

MALICIOUS URL DETECTION USING MACHINE LEARNING ALGORITHMS

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Abstract—Currently, the risk of network information insecurity is increasing rapidly in number and level of danger. The methods mostly used by hackers to day is to attack end to end technology and exploit human vulnerabilities. These techniques include social engineering, phishing, pharming, etc. One of the steps in conducting these attacks is to deceive users with malicious Uniform Resource Locators (URLs). As a results, malicious URL detection is of great interest now a days. There have been several scientific studies showing a number of methods to detect malicious URLs based on machine learning and deep learning techniques. In this paper, we propose a malicious URL detection method using machine learning techniques based on our proposed URL behaviors and attributes. Moreover, big data technology is also exploited to improve the capability of detection malicious URLs based on abnormal behaviors. In short, the proposed detection system consists of a new set of URLs features and behaviors, a machine learning algorithm, and a big data technology. The experimental results show that the proposed URL attributes and behavior can help improve the ability to detect malicious URL significantly. This is suggested tha the proposed system may be considered as an optimized and friendly used solution for malicious URL detection.

Keywords—URL; malicious URL detection; feature extraction; feature selection; Machine learning

1. INTRODUCTION

Uniform Resource Locator (URL) is used to refer to resources on the Internet. In [1], Sahoo et al. presented about the characteristics and two basic components of the URLs: protocol identifier, which indicates what protocol to use, and resource name, which specifies the IP address or the domain name where the resource is located. It can be seen that each URL has a specific structure and format. Attackers often try to change one or more components of the URL's structure to deceive users for spreading their malicious URL. Malicious URLs are known as links that adversely affect users. These URLs will redirect users to resources or pages on which attackers can execute codes on users' computers, redirect users to unwanted sites, malicious website, or other phishing site, or malware download. Malicious URLs can also be hidden in download links that are deemed safe and can spread quickly through file and message sharing in shared networks. Some attack techniques that use malicious URLs include [2, 3, 4]: Drive-by Download, Phishing and Social Engineering, and Spam. According to statistics presented in [5], in 2019, the attacks using spreading malicious URL technique are ranked first among the 10 most common attack techniques. Especially, according to this statistic, the three main URL spreading techniques, which are malicious URLs, URLs, there are two main trends at present as malicious URL detection based on signs or sets of rules, and malicious URL detection based on behavior analysis techniques [1,2]. The method of detecting malicious URLs based on a set of markers or rules can quickly and accurately detect malicious URLs.

However, this method is not capable of detecting new malicious URLs that are not in the set of predefined signs or rules. In our research, machine learning algorithms are used to classify URL. Machine learning algorithms are a part of the whole malicious URL detection system. Two supervised machine learning algorithms are used, Support vector machine (SVM) and Random forest (RF).

The paper is organized as follows. Section II reviews some recent works in the literature on malicious URL detection. The proposed malicious URL detection system using machine learning is presented in Section

III. In this section, the new features for URLs detection process are also described in details. Experimental results and discussions are provided in Section IV. The paper is concluded by Section V.

2. RELATED WORK

2.1 Signature based Malicious URL Detection

Studies on malicious URL detection using the signature sets had been investigated and applied long time ago [6,7,8]. Most of these studies often use lists of known malicious URLs; otherwise URLs will be considered as safe. The main disadvantage of this approach is that it will be very difficult to detect new malicious URLs that are not in the given list.

2.2 Machine Learning based Malicious URL Detection

There are three types of machine learning algorithms that can be applied on malicious URL detection methods, including supervised learning, unsupervised learning, and semi supervised learning. And the detection method sare based on URL behaviors.

The behaviors and characteristics of URLs can be divided into two main groups, static and dynamic. In their studies [9, 10, 11] authors presented methods of analyzing and extracting static behavior of URLs, including Lexical, Content, Host, and Popularity-based. The machine learning algorithms used in these studies are Online Learning algorithms and SVM. Malicious URL detection using dynamic actions of URLs is presented in [12, 13]. In this paper, URL attributes are extracted based on both static and dynamic behaviors. Some attribute group sare investigated, including Character and semantic groups; Abnormal group in websites and Host-based group; Correlated group.

2.3 Malicious URL Detection Tools

- URLVoid: URLVoid is a URL checking program using multiple engines and blacklists of domains. Some examples of URLVoid are Google Safe Browsing, Norton Safe Web and My WOT. The advantage of the Void URL tool is its compatibility with many different browsers as well as it can support many other testing services. The main disadvantage of the Void URL tool is that the malicious URL detection process relies heavily on a given set of signatures.

- Dr.Web Anti-Virus Link Checker: Dr.Web Anti Virus Link Checker is an add-on for Chrome, Firefox, Opera, and IE to automatically find and scan malicious content on a download link on all social networking links such as Facebook, Vk.com, Google+.

Comodo Site Inspector: This is an malware and security hole detection tool. This helps users check URLs so enables webmaster to setup daily checks by

- downloading all the specified sites and run them in a sandbox browser environment.

- Some other tools: Among a forementioned typical tools, there are some other URL checking tools, such as UnShorten.it, Virus Total, Norton Safe Web,

Site Advisor (by McAfee), Sucuri Browser Defender, Online Link Scan, and Google Safe Browsing Diagnostic.

From the analysis and evaluation of malicious

URL detection tools presented above, it is found that the majority of current malicious URL detection tools are signature-based URL detection systems. Therefore, the effectiveness of these tools is limited.

3. Proposed Method

3.1 The Model

Fig. 1 presents the proposed malicious URL detection system using machine learning. The malicious URL detection model using machine learning contains two stages: training and detection.

- Training stage: To detect malicious URLs, it is necessary to collect both malicious URLs and clean URLs. Then, all the malicious and clean URLs are correctly labeled and proceeded to attribute extraction. These attributes will be the best basis for determining which URLs are clean and which are malicious. Details of these attributes will be presented in details in this paper. Finally, this dataset is divided into 2 subsets: training data used for training machine learning algorithms, and testing data used for testing process. If the classification performance of the machine learning model is good (high classification accuracy), the model will be used in the detection phase.
- Detection phase: The detection phase is performed on each input URL. First, the URL will go through attribute extraction process. Next, these attributes are input to the classifier to classify whether the URL is clean or malicious.

3.2. URL Attribute Extraction and Selection

In [1], the authors listed some main attribute groups for malicious URL detection as follows.

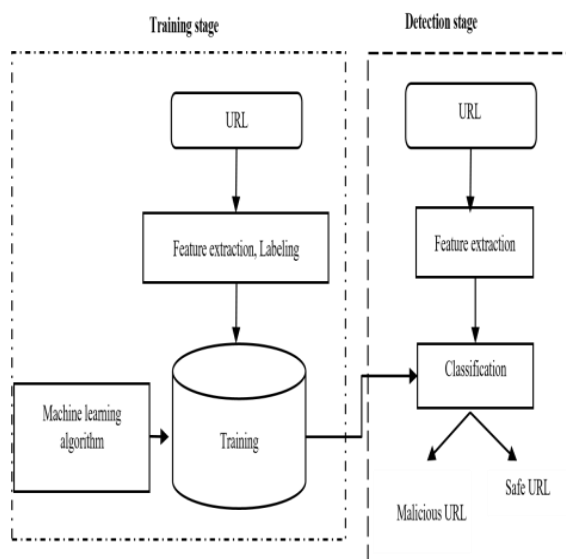


Fig. 1. Malicious URL Detection Model using Machine Learning.

Lexical features: these features include URL length, main domain length, maximum token domain length, path average length, average token length in domain. Host-based Features: these features are extracted from the host characteristics of the URLs. These attributes indicate the location of malicious servers, the identity of malicious servers, the degree of impact of several host-based features that contribute to the URL's malicious level.

Above are the three main attribute groups commonly used by researchers to detect malicious URLs. However, each study has its own decision on suitable attributes and characteristics for each particular experimental dataset. However, in each attribute group some new attributes and characteristics of the URL to optimize the ability to detect malicious URLs are proposed. The new attributes for malicious URL detection in this research are listed in Tables I, II, and III

no	Featuregroup	Feature	Datatype
1	Lexicalgroup	Num Dots	numeric
2		Subdomainlevel	numeric
3		Pathlevel	numeric
4		Urllength	numeric
5	Host-basedfeaturegroup	PctExtResourceUrls*	float
6		ExtFavicon*	boolean
7		InsecureForms*	boolean

Table1:ListofUrl

All attributes marked “*” in Tables I, II, III are newly extracted and selected in this research. Besides, in previous researches, authors tend to use feature extraction and selection method based on a group of predefined features. However, those recommended features are specialized and not popular. As a result, it is usually difficult to implement those features in other works, and to re-evaluate the detection performance of those features. In this work, we try to combine basic features to formulate new ones.

3.3. Machine Learning Algorithm Selection

The application of machine learning algorithms in detecting malicious URL has been studied and applied widely [1]. In this paper, two commonly used supervised machine learning algorithms, RF and SVM [15, 21], are used.

In this research, machine learning algorithms are the last puzzle to complete our proposed malicious URL detection system. Those algorithms are suitable to utilize the usefulness of four new features selected for malicious URL detection. The machine learning algorithms are already well investigated in the literature. In this work, SVM and RF are selected as an example to illustrate the good performance of the whole detection system, and are not our main focus. Readers are encouraged to implement some other algorithms such as Naïve Bayes, Decision trees, k-nearest neighbors, neural networks, etc.

In order to explore the effectiveness of using these two algorithms, different adjustments of parameters are implemented.

3.4 Random Forest Algorithm

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat steps 1 & 2.

Step-5: For new data points find the predictions of each decision tree and assign the new data points to the category that wins the majority votes.

4. Results and Discussion

4.1 Dataset and Experiment Environments

1) *Experiment dataset:* The experimental dataset for malicious URL detection model includes: 470,000 URLs collected from [16, 17, 22, 23], of which about 70,000 URLs are malicious and 400,000 URLs are safe. All these URLs are checked by Virus Total tool to verify the label of each URL. The completed dataset is stored using CSV format. Each URL

2) *Experimental setup:* The dataset of both safe and malicious URLs mentioned above is divided into

2 subsets. About 80% of the dataset, 470,000 URLs (400,000 safe URLs, 70,000 malicious URL), is used for training, and about 20% of the dataset, about 10,000 URLs (5,000 malicious URLs, 5,000 safe URLs), is used for testing. The experiment is repeated many times with both SVM and RF algorithm. Different parameter settings are used in different runs.

3) Experiment dataset

- Setup environment: Python version 3.6; Spark version 2.3.0; Hadoop version 2.7; Java (JDK) 8; Ubuntu 18.04.
- Hardware: RAM 16GB; Intel(R) Xeon(R) CPU E52640v3 @ 2.60GHz.

4.2. Evaluation

1) *Evaluation metrics*: Accuracy: the percentage of correct decisions among all testing samples $acc = \frac{TP + TN}{TP + TN + FP + FN}$

(1) where: *TP* - True positive is the number of malicious URLs correctly labeled; *FN* - False negative is the number of malicious URLs misclassified as safe; *TN* - True negative is the number of safe URLs correctly labeled; *FP* - False positive is the number of safe URLs misclassified as malicious.

Confusion matrix: is a two-way table representing how many samples are reclassified into which label accordingly.

Precision: is the percentage of malicious URLs correctly labeled (*TP*) among all malicious URLs labeled by the classifier (*TP + FP*).

$Precision = \frac{TP}{TP + FP}$

*Precision * Recall*

FPR (False prediction rate) is calculated as:

$FPR = \frac{FP}{FP + TN}$

$FPR * 100\%$

$FPR * TN$

2) Results

- Training performance

To evaluate the training performance of the machine learning algorithm, both two data subsets are used individually. Each of these data subsets has different data size as well as different distribution of data labels, which may result in different training performances. The results are represented in Table V. Experimental results show that the RF with 100 trees gives the best predictive result. In return, the training time of the RF is slightly longer than SVM, but the testing time is not much different. The accuracy of the second dataset is reduced due to the unbalance between safe and malicious URLs of the data. As expected, RF algorithm, with its fast speed and high accuracy, is very suitable for classification problem. Besides, in our research, when machine learning algorithms are combined with Spark libraries, the training and testing time can be reduced significantly. Spark ML Machine Learning is and supports many machine learning.

5. Conclusion :

This paper presents a machine learning-based solution for malicious URL detection. The empirical findings in Tables V and VI have demonstrated the efficacy of the extracted characteristics. Unlike many other traditional articles, we don't use special qualities in this study or try to build enormous datasets to increase the accuracy of the system. The processing speed and accuracy of the system are determined by the combination of simple-to-calculate qualities and large data processing technologies to ensure the balance of the two elements. The findings of this study can be used and put into practice in information security technologies and systems. A free program to identify fraudulent URLs

on websites has been created [20] on the findings of this paper.

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