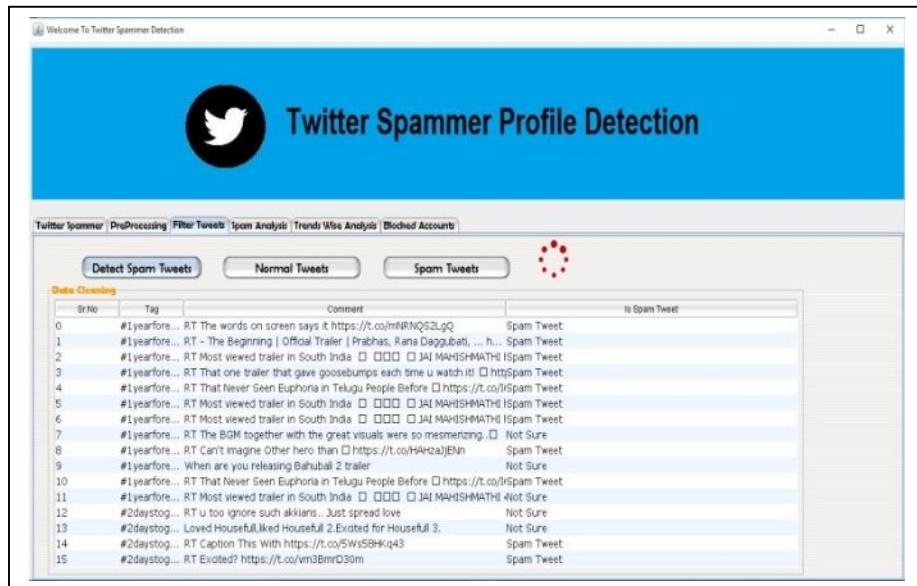


Fig 4. Phase 3: Analysis and Detection of SPAM tweets

After this, the details of SPAM account with the Tweets & Location are displayed.

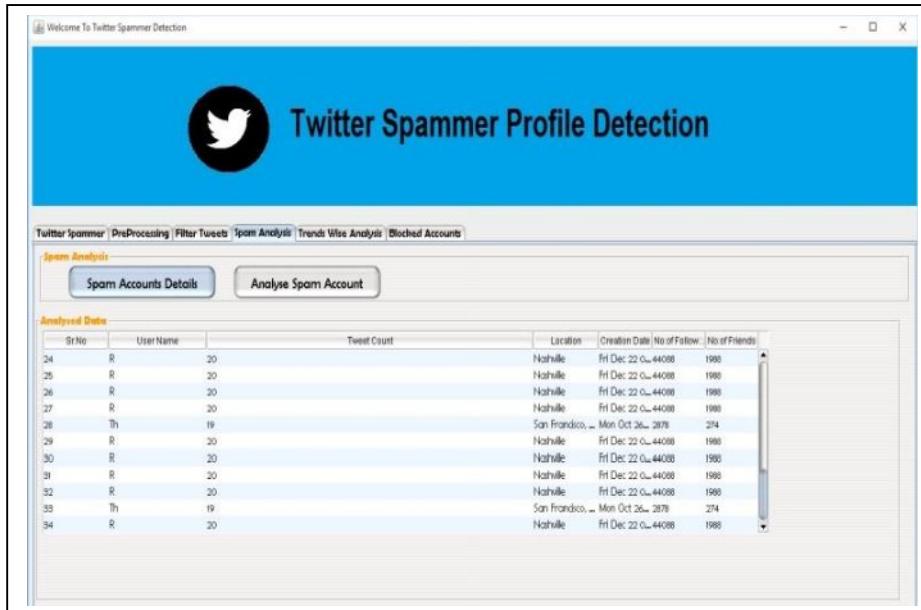


Fig. 5 Phase 4: SPAM Account Details

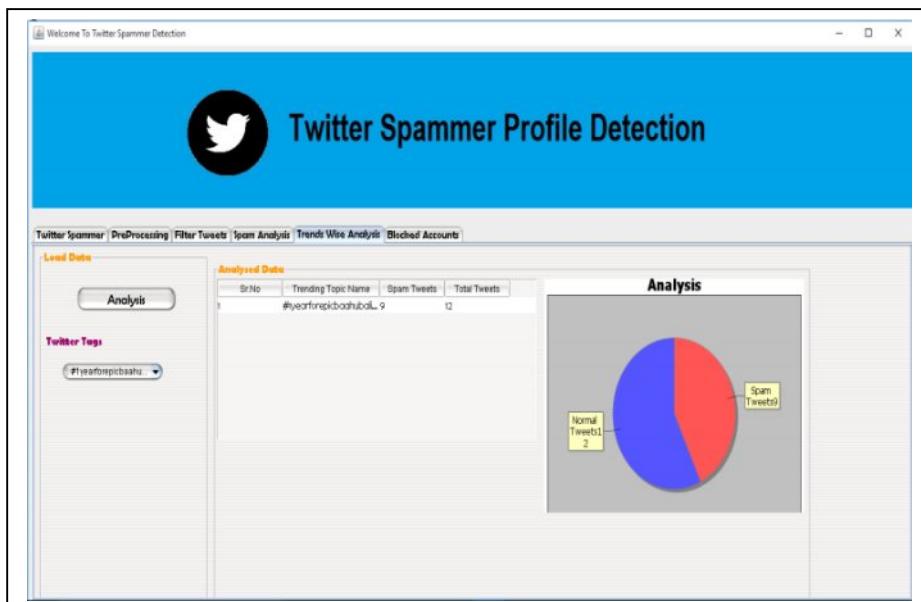


Fig 6. Phase 5: Trends Wise Analysis for a particular Hashtag

6 Conclusion and Future Work

Twitter spammer profile detection makes the efficient use of classifiers so as to differentiate between legitimate accounts and spam profiles. Our approach is novel in its own way due to the inclusion of enhanced feature vectors for building the classification which shall be a proponent as compared to the other existing models. Thus it will enhance the user experience on twitter the way for a nuisance free social networking.

Future work in this regard can comprise of mining Tweets to ascertain even more unique feature sets and discover new techniques of classification that can make twitter spam detection even more accurate in the long run.

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