Unveiling The Power of Extreme Learning Machine: Combatting Spam and Identifying Fake Users on Twitter

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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 for daily life. The prominent social networking sites have turned into a target platform for the spammers to disperse a 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 that 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). This work proposes the detection of spammers and fake user identification on Twitter data using extreme learning machine (ELM) and compared the obtained results with various machine learning algorithms like random forest, naevi bayes and support vector machine. 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 (iv) 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.

1. Introduction

In recent years, MSNs such as Twitter, Facebook and Sina Weibo have become important platforms for people to obtain information, spread information and make friends. Twitter's monthly active users (MAU) were 200 million in 2012, and the figure rose to 328 million in 2017, with 20 million tweets being posted every hour. While MSNs enrich people's lives, some security issues have emerged. Attackers spread attacks through MSNs, such as phishing, [1] drive-by download, malicious code injection and so on. According to new research, up to 15 percent of Twitter accounts are in fact bots rather than people. Malicious URLs are one of the most common methods used by attackers to initiate cyberattacks [2]. Attackers trick users into clicking malicious URLs, clicking pictures containing malicious URLs, scanning QR codes with malicious URLs, and so on by disguising themselves as well-known accounts, advertisements of discounted merchandise, or by using mutual trust between friends. In these ways, attackers lure victims to a phishing website for phishing attacks or embed malicious software in the victim's computer to control the target host or perform an APT attack, which will cause huge losses to individuals, businesses, governments and organizations.

Many MSNs use blacklist techniques to filter URLs sent by users, such as Google Safe Browsing, Phishing Tank, URIBL, and so on. However, there is often a delay in blacklist technology, and research shows that 90 percent of victims click on malicious URLs before they are blacklisted [3]. In order to provide users with a secure MSN environment, researchers have proposed many strategies to deal with online social network attacks. Existing detection methods are mainly divided into two categories. The first category includes detection algorithms based on the relation graph of social networks. Many kinds of relations exist in social networks, so researchers use relations in social networks to build a social graph. By analyzing the characteristics of the user's location in the graph, a detection algorithm can be designed based on the graph to identify suspicious messages or users. The second category includes detection methods based on machine learning algorithms.

2. Literature Survey

Feng et. al [4] proposed a multistage and elastic detection framework based on deep learning, which sets up a detection system at the mobile terminal and the server, respectively. Messages are first detected on the mobile terminal, and then the detection results are forwarded to the server along with the messages. We also design a detection queue, according to which the server can detect messages elastically when computing resources are limited, and more computing resources can be used for detecting more suspicious messages. We evaluate our detection framework on a Sina Weibo dataset. The results of the experiment show that our detection framework can improve the utilization rate of computing resources and can realize real-time detection with a high detection rate at a low false positive rate. Damiani et. al [5] proposed a decentralized privacy-preserving approach to spam filtering. Our solution exploits robust digests to identify messages that are a slight variation of one another and a structured peer-to-peer architecture between mail servers to collaboratively share knowledge about spam. Hu et. al [6] investigated whether sentiment analysis can help spammer detection in online social media. In particular, we first conduct an exploratory study to analyse the sentiment differences between spammers and normal users, and then present an optimization formulation that incorporates sentiment information into a novel social spammer detection framework. Experimental results on real-world social media datasets show the superior performance of the proposed framework by harnessing sentiment analysis for social spammer detection.

Mateen et. al [7] proposed a hybrid technique which uses content-based as well as graph-based features for identification of spammers on twitter platform. We have analysed the proposed technique on real Twitter dataset with 11k uses and more than 400k tweets approximately. Our results show that the detection rate of our proposed technique is much higher than any of the existing techniques. Wu et. al [8] proposed a hybrid semisupervised learning model titled hybrid PU-learning-based spammer detection (hPSD) for spammer detection to leverage both the users' characteristics and the user-product relations. Specifically, the hPSD model can iteratively detect multitype spammers by injecting different positive samples, and allows the construction of classifiers in a semisupervised hybrid learning framework. Comprehensive experiments on movie dataset with shilling injection confirm the superior performance of hPSD over existing baseline methods. The hPSD is then utilized to detect the hidden spammers from real-life Amazon data. A set of spammers and their underlying employers are successfully discovered and validated. These demonstrate that hPSD meets the real-world application scenarios and can thus effectively detect the potentially deceptive review writers.

Thomas et. al [9] presented Monarch, a real-time system that crawls URLs as they are submitted to web services and determines whether the URLs direct to spam. We evaluate the viability of Monarch and the fundamental challenges that arise due to the diversity of web service spam. We show that Monarch can provide accurate, real-time protection, but that the underlying characteristics of spam do not generalize across web services. In particular, we find that spam targeting email qualitatively differs in significant ways from spam campaigns targeting Twitter. We explore the distinctions between email and Twitter spam, including the abuse of public web hosting and redirector services. Finally, we demonstrate Monarch's scalability, showing our system could protect a service such as

Twitter -- which needs to process 15 million URLs/day -- for a bit under $800/day. Wang et. al [10] proposed a novel concept of a heterogeneous review graph to capture the relationships among reviewers, reviews and stores that the reviewers have reviewed. We explore how interactions between nodes in this graph can reveal the cause of spam and propose an iterative model to identify suspicious reviewers. This is the first time such intricate relationships have been identified for review spam detection. We also develop an effective computation method to quantify the trustiness of reviewers, the honesty of reviews, and the reliability of stores. Different from existing approaches, we don't use review text information. Our model is thus complementary to existing approaches and able to find more difficult and subtle spamming activities, which are agreed upon by human judges after they evaluate our results.

Shehnepoor et. al [11] proposed a novel framework, named NetSpam, which utilizes spam features for modeling review data sets as heterogeneous information networks to map spam detection procedure into a classification problem in such networks. Using the importance of spam features helps us to obtain better results in terms of different metrics experimented on real-world review data sets from Yelp and Amazon Web sites. The results show that NetSpam outperforms the existing methods and among four categories of features, including review-behavioral, user-behavioral, review-linguistic, and user-linguistic, the first type of features performs better than the other categories. Masood et. al [12] performed 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 (iv) 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 platform.

3. Proposed System Design

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. So the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent as shown in Figure 1.

3.1 Extreme learning machine

Extreme learning machines are feedforward neural networks for classification, regression, clustering, sparse approximation, compression and feature learning with a single layer or multiple layers of hidden nodes, where the parameters of hidden nodes (not just the weights connecting inputs to hidden nodes) need to be tuned. These hidden nodes can be randomly assigned and never updated (i.e., they are random projection but with nonlinear transforms), or can be inherited from their ancestors without being changed. In most cases, the output weights of hidden nodes are usually learned in a single step, which essentially amounts to learning a linear model. The name "extreme learning machine" (ELM) was given to such models by its main inventor Guang-Bin Huang. Extreme learning machines are feed-forward neural networks having a single layer or multiple layers of hidden nodes for classification, regression, clustering, sparse approximation, compression, and feature learning, where the hidden node parameters do not need to be modified. These hidden nodes might be assigned at random and never updated, or they can be inherited from their predecessors and never modified. In most cases, the weights of hidden nodes are usually learned in a single step which essentially results in a fast-learning scheme.

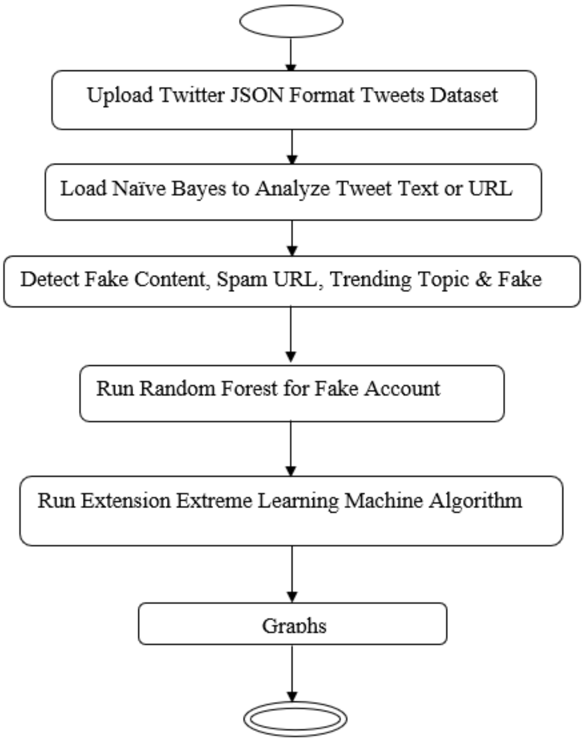


Figure 1. Proposed system design.

These models, according to their inventors, are capable of producing good generalization performance and learning thousands of times quicker than backpropagation networks. These models can also outperform support vector machines in classification and regression applications, according to the research. Although today the Perceptron is widely recognized as an algorithm, it was initially intended as an image recognition machine. It gets its name from performing the human-like function of perception, seeing, and recognizing images. Interest has been centered on the idea of a machine which would be capable of conceptualizing inputs impinging directly from the physical environment of light, sound, temperature, etc. — the "phenomenal world" with which we are all familiar — rather than requiring the intervention of a human agent to digest and code the necessary information. Rosenblatt's perceptron machine relied on a basic unit of computation, the neuron. Just like in previous models, each neuron has a cell that receives a series of pairs of inputs and weights. The major difference in Rosenblatt's model is that inputs are combined in a weighted sum and, if the weighted sum exceeds a predefined threshold, the neuron fires and produces an output.

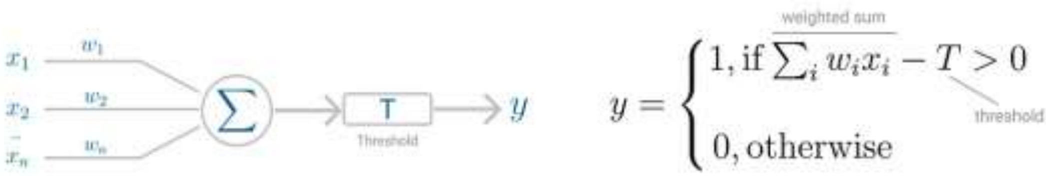
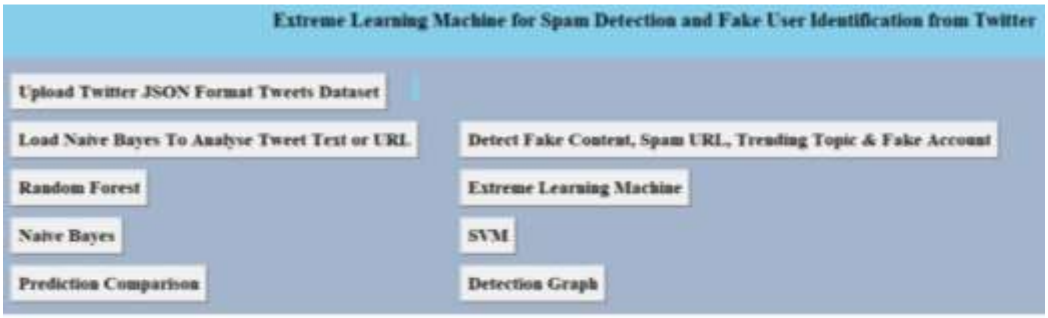


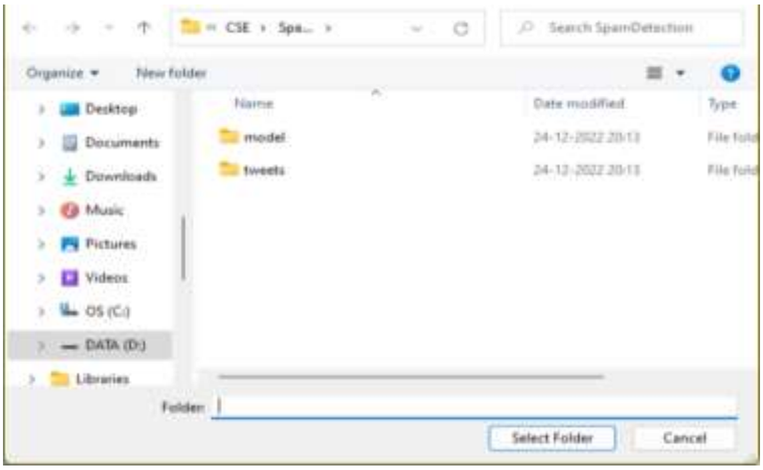
Figure 2: Perceptron neuron model (left) and threshold logic (right).

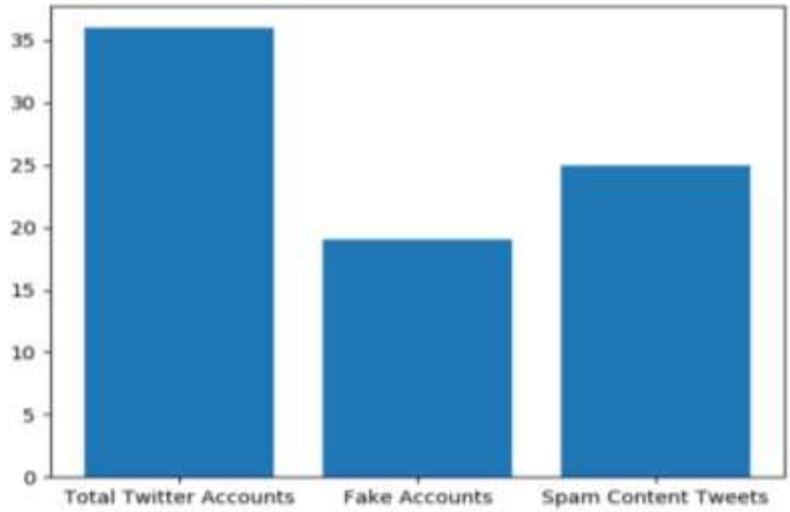
Threshold T represents the activation function. If the weighted sum of the inputs is greater than zero the neuron outputs the value 1, otherwise the output value is zero.

4. Results and description

In below screen click on 'Upload Twitter JSON Format Tweets Dataset' button and upload tweets folder







In above graph x-axis represents total tweets, fake account and spam words content tweets and y-axis represents count of them.

5. Conclusion

It is estimated that 35 billion spam email messages per day were generated in 2004. These messages are nuisance to the receivers and in addition create low availability and network congestion. The problem of spam in VoIP networks has to be solved in real time compared to e-mail systems. Many of the techniques devised for e-mail spam detection rely upon content analysis and in the case of VoIP it is too late to analyse the media after picking up the receiver. So, we need to stop the spam calls before the telephone rings. The proposed algorithm is ELM. In computing, trust has traditionally been a term relating to authentication, security, or a measure of reliability. When it comes to receiving or rejecting a voice call social meaning of trust is applied and reputation of the calling party is analyzed.

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