DEEP LEARNING METHOD IN NETWORKING INTRUSION DETECTION USING BAT ALGORITHM

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ABSTRACT:

Social networking sites engage millions of users around the world. The users' interactions with these social sites, such as Twitter and Facebook have a tremendous impact and occasionally undesirable repercussions fordaily life. The prominent social networking sites have turned into a target platform for the spammers to dispersea huge amount of irrelevant and deleterious information. Twitter, for example, has become one of the most extravagantly used platforms of all times and therefore allows an unreasonable amount of spam. Fake users send undesired tweets to users to promote services or websites that not only affect legitimate users but also disrupt resource consumption. Moreover, the possibility of expanding invalid information to users through fake identities has increased those results in the unrolling of harmful content. Recently, the detection of spammers and identification of fake users on Twitter has become a common area of research in contemporary online social Networks (OSNs). In this paper, we perform a review of techniques used for detecting spammers on Twitter. Moreover, a taxonomy of the Twitter spam detection approaches is presented that classifies the techniques based on their ability to detect: (i) fake content, (ii) spam based on URL, (iii) spam in trending topics, and fake users. The presented techniques are also compared based on various features, such as user features, content features, graph features, structure features, and time features. We are hopeful that the presented study will be a useful resource for researchers to find the highlights of recent developments in Twitter spam detection on a single. It has become quite unpretentious to obtain any kind of information from any source across the world by using the Internet. The increased demand of social sites permits users to collect abundant amount of information and data about users. Huge volumes of data available on these sites also draw the attention of fake users [1]. Twitter has rapidly become an online source for acquiring real-time information about users. Twitter is an Online Social Network (OSN) where users can share anything and everything, such as news, opinions, and even their moods. Several arguments can be held over different topics, such as politics, current affairs, and important events. When a user tweets something, it is instantly conveyed to his/her followers, allowing them to outspread the received information at a much broader level [2]. With the evolution of OSNs, the need to study and analyze users' behaviors in online social platforms has intensified. Many people who do not have much information regarding the OSNs can

easily be triced by the fraudsters. There is also a demand to combat and place a control on the people who use OSNs only for advertisements and thus spam other people's accounts. Recently, the detection of spam in social networking sites attracted the attention of researchers. Spam detection is a difficult task in maintaining the security of social networks. It is essential to recognize spams in the OSN sites to save users from various kinds of malicious attacks and to preserve their security and privacy. These hazardous maneuvers adopted by spammers cause massive destruction of the community in the real world. Twitter spammers have various objectives, such as spreading invalid information, fake news, rumors, and spontaneous messages. Spammers achieve their malicious objectives through advertisements and several other means where they support different mailing lists and subsequently dispatch spam messages randomly to broadcast their interests. These activities cause disturbance to the original users who are known as non-spammers. In addition, it also decreases the repute of the OSN platforms. Therefore, it is essential to design a scheme to spot spammers so that corrective efforts can be taken to counter their malicious activities [3]. Several research works have been carried out in the domain of Twitter spam detection. To encompass the existing state- of the-art, a few surveys have also been carried out on fake user identification from Twitter. Tingmin et al. [4] provide a survey of new methods and techniques to identify Twitter spam detection. The above survey presents a comparative study of the current approaches. On the other hand, the authors in [5] conducted a survey on different behaviors exhibited by spammers on Twitter social network. The study also provides a literature review that recognizes the existence of spammers on Twitter social network. Despite all the existing studies, there is still a gap in the existing literature. Therefore, to bridge the gap, we review state-of- the-art in the spammer detection ad fake user identification on Twitter. Moreover, this survey presents a taxonomy of the Twitter spam detection approaches and attempts to offera detailed description of recent developments in the domain. The aim of this paper is to identify different approaches of spam detection on Twitter and to present a taxonomy by classifying these approaches into several categories. For classification, we have identified four means of reporting spammers that can be helpful in identifying fake identities of users. Spammers can be identified based on: (i) fake content, (ii) URL based spam detection, (iii) detecting spam in trending topics, and (iv) fake user identification. Table1provides a comparison of existing techniques and helps users to recognize the significance and effectiveness of the proposed methodologies in addition to providing a comparison of their goals and results. Table2 compares different features that are used for identifying spam on Twitter. We anticipate that this survey will help readers find diverse information on spammer detection techniques at a single point. This article is structured such that Section II presents the taxonomy for the spammer detection techniques on Twitter. The comparison of proposed methods for detecting spammers on Twitter is discussed in Section III. Section IV presents an overall analysis and discussion, whereas Section V concludes the paper and highlights some directions for future.

II. SPAMMER DETECTION ON TWITTER

In this article, we elaborate a classification of spammer detection techniques. Fig.1shows the proposed taxonomy for identification of spammers on Twitter. The proposed taxonomy is categorized into four main classes, namely, (i) fake content, (ii) URL based spam detection, (iii) detecting spam in trending topics, and (iv) fake user identification. Each category of identification methods relies on a specific model, technique, and detection algorithm. The first category (fake content) includes various techniques, such as regression prediction model, malware alerting system, and L fun scheme approach. In the second category (URL based spam detection), the spammer is identified in URL through different machine learning algorithms. The third category (spam in trending topics) is identified through Naïve Bayes classifier and language model divergence. The last category (fake user identification) is based on detecting fake users through hybrid techniques. Techniques related to each of the spammer identification categories are discussed in the following subsections.

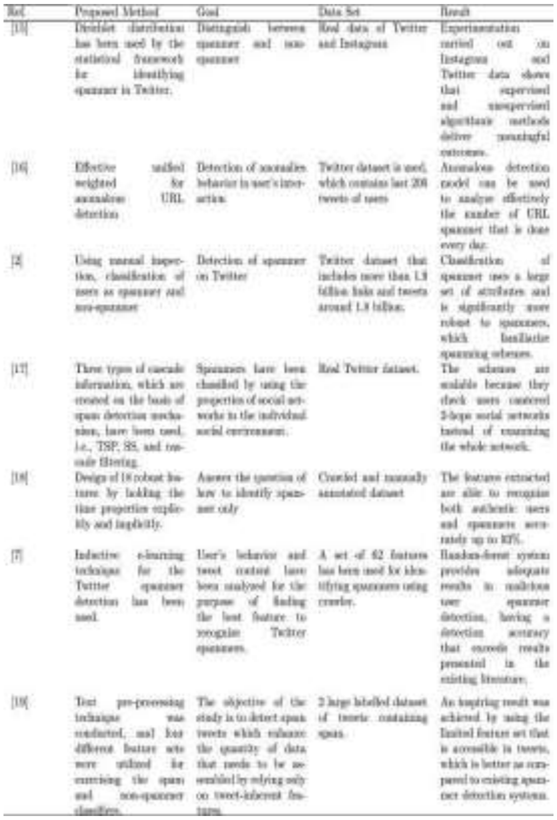
A.FAKE CONTENT BASED SPAMMERDETECTION

Gupta et al. [6] performed an in-depth characterization of the components that are affected by the rapidly growing maliciouscontent. It was observed that a large number of people with high social profiles were responsible for circulating fake news. To recognize the fake accounts, the authors selected, the accounts that were built immediately after the Boston blast and were later banned by Twitter due to violation of terms and conditions. About 7.9 million distinctive tweets were collected by 3.7 million distinctive users. This dataset is known as the largest dataset of Bostonblast. The authors performed the fake content categorizationthrough temporal analysis where temporal distribution of tweets is calculated based on the number of tweets posted per hour. Fake tweet user accounts were analyzed by the activities performed by user accounts from where the spam tweets were generated. It was observed that most of the fake tweets were shared by people with followers.

Subsequently,the sources of twet analysis we analyzed by the medium from where the tweets were posted. It was found that most of the tweets containing any information were generated through mobile devices and non-informative tweets were generated more through the Web interfaces. The role of user attributes in the identification of fake content was calculated through:(i) the average number of verified accounts that were either spam or non-spam and

(ii) the number of followers of the user accounts. The fakecontent propagation was identifiedthrough the metrics thatinclude: (i) social reputation, (ii) global engagement, (iii)topic engagement, (iv) likability, and (v) credibility. Afterthat, the authors utilized regression prediction model toensure the overall impact of people who spread the fakecontent at that time and also to predict the fake contentgrowth in future. Concone et al. [7] presented amethodology that provides malignant alerting by using aspecified set of tweets in real-time conquered through the Twitter API. Afterwards, features into new ones, that is, computing new features as some functions of the old ones[6]. Although stemming is considered by the TextClassification community to amplify the classifiersperformance, there are some he batch of tweets considering the same topic is sum up to generate an alert. The proposed architecture is used to evaluate Twitter posting, recognizing the advancement of admissible event, and reporting of that event itself. The proposed approach utilizes the information contained in the tweets when a spam or malware is recognized by the users or the report of security has been released by the certified, the batch of tweets considering the same topic is sum up to generate an alert. The proposed architecture is used to evaluate Twitter posting, recognizing the advancement of admissible event, and reporting of that event itself. The proposedapproach utilizes the information contained in the tweets when a spam or malware is recognized by the users or the report of security has been released by the certified. Doubts on the actual importance of aggressive stemming, such as performed by the Porter Stemmer [7]. An ancillary feature engineering choice is the representation of the feature value [8]. Often a Boolean indicator of whether the word occurred in the document is sufficient. Most of the text categorization algorithms in the literature represent documents as collections of words. An alternative which has not been sufficiently explored is the use of word meanings, also known as senses. Kehagias et al. using several algorithms, they compared the categorization accuracy of classifiers based on words to that of classifiers based on sense[9]. Methods for feature subset selection for text document classification task use an evaluation function that is applied to a he batch of tweets considering the same topic is sum up to generate an alert. The proposed architecture is used to evaluate Twitter posting, recognizing the advancement of admissible event, and reporting of that event itself. The proposed approach utilizes the information contained in the tweets when a spam or malware is recognized by the users or the report of security has been released by the certified, the batch of tweets considering the same topic is sum up to generate an alert. The proposed architecture is used to evaluate Twitter posting, recognizing the advancement of admissible event, and porting of that event itself. The proposedapproach utilizes the information contained in the tweets when a spam or malware is recognized by or the report of security has been released by the certified or when the window size reaches the maximum, (iv) alert subsystem that is used when the event is established, the system groups up the tweets that are relevant to the same topic where tweets are distinguished with the cluster barycenter and the one that is nearest to the cluster center is chosen as the representative of the whole system cluster, and (v) feedback analysis. The approach is claimed to be efficient and effective for the detection of some invasive and admirable malignant activities in circulation. Moreover, Eshraqi et al. [8] determined different features to detect the spam and then with the help of a den stream based clustering algorithm,

recognize the spam tweets. Some user accounts were selected from various datasets and afterwards random tweets were selected from these accounts. The tweets are subsequently categorized as spam and no spam. The authors claimed that the algorithm can divide the data into spam and non-spam with high accuracy and fake tweets maybe recognized with high accuracy and precision. Various features can be used to determine the spams. For example, feature based on the graph is a state in which Twitter is shaped as a social model of a graph. If the number of followers is low in comparison with the number of followings,the credibility of an account is low and the possibility that theaccount is spam is relatively high. Likewise, feature basedon content includes tweets reputation, HTTP links, mentionsand replies, and trending topics. For the time feature, if manytweets are sent by a user account in a certain time interval,then it is a spam account. The dataset of the study comprised50,000 user accounts. The approach identified the spammersand fake tweets with high accuracy.A Lfun (learning for unlabeled tweets) scheme, which isused to handle various problems in the detection of Twitterspam, has been presented by Chenet al. [9]. Their frameworkcomprises two components, i.e., learn from detectedtweets (LDT) and learn from human labelling (LHL). The twocomponents are used to automatically generate spam tweetsfrom the given set of unmarked tweets that are easily collectedfrom the Twitter network side. Once the labelled spam tweetsare obtained, random forest algorithm is used to perform classification. The performance of the scheme is evaluated while detecting drifted spam tweets. The experiments were performed on the real-world data of ten continuous dayswith each day having 100K tweets each for the spam andnon- spam. The F-measure and the detection rate were usedto evaluate the performance of the presented scheme. The results of the proposed approach showed that the methodology improves the accuracy of spam detection significantly inthe real- world situations.Furthermore, Themethod was applied on the Twitter fake news dataset andthe model was trained against a crowd sourced worker basedon the assessment of journalists. The two Twitter datasetswere used to study the integrity in OSNs. The first datasetCREDBANK, a crowd- sourced dataset, was used to evaluatethe accuracy of events in Twitter whereas the second datasetcalled PHEME is a journalist-labelled dataset of possiblerumors in Twitter and journalistic evaluation of their accuracy.A total of 45 features were described that fall intofour categories: structural feature, user feature, content feature,and temporal features. Aligning labels in PHEME andBUZZFEED contain classes that describe whether a story isfake or true. Results of the analysis are helpful in studyinginformation on social media to know where such stories support similar pattern.



Ref.	Proposed Method	Goal	Data Set	Result
[15]	Dirichlet distribution has been used by the statistical framework for identifying spammer in Twitter.	Distinguish between spammer and non-spammer	Real data of Twitter and Instagram	Experimentation carried out on Instagram and Twitter data shows that supervised and unsupervised algorithms methods deliver meaningful outcomes.
[16]	Effective unified weighted for anomalous URL detection	Detection of anomalies behavior in user's interaction.	Twitter dataset is used, which contains last 200 tweets of users	Anomalous detection model can be used to analyze effectively the number of URL spammer that is done every day.
[2]	Using manual inspection, classification of users as spammer and non-spammer	Detection of spammer on Twitter	Twitter dataset that includes more than 1.9 billion links and tweets around 1.8 billion.	Classification of spammer uses a large set of attributes and is significantly more robust to spammers, which familiarize spamming schemes.
[17]	Three types of cascade information, which are created on the basis of spam detection mechanism, have been used, i.e., TSP, SS, and cascade filtering.	Spammers have been classified by using the properties of social networks in the individual social environment.	Real Twitter dataset.	The schemes are scalable because they check users centered 2-hops social networks instead of examining the whole network.
[18]	Design of 18 robust features by holding the time properties explicitly and implicitly.	Answer the question of how to identify spammer only	Crawled and manually annotated dataset	The features extracted are able to recognize both authentic users and spammers accurately up to 93%.
[7]	Inductive e-learning technique for the Twitter spammer detection has been used.	User's behavior and tweet content have been analyzed for the purpose of finding the best feature to recognize Twitter spammers.	A set of 62 features has been used for identifying spammers using crawler.	Random-forest system provides adequate results in malicious user spammer detection, having a detection accuracy that exceeds results presented in the existing literature.
[19]	Text pre-processing technique was conducted, and four different feature sets were utilized for exercising the spam and non-spammer classifiers.	The objective of the study is to detect spam tweets which enhance the quantity of data that needs to be assembled by relying only on tweet-inherent features.	2 large labelled dataset of tweets containing spam.	An inspiring result was achieved by using the limited feature set that is accessible in tweets, which is better as compared to existing spammer detection systems.

TABLE 1. Comparison between proposed methodsfor spam detection in Twitter.

B. URL BASED SPAM DETECTION

Chen et al. [11] performed an evaluation of machine learning algorithms to detect spam tweets. The authors analyzed the impact of various features on the performance of spam detection, for example: (i) spam to non-spam ratio,

(ii) size of training dataset, (iii) time related data, (iv) factor discretization, and (v) sampling of data. To evaluate the detection, first, around 600 million public tweets were collected and subsequently the authors applied the Trend micro's web reputation system to identify spam tweets as much as possible. A total of 12 lightweight features were also separated to distinguish non-spam and spam tweets from this identified dataset. The characteristics of identified features were represented by cdf figures. These features are grasped to machine learning based spam classification, which are later used in the experiment to evaluate the detection of spam. Four datasets are sampled to reproduce different scenarios. Since no dataset is available publicly for the task, few datasets were used in previous researches. After the identification of spam tweets, 12 features were gathered. These features are divided into two classes, user- based features and tweet-based features. The user-based features are identified through various objects such as account age and number of user favorites, lists, and tweets. The identified user-based features are parsed from the

JSON structure. On the other hand, the tweet- based features include the number of (i) retweets, (ii) hashtags,

(iii) user mentions, and (iv) URLs. The result of evaluation shows that the changing feature distribution reduced the performance whereas no differences were observed in the training dataset distribution.

C.DETECTING SPAM IN TRENDING TOPIC

Gharge et al. [3] initiate a method, which is classified on the basis of two new aspects. The first one is the recognition of spam tweets without any prior information about the users and the second one is the exploration of language for spam detection on Twitter trending topic at that time. The system framework includes the following five steps.

1. The collection of tweets with respect to trending topics onTwitter. After storing the tweets in a particular file format, the tweets are subsequently analyzed.
2. Labelling of spam is performed to check through all datasets that are available to detect the malignant URL.
3. Featureextractionseparatesthe characteristics construct based on the language model that uses language as a tool and helps in determining whether the tweets are fake or not.4.The classification of data set is performed by shortlisting the set of tweets that is described by the set of features provided to the classifier to instruct the model and to acquire the knowledge for spam detection.

5.The spam detection uses the classification technique to accept tweets as the input and classify the spam and no spam. The experimental setup was prepared for determining the accuracy of the system. For this purpose, a random sample set of 1,000 tweets was collected from which 60% were legal and the rest were defected. Stafford et al. [12] examined the degree to which the trending affairs in Twitter are exploited by spammers. Although numerous methods to detect the spam have been proposed, the research on determining the effects of spam on Twitter.

D.FAKE USER IDENTIFICATION

A categorization method is proposed by Er³ahin et al. [1] to detect spam accounts on Twitter. The dataset used in the study was collected manually. The classification is performed by analyzing user-name, profile and background image, number of friends and followers, content of tweets, description of account, and number of tweets. The dataset comprised 501 fake and 499 real accounts, where 16 features from the information that was obtained from the Twitter APIs were identified. Two experiments were performed for classifying fake accounts. The first experiment uses the Naïve Bayes learning algorithm on the Twitter dataset including all aspects without discretization, whereas the second experiment uses the Naïve Bayes learning algorithm on the Twitter dataset after the discretization.

III. COMPARISON OF APPROACHES FORSPAMDETECTION ON TWITTER

This section provides the comparison of proposed methodology along with their goals, datasets that are used to analyze spams, and results of the experiments of each method,as shown in Table1.

A.ANOMALY DETECTION BASED ON URL Chauhan

et al. [16] proposed a methodology for the detection of anomalous tweets. The type of abnormality that is distributed on Twitter is the type of URL anomaly. Anomalous users use various URL links for creating spams. The proposed methodology ,which is used to identify various anomalous activities from social networking sites, for example, Twitter, comprises the following features.1.URL ranking in which the URL rank is identifiedsuch that how authentic a URL is.

2. Similarity of tweets includes posting of same tweets againand again.
3. Time difference between tweets involves posting of five or more tweets during the time period of one minute.
4. Malware content consists of malware URL that candamage the system.
5. Adult content contains posts that consist of adult content. For analyzing the anomalous behavior of Twitter based onURL, the

dataset is prepared by accumulating 200 tweets ofa user

B.MACHINE LEARNING ALGORITHMS

Benevenuto et al. [2] examined the problem of spammerdetection on Twitter. For this, a large dataset of Twitter iscollected that contains more than 5400 million users, 1.8 billiontweets, and 1.9 billion links. After that, the number offeatures, which are associated with tweet content, and thecharacteristics of users are recognized for the detection ofspammers. These features are considered as the characteristicsof machine learning process for categorizing users,i.e., to know whether they are spammers or not. In order torecognize the approach for detecting spammers on Twitter, the labelled collection in pre-classification of spammer andnon-spammers has been done. Crawling Twitter has beenlaunched to gather the IDs of users, which are about 80 million.Twitter allocates a numeric ID to each user which distinctivelyidentifies the profile of each user. Next, those stepsare taken which are needed for the construction of labelledcollection and acquired various desired properties. In otherwords, steps which are essential to be examined to develop thecollection of users that can be labelled as spammers or no spammers.At the end, user attributes are identified based ontheir behavior, e.g., who they interact with and what is the frequency of their interaction.

C.MISCELLANEOUS METHODS Chen et al. [28] conducted a study on large-scale Twitter dataset and presented an explanation of content polluter .Some novel features are also proposed and combined with other frequently used features to detect the spam. The features were categorized into two classes, namely direct and indirect features. Direct features, which can be obtained from the unprocessed JSON tweets, are further categorized into tweet based and profile-based features. The indirect features cannot be extricated from the unprocessed JSON tweets such as history of tweets, social relationship, etc.

IV. DISCUSSION

From the survey, we analyzed those malicious activities onsocial media are being performed in several ways. Moreover, the researchers have attempted to identify spammers or unsolicited bloggers by proposing various solutions. Therefore, to combine all pertinent efforts, we proposed ataxonomy according to the extraction and classification methods. The categorization is based on various classifications such as fake content, URL based, trending topics, and by identifying fake users. The first major categorization in the taxonomy is of technique sproposed for detecting spam, which is injected inthe Twitter platform through fake content. Spammers generally combine spam data with a topic or keywords that aremalicious or contain the type of words that are likely to be spam. The second categorization considers the techniques for spam detection based on URLs.

V. CONCLUSION AND FUTURE RESEARCHDIRECTIONS

In this paper, we performed a review of techniques usedfor detecting spammers on Twitter. In addition, we also presenteda taxonomy of Twitter spam detection approachesand categorized them as fake content detection, URL basedspam detection, spam detection in trending topics, and fakeuser detection techniques. We also compared the presentedtechniques based on several features, such as user features,content features, graph features, structure features, and timefeatures. Moreover, the techniques were also compared interms of their specified goals and datasets used. It is anticipatedthat the presented review will help researchers findthe information on state- of-the-artTwitterspam detectiontechniques in a consolidated form.Despite the development of efficient and effectiveapproaches for the spam detection and fake user identification on Twitter [34], there are still certain open areas that requireconsiderable attention by the researchers. The issues arebriefly highlighted as under:False news identification on social media networks isan issue that needs to be explored because of the seriousrepercussions of such news at individual as well as collective level [25]. Another associated topic that is worthinvestigating is the identification of rumor sources on socialmedia. Although a few studies based on statistical methodshave already been conducted to detect the sources of rumors, more sophisticated approaches, e.g., social network- basedapproaches, can be applied because of their proven effectiveness.

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