Semi-Supervised Spam Detection in Twitter Stream

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Abstract

Most existing techniques for spam detection on Twitter aim to identify and block users who post spam tweets. In this paper, we propose a Semi-Supervised Spam Detection (S3D) framework for spam detection at tweet-level. The proposed framework consists of two main modules: spam detection module operating in real-time mode, and model update module operating in batch mode. The spam detection module consists of four light-weight detectors: (i) blacklisted domain detector to label tweets containing blacklisted URLs, (ii) near-duplicate detector to label tweets that are near-duplicates of confidently pre-labeled tweets, (iii) reliable ham detector to label tweets that are posted by trusted users and that do not contain spammy words, and (iv) multi-classifier based detector labels the remaining tweets. The information required by the detection module are updated in batch mode based on the tweets that are labeled in the previous time window. Experiments on a large scale dataset show that the framework adaptively learns patterns of new spam activities and maintain good accuracy for spam detection in a tweet stream.

1 Introduction

Micro-blogging services have attracted the attention of not only legitimate users but also spammers. It is reported that 0.13% of messages advertised on Twitter are clicked, which is two orders of magnitude higher than that of email spam [10]. High click-rate and effective message propagation make Twitter an attractive platform for spammers. Increasing spamming activities have adversely affect user experience as well as many tasks such as user behaviour analysis and recommendation.

Most of the existing studies on Twitter spam focus on account blocking, which is to identify and block spam users, or spammers. Hu et al. utilized social graph and the tweets of a user and formulated spammer detection as an optimization problem [12]. Similarly, information extracted from user’s tweets, demographics, shared URLs, and social connection are utilized as features in standard machine learning algorithms to detect spam users [13]. However, account blocking approach is less effective for spammers who may act as legitimate users by posting non-spam content regularly. Blocking spammers may even hurt a legitimate user who happens to grant permission to a third-party application that posts spammy tweets under her username. This legitimate account may be blocked because of such spam tweets. Furthermore, spammers change their tweet content and strategies to make their tweets and activities look like legitimate [1]. While identifying and blocking spammer accounts remain a crucial and challenging task, tweet-level spam detection is essential to fight against spamming at a more fine-grained level, and helps to timely detect spam tweets instead of waiting for users to be detected as spammers. Similarly, Chen et al. suggested that training dataset should be continuously updated in order to deal with changing distribution of features in tweet stream [4].

In this paper, we propose a semi-supervised framework for spam tweet detection. The proposed framework mainly consists of two main modules: (i) four light-weight detectors in the spam tweet detection module for
detecting spam tweets in real-time, and (ii) updating module to periodically update the detection models based on the confidently labeled tweets from the previous time window. The detectors are designed based on our observations made from a collection of 14 million tweets, and the detectors are computationally effective, suitable for real-time detection. More importantly, our detectors utilize classification techniques at two levels, tweet-level and cluster-level. Here, a cluster is a group of tweets with similar characteristics. With this flexible design, any features that may be effective in spam detection can be easily incorporated into the detection framework. The framework starts with a small set of labeled samples, and update the detection models in a semi-supervised manner by utilizing the confidently labeled tweets from the previous time window. This semi-supervised approach helps to learn new spamming activities, making the framework more robust in identifying spam tweets.

2 Related Work

Spam is a serious problem on almost all online media and spam detection has been studied for many years. Spammers may use different techniques on different platforms so spam detection technique developed for one platform may not be directly applicable on other platforms. Thomas et al. [19] reported that spam targeting email is significantly different from spam targeting Twitter. In Twitter, there are different types of spamming activities such as link farming [9], spamming trending topics [1], phishing [5], aggressive posting using social bot [6], to name a few. These different activities pollute timeline of users as well as Twitter search results.

Many social spam detection studies focus on the identification of spam accounts. Lee et al. [13] analyzed and used features derived from user demographics, follower/following social graph, tweet content and temporal aspect of user behavior to identify content polluters. Hu et al. exploited social graph and tweets of a user to detect spam detection on Twitter. They formulated spammer detection task as an optimization problem [12]. Online learning has been utilized to tackle the fast evolving nature of spammer [11]. They have utilized both content and network information and incrementally update their spam detection model for effective social spam detection.

Tan et al. [18] proposed an unsupervised spam detection system that exploits legitimate users in the social network. Their analysis shows the volatility of spamming patterns in social network. They have utilized non-spam patterns of legitimate users based on social graph and user-link graph to detect spam pattern. Gao et al. [8] identified social spam by clustering posts based on text and URL similarities and detecting large clusters with bursty posting patterns.

Removing spam users cannot filter every spam message as spammer may create another account and restart spamming activity. This calls for tweet-level spam detection. Inspired from content-based techniques for emails, [15] utilized standard classifiers to detect spam tweets. Language modeling approach has been used to compute the divergence of trending topic, suspicious message, and title of the page linked in the tweet [14]. Similarly, Castillo et al. [3] analyzed the credibility of tweets on trending topics based on users’ tweeting and retweeting behaviors, tweet content and link present in the tweets. As spammers keep on evolving over time, hence semi-supervised approach is suitable for tracking such changing spamming activities. Semi-supervised spam detection approach has been utilized to identify spam on voice-over-IP call [21]. Similarly, a semi-supervised approach is reported to have better performance than supervised approach for malware detection task [16]. However, to the best of our knowledge semi-supervised approach has not be utilized to detect spam tweets. Our proposed method is capable of continuously updating itself by using semi-supervised approach.
3 Semi-supervised Spam Detection

The proposed S3D contains two main modules as shown in Figure 1. Assuming that we have all the information (e.g., a blacklist of spamming domains, and trained classification models), the tweets are labeled as spam and non-spam (also known as “ham”) tweets using the four detectors in real-time. The required information is updated periodically based on the confidently labeled tweets from the previous time window, in a semi-supervised manner. Next, we detail the main modules.

3.1 Spam Tweet Detection in Real-Time

For efficiency reason, the tweets are labeled by four lightweight detectors from four perspectives, in an order of the easiest to hardest in terms of difficulty in detection. Once a label is assigned by one of the detectors, the tweet need not pass to the next detector.

Blacklisted Domain Detector. Spammers promote their services/products by posting links in their tweets [8]. An effective way of spam detection is to detect tweets containing links from blacklisted domains. The list of blacklisted domains is to be updated at the end of each time window utilizing confidently labeled tweets, during batch update.

Near-Duplicate Detector. Tweets that are near-duplicates of pre-labeled spam/ham tweets are assigned the same labels accordingly. The near-duplicate tweets are detected by using the MinHash algorithm [2], which has shown effectiveness for labeling spam tweets [17]. More specifically, a signature is computed for each tweet by concatenating the three minimum hash values computed from the tweet’s uni-gram, bi-gram, and tri-gram representations, respectively. If two or more tweets have the same signature, then the tweets are considered near-duplicates. If a cluster of near-duplicate tweets hashed to the same signature has been labeled as spam or ham tweets, the new tweet having the same signature receives the same label.

Reliable Ham Tweet Detector. Tweets posted by legitimate users can be considered as ham tweets, however; spammers may pretend as legitimate users and after gaining acceptance from other users they post spam tweets [22]. Hence, we consider a tweet to be a reliable ham tweet if it satisfies two conditions: (i) the tweet does not contain any spammy words, and (ii) the tweet is posted by a trusted user.

Spammy words are that words whose probability of occurrence is larger in spam than in ham tweets. For example, word followme is likely to appear in spam tweets but the word may appear in ham tweet as well. Specifically, let $p_s(w)$ be the probability of word $w$ appearing in the spam tweets, and $p_h(w)$ be the probability of $w$ in ham tweets. Then $w$ is a spammy word if $p_s(w) > p_h(w)$. In our implementation, words that are shorter than 3 characters in length are ignored.

A trusted user is a user who has never posted any spam tweet and has posted as least 5 confident ham tweets. A tweet is a confident ham tweet if the tweet does not contain any spammy words and is predicted to be ham by all the component classifiers in the tweet classification detector. The clusters of near-duplicate tweets will also be predicted as “clusters of spam” or “clusters of ham” by multiple classifiers. The tweets in a cluster which is predicted to be ham cluster by all classifiers are also considered as confident ham tweets.

During the batch update, the list of trusted users and the list of spammy words are updated.

Multi-classifier based Detector. Tweets that are not labeled in any of the previous steps are processed and labeled in this step. Here, we develop a spam detector by using three efficient classifiers, namely Naïve Bayes (NB), Logistic Regression (LR), and Random Forest (RF). The three classifiers use different classification techniques, i.e., generative, discriminative, and decision tree-based classification models. A full spectrum of features is extracted to represent each tweet. Listed in Table 3 in the column titled “Features for tweet representation”, the features include hashtag-based features, content-based features, user-based features, and domain-based features. Most features are self-explanatory and we only elaborate two features, categorical hashtag, and top domains. Categorical words are the words used in one of the top-level categories in Yahoo! hierarchy, or words used to categorize content in four Web sites: BBC, CNN, NYTimes and Reddit. There are 75 categories including sports, technology, business, movie, jobs etc. The binary feature is 1 if the hashtag is one of the categorical words. The domain
feature is based on the domain of the URLs contained in tweets. Domain ranking is from alexa.com. A tweet is labeled as spam if at least two of the three classifiers predict the tweet to be spam; otherwise the tweet is labeled as ham.

### 3.2 Model Update in Batch Mode

The time window for the update is set to be one day in our experiments. The key desideratum is to identify the confidently labeled data of the previous time window.

**Confidently Labeled Tweets.** Tweets that are labeled by the first three detectors (i.e., blacklisted domain, near-duplicate, and reliable ham tweet) are considered as confidently labeled tweets. For the classifier based detector, recall that we use three classifiers each is based on a different classification technique. Tweets that are labeled as spam by all the three classifiers are considered as confidently labeled spam tweets. Similarly, tweets that do not contain any spammy words and are labeled as ham by all the three classifiers are confidently labeled ham tweets. Excluding ham tweets containing spammy words (e.g., followme) helps to prevent the deviation of classifier from a burst of spammy words in ham tweets.

The identified confidently labeled spam tweets are utilized to update blacklist domains, and confidently labeled ham tweets are utilized to identify trusted users.

**Near-duplicate Cluster Labeling.** Recall that the near-duplicate detector computes a signature for each tweet to check if the tweet is a near-duplicate of a labeled cluster. If the signature of a tweet does not match any pre-labeled signature, then the tweet is passed to the next level detectors.

After each time window, all the tweets that do not match pre-labeled clusters but having the same signature are grouped into a new cluster; i.e., each cluster is a collection of near-duplicate tweets. Next, we label the clusters each containing at least 10 tweets and if the labels are of high confidence, then the signatures of these newly labeled confident clusters will be used by the near-duplicate detector in the next time window. Recall that all the tweets have been labeled as spam and ham tweets (see Figure 1), an easy approach to label these clusters is to perform a majority voting. Specifically, if there are more spams in a cluster than ham tweets, then the cluster is labeled as a spam cluster. However, the majority voting approach solely relies on the predicting power of the detectors and may not capture the new spamming patterns in the most recent time window. Moreover, because tweets in a cluster are near-duplicates, their labels assigned by the detectors are mostly the same. For this reason, we also employ a feature-based classifier.

Each cluster is represented with hashtag-based features, content-based features, user-based features, and domain-based features, as listed in Table 3, the third column. Many of the features used here are adopted from existing studies [3,7]. Different from tweet classification (features listed in the second column), the cluster-level features represent the collective information obtained from all the tweets in the cluster. The clusters represented in feature-space are classified using a logistic regression classifier.

We consider a cluster to be a confidently labeled cluster if the labels predicted by the feature-based cluster classifier and the majority voting of the tweet labels are the same.

**Update Detector Models.** After finding the confidently labeled tweets and clusters, the models used by the detectors are updated accordingly including blacklisted domains, labeled clusters, trusted users and tweet classification models. Blacklisted domains are updated by including domains having at least 5 tweets in the last time window and at least 90% of the tweets are confidently labeled as spam tweets. A user having at least 5 tweets and all tweets are confidently labeled ham tweets is considered as a trusted user. The classification models of the three classifiers are retrained by including the newly labeled confident tweets of the last time window.

By updating the detection models in batch mode, the proposed semi-supervised spam detection framework is capable of capturing new vocabulary and new spamming behaviours, which makes the framework robust and adaptive to deal with the dynamic nature of spamming activities.

### 3.3 Computational Efficiency

All the four spam detectors are computational effective, hence the proposed framework is capable of labeling tweet stream in real-time. We conduct experiments on a desktop PC with octa-core Intel processor of 3.70GHz and 16 GB RAM. In our experiments, all the detectors
are carried out on a single-core of the processor, except random forest classifier which utilizes all the cores of the processor. Empirically, we found that on average it takes 0.495 ms to label a tweet where more than 50% of the time is used for feature extraction. Note that, our code is not optimized for real-time setting, and efficiency can be further improved by parallelising the detectors.

4 Experiment and Discussion

We used 15 days of data from HSpam14 dataset [17] in our experiments. HSpam14 contains 14 million tweets, collected by using the trending topics on Hashtags.org for two months, May and June 2013. In this research, we use 15 days of tweets (May 17 - 31, 2013) where each day has more than 35 thousand tweets. The time window for batch mode update is set to be a day. Almost all tweets in HSpam14 are labeled to be spam and ham and the remaining small portion are labeled as unknown for not being able to determine their labels even with manual inspection. Note that, more than 80% of tweets in HSpam14 are labeled automatically and the manually labeled tweets are biased to spams.

We simulate a tweet stream in our experiments. On the first day, the detectors in S<sup>3</sup>D are trained by using the manually labeled tweets and the reliable ham tweets in the HSpam14 dataset (the released HSpam14 dataset contains the detailed labels of the tweets, i.e., on which step a tweet was labeled during dataset construction). These training tweets are utilized to create the initial set of blacklisted domains, labeled clusters, trusted users, labeled tweets and spammy words. There are 48849 spam tweets and 22185 ham tweets. The remaining tweets on the first day and all the tweets of the remaining 14 days are used for testing purpose. Because not all tweets in HSpam14 are manually labeled, to ensure the accuracy of the evaluation in our experiments, we manually label 300 randomly selected tweets from each time window to evaluate the performance of the system<sup>1</sup>. The performance is evaluated using the commonly used metric: Precision, Recall, and $F_1$.

Supervised spammer detection on Twitter such as [7, 13] focus on spammer detection whereas our work is on tweet-level spam detection. Hence, these spammer detection systems cannot be compared with our proposed method. Previous tweet-level spam detection studies used off-the-shelf classifiers namely, Naïve Bayes, Logistic Regression and Random Forest classifier, in supervised settings. We have also used these methods to compare the performance with that of our proposed system. More specifically, tweet classification using logistic regression reported in this paper is similar to the work on information credibility [3] and also similar to the method reported in [14]. Most of the features described in the information credibility paper except propagation related features are used in the S<sup>3</sup>D as well. Propagation related features are not available in HSpam14 dataset so those features could not be used. Similarly, Naïve Bayes and Random Forest classifiers are used in [14, 15, 20] for tweet-level spam detection. Random Forest classifier is found to be superior among all the other methods [15, 20]. In our experiments, we compare the results of S<sup>3</sup>D with the classification results of using these classifiers in supervised setting.

4.1 Result and Discussion

S<sup>3</sup>D has four detectors as shown in Figure 1. Table 1 reports the percentage of tweets labeled by each detector. It shows that 5.55% of the tweets are labeled by the blacklisted domain detector and 6.61% of the tweets are labeled by the near-duplicate detector. Reliable ham tweet detector has very low coverage of 0.64%. The low coverage is due to the fact that the HSpam14 dataset was collected based on popular hashtags, not on user basis [17]. In other words, the dataset does not contain all tweets of any user. Because a trusted user should have at least 5 ham tweets, only a small set of users can be identified as trusted users. Remaining 87.20% of tweets are labeled by the last detector, tweet classifier. Next, we report the spam detection performance of S<sup>3</sup>D with more focus on the tweet clas-
We now report the performance of the following five methods for the spam tweet detection task.

- **Naive Bayes (NB)**: This method reports the prediction results of the Naive Bayes classifier rely on the training data of the first day.
- **Logistic Regression (LR)**: This method reports the prediction results of the Logistic Regression classifier rely on the training data of the first day.
- **Random Forest (RF)**: This method reports the prediction results of the Random Forest classifier rely on the training data of the first day.
- **S\textsuperscript{3}D-Update**: The results of the S\textsuperscript{3}D framework without batch update. That is, the detectors in the framework fully rely on the training data of the first day, the same as the three classifiers above.
- **S\textsuperscript{3}D**: The results of the proposed S\textsuperscript{3}D framework, with model update after each time window.

Figure 2 plots the Precision, Recall and F\textsubscript{1} scores of the five methods. Observe S\textsuperscript{3}D achieves the best F\textsubscript{1} scores. The significant better F\textsubscript{1} scores against S\textsuperscript{3}D-Update over all days shows that semi-supervised approach is suitable for real-time spam detection in Twitter as it learns new spamming patterns continuously. Comparing S\textsuperscript{3}D with the F\textsubscript{1} scores of NB, LR and RF shows that proposed method is superior to standard supervised methods. Observe F\textsubscript{1} scores of S\textsuperscript{3}D is consistent over time compare to other methods. It is observed that precision of RF is best for 3 days but recall is the lowest of all. In contrast, NB has good recall at the expense of lower precision. The results show that proposed S\textsuperscript{3}D method is effective to capture spam tweets effectively.

The sudden rise of the F\textsubscript{1} scores on the 12\textsuperscript{th} day is due to a large number of relatively easy to detect spam tweets in that day. In HSpam14 dataset, the tweets were collected by using trending keywords of each day which leads to change in the distribution of words of each day. The significant fluctuation of performance of S\textsuperscript{3}D may be due to the changing distribution of dataset in each time window. However, as S\textsuperscript{3}D continuously learns new patterns and vocabulary, its performance is found to be more consistent compare to other methods. More specifically, Figure 3(a) plots the number of blacklisted domains, confidently labeled near-duplicate clusters and trusted users. It shows that S\textsuperscript{3}D keeps on utilizing new knowledge obtained from earlier labeled tweets and clusters to improve the capability of spam tweets detection. Furthermore, we have also used top 10,000 frequent uni-/bi- and tri-grams computed at the end of each time window to update the model to deal with vocabulary change (see Table 3).
In $S^3D$, we identify the confidently labeled tweets and the confidently labeled near-duplicate clusters. The confidently labeled tweets and clusters are utilized to learn new models for the detectors. The quality of these confidently labeled tweets and clusters are therefore crucial for the performance of $S^3D$. Here, we evaluate the quality of these tweets and clusters, plotted in Figure 3(b). The confident clusters are evaluated by manually labeled 47 randomly selected clusters on each day, which is the smallest number of confidently labeled clusters produced over the 15 days. Figure 3(b) shows that the precision of confident clusters is almost perfect for both spam and ham clusters. The figure also shows that the precision of confidently labeled spam and ham tweets are consistently above 95%. Adding such clusters and tweets in the training process makes $S^3D$ capable of capturing emerging spamming activities as well as new vocabulary.

### 4.2 Feature Analysis

There are four types of features used to represent tweet and cluster for classification (see Table 3). In our experiments, we observe that normalization of features gives better performance than without normalization. Because users’ followers, followees and total tweets exhibit power law distributions. The features derived from these values are normalized based on percentile. Features such as length of a tweet in characters and words show normal distribution which are normalized by the maximum value. Based on the Gini impurity score, we identify the top-15 most effective features for tweet classification and cluster classification respectively. These features are highlighted in Table 3 in “$(x)$” format, where $x$ is the top ranking position.

It is observed that 10 out of the top-15 most effective features are vocabulary-based features for tweet classification whereas in the case of cluster classification only 3 out of the top-15 features are vocabulary-based features. Meta-data of a tweet contains information only about the single tweet which is comparatively less informative. In contrast, a cluster contains a number of tweets, hence meta-data based features represent the collective information of tweets in the cluster and are comparatively more informative. For example, if there is a tweet from a user whose account creation date is known and has very few followers and followees, it is hard to determine that tweet posted by this user is ham or spam. In contrast, if there is a group of users whose accounts are created around the same time and all having very few number of followers and followees, and posting near-duplicate tweets, then the tweets in this cluster are likely to be spam.

Table 2 lists the top-15 vocabulary-based features (uni-gram, bi-gram and tri-gram). Only uni-gram and bi-gram vocabulary appear in the top ranked list. One possible reason for tri-gram features not in the list may be due to the sparsity of the tri-gram vocabulary in the dataset. It is interesting to note that most of the top words based on Gini-impurity score are the same as the list of hashtags having the highest spammy-index reported in [17].
Table 3: Features used to represent tweets and clusters for classification; \textit{FoT} means \textit{Fraction of Tweets} and \textit{FoU} means \textit{Fraction of Users}. The top-15 most effective features for tweet classification and cluster classification based on the Gini impurity score are indicated by the numbers \((x)\) following the features \((1 \leq x \leq 15)\).

| Type   | Features for tweet representation | Features for cluster representation |
|--------|-----------------------------------|-------------------------------------|
| \textbf{Hashtag} | Contains hashtag | \textit{FoT} having hashtag \((3)\) |
|        | Contains more than 2 hashtags \((1)\) | \textit{FoT} having more than 2 hashtags \((5)\) |
|        | Contains spammy hashtag \((2)\) | \textit{FoT} having spammy hashtag \((14)\) |
|        | Contains categorical hashtag \((7)\) | \textit{FoT} having categorical word as hashtag |
|        | Contains capitalized hashtag \((8)\) | \textit{FoT} having capitalized hashtag \((4)\) |
| \textbf{Content} | Fraction of words that are spammy | \textit{FoT} having spammy words |
|        | Contains question mark | \textit{FoT} having question mark |
|        | Contains money sign | \textit{FoT} having money sign |
|        | Contains exclamation sign \((13)\) | \textit{FoT} having positive emoticons \((7)\) |
|        | Contains negative emoticons | \textit{FoT} having negative emoticons |
|        | Contains positive words | \textit{FoT} having positive words |
|        | Contains negative words | \textit{FoT} having negative words \((8)\) |
|        | Fraction of uppercase characters \((9)\) | \textit{FoT} that are retweet \((6)\) |
|        | Contains URL \((11)\) | \textit{FoT} having URL |
|        | Is retweet | Mentions per tweet \((15)\) |
|        | Contains mention \((14)\) | \textit{FoT} tweets having first person pronoun |
|        | Contains first person pronoun | \textit{FoT} tweets having second person pronoun |
|        | Contains second person pronoun | \textit{FoT} tweets having third person pronoun |
|        | Contains third person pronoun | \textit{FoT} tweets having third person pronoun |
|        | Normalized length of the tweet in word | Median tweet length in words/\text{max tweet length} |
|        | Normalized length of the tweet in character \((10)\) | Median tweet length in characters/140 |
|        | Contains top \(10,000\) uni-/bi-/tri-gram of last time window | Contains top \(10,000\) uni-/bi-/tri-gram of the last time window |
|        | Day of the week in which the tweet is posted | Ratio of spamb tweets in the cluster \((1)\) |
| \textbf{User} | Has less than 5 percentile followers \((3)\) | \textit{FoU} having less than 5 percentile followers |
|        | Has less than 5 percentile followees \((6)\) | \textit{FoU} having less than 5 percentile followees |
|        | Has more than 50 percentile total tweets | \textit{FoU} having more than 50 percentile total tweets |
|        | Percentile followers of the user \((15)\) | Median percentile of followers of users |
|        | Percentile followers of the user | Median percentile of followers of users |
|        | Percentile total tweet count of the user | Median percentile of total tweets of the users \((11)\) |
|        | User profile contains description \((5)\) | \textit{FoU} having description in profile |
|        | User profile description contains spammy words | \textit{FoU} having spammy words in description |
|        | User profile has url | \textit{FoU} having URL in profile |
|        | User profile has location info | \textit{FoU} having location info in profile |
|        | User profile has time-zone info | \textit{FoU} having timezone info in profile |
|        | Followers-followees ratio \((4)\) | \textit{FoU} having followers greater than followee |
|        | User’s normalized age \((12)\) | Median normalized age of users |
|        | Fraction of post by the dominating user \((9)\) | Fraction of post by the dominating user \((9)\) |
|        | Percentile followers of the user tweeting the most | Percentile followers of the user tweeting the most |
|        | Percentile followees of the user tweeting the most | Percentile followees of the user tweeting the most |
|        | Percentile total tweets of the user tweeting the most | Percentile total tweets of the user tweeting the most |
|        | Tweets per user | Tweets per user |
|        | Standard deviation of normalized age of users \((13)\) | Standard deviation of normalized age of users \((13)\) |
|        | Percentile followers of the most followed user | Percentile followers of the most followed user |
|        | Percentile followees of the most followed user | Percentile followees of the most followed user |
|        | Percentile total tweets of the most followed user | Percentile total tweets of the most followed user |

| \textbf{Domain} | URL from top 100 domains | \textit{FoT} having URL from top 100 domains |
|                | URL from top 1000 domains | \textit{FoT} having URL from top 1000 domains |
|                | URL from top 10000 domains | \textit{FoT} having URL from top 10000 domains |
5 Conclusion

In this paper, we propose a semi-supervised spam detection framework, named S3D. S3D utilizes four lightweight detectors to detect spam tweets on real-time basis and update the models periodically in batch mode. The experiment results demonstrate the effectiveness of semi-supervised approach in our spam detection framework. In our experiment, we found that confidently labeled clusters and tweets make the system effective in capturing new spamming patterns. Due to the limited user information in the dataset, we have used the simple technique to deal with user-level spam detection. However, we argue that the user-level spam detection can be incorporated into S3D, which is part of our future work.

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