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Research article

Phishing Detection on URLs Using Machine Learning

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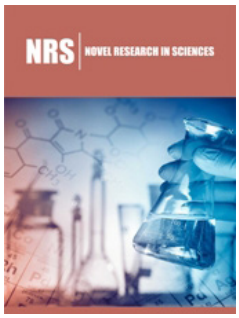

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Abstract

This research will propose a client side based phishing detection extension for Google Chrome browser that can assist in detecting and warning users about the websites they are currently browsing in real-time. This would be achieved by using random forest classifier a machine learning method, as based on past research done it concludes that it performs far better than other machine learning techniques in the field of detecting Phishing. Most common method of obtaining this is by providing the classification on a server and then performing a request to the server via the extension plugin to get the result. Unlike this method, this research will emphasize on running the classification on the browser instead. This is done because it has several advantages running on a client side as it provides a better privacy to the users since their browsing data and pattern is not compromised as it does not leave their machine. This will also make the detection plugin independent towards latency issues. This research mainly will focus on implementing machine learning in JavaScript for it to run on a browser as an extension since JavaScript does not have much library support towards Machine Learning and also to keep in mind of the users machines performance. This approach should be made with the intention of having it lite in order to achieve the capability to allow as much users as possible to use it. Random forest classifier for this project will be trained traditionally based on the phishing dataset 2 using Python scikit, and parameters of this model will then be exported in a JSON format to be used together with JavaScript.

Keywords: Phishing; Python; Machine learning; Java script

Introduction

Phishing has been accounted for many fraudulent incidents on the internet in the recent years, and it is showing no sign of stopping anytime soon. So, what is phishing? It is a term that is used to describe a malicious individual or a group of individuals who scam users. This is done by sending emails or creating web pages that are designed to collect an individual's online credentials, credit card details or other login information's. The concept of detecting phishing websites is usually done by looking through a huge database or a directory that contains all the malicious sites that has been logged by internet users or community members. An effective way for end users to benefit from phishing detection is by having the option to use an extension plugin that works on real time, as it gives them real time indication of what they are surfing and as well as if they are safe while browsing. With these issues in mind, and how it affects the security aspect of users on the internet and as well as giving concerns to privacy to the user, this research will be implemented as a google chrome extension that can achieve the ability to do classification without needing a 3rd party server to do so.

Understanding the problem

In order to begin the development of a google chrome browser extension, it should emphasize on the ability to alert and warn the users if they accidentally visited a phishing webpage. This chrome extension will also be developed keeping in mind that, it should not have any 3rd party servers or API present to call services as this gives a narrow path for hackers to target users browsing pattern. Lastly, this extension plugin will also provide an instantaneous detection service that warns users as they view a phishing website, just so they avoid entering any confidential information before it is too late.

Background information and work

One most popular directory-based approach is PhishTank [1]. What Phish Tank offers is a very collaborative data house regarding all the phishing websites on the World Wide Web with information's regarding the website to indicate how severe it is to have users aware. Another feature Phish Tank offers, is their open API availability for allowing researchers, developers to integrate it into their phishing tools without any cost behind it. Based on that availability, Phish Tank is considered as a directory that contains all phishing websites reported by community members around the world which aids developers when they use their API for phishing detection purposes. Another API that exists which helps in developing tools for phishing detection is from Google called Safe Google Browsing API [2], but it also follows the same directory-based approach as Phish Tank. The downside of this approach is that there is always a constant influx of new phishing websites in the web and this cannot always be updated in a real time moment and it will also require huge rate of contribution from community members to always update their directories with new updated phishing websites that exist. Detection of phishing methods is based on server base side and client base side. One of the existing google chrome extension plugin that follows a rule-based concept is called Phish Detector [3], which allows eligibility to detect phishing websites without the usage of an external web service. While implementing such plugin is much easier from a client side, it cannot be compared to how accurately it will be whilst being compared to machine learning approach techniques.

Another tool that works with rule-based concepts is PhishNet, where it uses a predictive method for blacklisting. The rules that are being adapted are being matched with a term called Top Level Domain (TLD) directory structure, IP addresses, and headers of HTTP responses. Stanford developed tool called SpoofGuard [4] works just like PhishNet mentioned above, butit considers rule-based approach using DNS, URLs, clickable links and images presented on the web-page. Author from the research paper "Feature extraction and classifying websites that are malicious based on their URL" [5] used a technique where he extracts the features to make a feature matrix that was substantially used to classify URLs. In their development, they extracted roughly 133 features and they only use sub-part of it which they concluded as feasible for their project. It was also not understood why they didn't specify their reasoning for choosing specific parameters to declare websites as malicious or not otherwise. Parameters that were set and used together with related respective algorithms in their projects were different to what we do plan to use for our development and project implementation. For our master's project, we have decided to only use one single algorithm that suites best and identifying what features that were given from our dataset would help us respectively. A research article "Comparing machine learning techniques for detection" [6] a comparative study was done between six various classifiers to understand which classifier will fit and work best in distinguishing a phishing URL and a legitimate URL. The authors concluded that Random Forest classifiers fit and worked best due to having lowest error rate among the five remaining classifier that was used for the comparative study. In an article regarding how using machine learning can aid in detecting phished URL [7], the author raises questions and awareness how phishing in general on the internet has rose significantly over the recent years and also discusses technique implementation on feature extraction and understanding what ideal machine learning algorithm will best fit the classification. While we don't particularly follow their exact measures of extracting features like details on traffic, page rank detail features, this paper provides an ideal footstep for understanding what features can be extracted based on our requirements for our project [8]. While in the paper, the author hasn't represented any indication of the best algorithm that fits these projects, we in our master thesis project will give a statistical analysis on why Random Forest classifiers is the best fit together with its accuracy for the chosen algorithm. Netcraft phishing protection basically works as a big neighborhood watch scheme. Once someone reports a potential phishing website into the community, it will then be investigated and if it's proven as a phishing website, the targeted URL will be blocked for their community members [9]. Phish Detector has a 100% success rate on detecting phishing attacks on online banking websites. To obtain positive accurate results, only use this tool on banking websites [10] as this extension does not work on other website domains.

Another existing phishing detector that exists in today's market is called cascaded phishing detector. It basically functions as a client side and as well as server-side tool where the client side is developed as a chrome extension. This is then followed up by injecting certain scripts to the respected websites to extract the relevant and related corresponding HTML DOMs [11,12]. This extension compared to the existing extensions that exist in the market only gives priority to the HTML DOMs to identify the prospect of being phished while disregarding the other parameters.

Analysis of the system

Functional system requirement: Extension plugin should provide a warning pop-up when they visit a website that is phished; therefore it should strictly follow the following:

a. Extension plugin ability to present the pop-up to the users screen should be quick enough to the point, users will be aware before entering any confidential or sensitive details into a phishing website.

b. Extension plugin should not need the facilities and services from an 3rd party service or APIs, due the reason that those services will always the potential to leak users browsing data and pattern when it gets compromised by hackers

c. Extension plugin will have the capability to also detect latest and new phishing websites

Non-Functional system requirement: Graphical User Interface design Interface developed should be done with the understanding that it must meet the simplicity of what users would like to see when they need an extension for detecting things, and also it needs to adhere to non IT literate users as well. It must also provide the exact information on what the user wants like identifying a phishing website quickly without needing to click on many options. The process of identifying phishing website should be taken directly from the web-page user wants to view through their URL and the result from it should be easily understood by the users. Most importantly, the extension plugin should have a pop-up that will notify the user regarding the website status of being phished.

Software requirements:

a. PyCharm software

b. Python language

c. Google chrome browser

d. Scikit-learn

e. NumPy

f. Liac-arff for dataset

Designing of the system

The architectural concept of the system begins by training a Random Forest classifier on dataset that contains URL features that can be classified as phishing, legitimate, and suspicious on python using Scikit learn. The result of the random forest classifier is then represented in a JSON format and as well as the classifier that has learnt will be represented in JSON format over HTTPS. Once this is achieved, a script that is implemented using JavaScript for web browser is developed which will use the exported JSON format model to provide classification of web pages that will be viewed over an users internet browser. The (Figure 1) displayed below will provide an understanding of the system architecture through a system diagram. The main functionality of the plugin extension that is being implemented is to issue a warning notification through a pop up towards the users browser screen in the circumstances if the user accidentally is on the verge of visiting a phishing website. To provide this, classifier should be done on the 17 selected features out of the 30 features that exist in the dataset. Dataset is in an arff file format therefore it needs to be loaded using arff library 1 that python supports. Reason why only 17 features are selected from 30 available features is based on the possibility that these selected features can be extracted without needing to be online from a client side rather than being extracted completely from a 3rd party server or service. Dataset that has been used for this implementation of project is then separated into, a training dataset and to a testing dataset. Using the training data, random forest is then trained on it and the results are exported in a JSON format over HTTPS2. From client side, the google chrome extension then performs an execution of script on every webpage it loads from the browser, and it then simultaneously converts the selected features that have been specified. As these specified features are once converted, google chrome extension plugin then proceeds to verify for the initial JSON model that is stored in cache. Together with the converted features and the model in JSON format, the script on the extension plugin can ideally run a classification. Once this is successfully achieved, a warning notification through a pop-up can be displayed towards the user, if the web-page the user is visiting is considered phishing. The process implementation of this extension plugin is very lite towards users computers and as well it gives the capability to detect phishing website in a quick effective manner.

Figure 1: Graphical user interface.

User interface design

The designing of the GUI of the plugin was made simple and feasible to attract all audience to use it, and also understands the contents it will be displaying needs to be easy to understand for all users, and all this is achieved by using mix of HTML3 and as well CSS4. The user interface will provide the main indication to user on how legitimate the web-page they are viewing through a large circle. This circle will change colour depending on how the websites

are being classified, if its phished or legitimate. The results that are derived from the classification are visually represented in the large circle with the following colour code:

a. Dark Green - Legitimate website and safe to view

b. Golden Orange - Suspecting possible phishing website

c. Crimson - Phished website

The percentage score represented in the chart is calculated in the frontend.js section of the development where legitmate Count(phishingCount+suspiciousCount+legitimateCount)*100

```
i.   function classify (tabId,result) {
ii.  var legitimate Count=0;
iii. var suspicious Count=0;
iv.  var phishing Count=0;
v.   for(var key in result) {
vi.  if (result[key]==”1”) phishing Count++;
vii. else if(result[key]==”0”) suspicious Count++;
viii. else legitimate Count++;
ix.  }
x.   LegitimatePercents[tabId]=legitimateCount/
(phishingCount+suspiciousCount+legitimateCount)*100;
```

Listing 1: code for obtaining and calculating legitimate Percent. This helps us to provide a justifiable score based on feature categorization into phishing or legitimate sites. One of the existing issue due to how this is calculated is, the percentage representation of sites can be confusing to users at initial glance since, without knowing how it is being calculated they might question the authenticity of the percentile score of classifying websites. This is something that is being constantly emphasized on for future work progress.

Extension plugin will also have the function to alert users when they are about to view a website if it is a possible phishing website, in-order to prevent any entry of confidential or sensitive information's from user into the web-page. Accuracy score, together with recall and precision results will also be available for users to view on a separate tab that can be accessed from the main plugin interface. The designed concept of the graphical user interface can be seen from (Figure 1) that is displayed below.

Design of model

Dataset that is being used for this project is initially downloaded from UCI dataset repository and then it is imported into an array with NumPy. The dataset that is loaded has 30 features with it, but it needs to be re-evaluated to figure out which specific features can be used and extracted on the browser extension plugin. This is done by manually testing each features on the plugin to identify which features are capable of working without needing a 3rd party service to give results. Accomplishing this, helped us identify the 17 specific features from the initial dataset that gives results without drastic loss in accuracy value coming from test data. While having more features being used from the dataset can easily provide better results value for accuracy but this would require more processing time to produce the result and this would not be following the gene scope of the project that was to provide a quick and effective phishing detection. It needs to be understood, the features that were chosen specifically will be a compensation for quicker result than for accurate results. (Table 1) will show the 17 features that have been selected. Once this is completed, dataset is then split into training and testing data where its 30% for testing data and the remaining 70% will be for training data.

Table 1: Features that were selected to identify phishing websites.

IP Address	No. of Sub Domains	Anchor
URL Length	HTTPS	Scripts & Link
Tiny URL	Favicon	SFH
@ symbol	Ports	mailto
Redirecting using//	HTTPS in URLs domain part	iFrames
(-) Prefix/Suffix in domain	Request URL	

Training of model

Training of the data obtained from pre-processing are loaded and random forest is then trained on the training data using scikit-learn. As it is known, Random Forest is part of an ensemble machine learning 5, which allowed us to use 10 estimators for our classification. The decision tree estimators works under CART algorithm6 and impurity of gini is reduced in each decision tree to provide the result. Cross Validation score is also done on the training data while the F17 score is calculated on the testing data. Lastly, the model that has been trained with results and parameters, it will be exported using JSON format.

Development of the System

Project that has been developed is divided into 2 different category, namely the backend which consists of classifier and dataset and frontend of the system. The work of backend is to pre-process the dataset that was used and also, train the models with Random Forest with chosen parameters and values. Front end of the system development mainly consists of JavaScript, also scripts to enable the contents to be functional, and scripts that's running on the backend like our Random Forest JavaScript. It also contains the relevant HTML files needed to create the graphical user interface (GUI).

Results

Testing with dataset

Test set that was used consisted data from the initial dataset was split into a 70 to 30 ratio. To make and implement a fully functional extension plugin, it was tested with many various phishing website that are obtained and listed from phish tank website1. Since phish tank is a large active community, it always has new phishing websites being listed in a frequent manner. With this in mind, it should be noted that the extension plugin that has been implemented for the project has the capability to detect new phishing websites that are added to the website as well. Initial dataset contains 1105 data points with 30 features. For pre-processing, we are splitting the Dataset 70 for training and 30 for testing and selecting 17 features specifically that can be used without needing a 3rd party service. Once the pre-process is successful, the results are saved into a JSON format file.

Feature extraction on extension plugin

For understanding how features are classified on websites, we extracted portal.gre.ac.uk for the 17 features which are logged in google chrome console. (Figure 2) displayed below will display the result that is logged on the console. It should also be noted that the features are always stored in pair values and these values are encoded as 1 to -1 where 1 is phished and -1 is legitimate websites.

Figure 2: Features that are extracted from portal.gre.ac.uk.

Classification in extension plugin GUI

Result of the classification is displayed on the extension plugin on the (Figure 3) below, through an indication that is displayed on a circle where dark green represents a legitimate website and crimson represents a phished website.

Figure 3: Classification result on the GUI.

Testing phase sample screenshots

The result that was displayed on the extension plugin while visiting a phished PayPal website obtained from Phish tank domain as shown in (Figure 4). As you can notice, the website has low 32% value of trust hence why the indication is in crimson, stating it is a phished website.

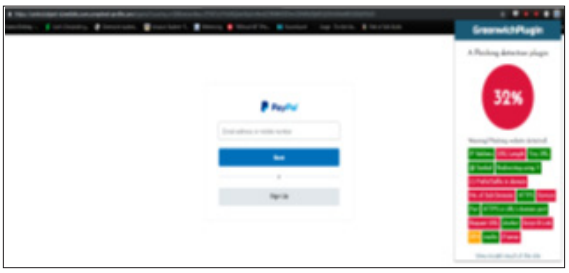

Figure 4: PayPal website.

Testing phase

Testing for this project was done manually by taking websites directly from phish tank and also from web history to find out if the classification is done properly without any fails. The reason why this was done rather than testing the model on a dataset with URLs was, since the existing dataset that was used in this project classifies URL features as either 1 as phishing, 0 as suspicious website, and -1 as legitimate on URL features on websites that is being viewed. This way, the extension provides a functionality to also predict new phishing websites as well because we are classifying websites based on URLs features rather than a complete URL. There were several problems that needed to be addressed after testing was done. When testing was completed, it came to our understanding that the accuracy score has dropped while porting the JSON format of the parameters and testing of random forest from Python to JavaScript. While this reason is unknown, the loss of accuracy was a trade with how quick the phishing detection was done on the browser. Another thing that came to attention was, while testing email URLs, URL for Gmail accounts were being prompted as a potential phishing website by the implemented popup feature in

this extension. The reason for this is uncertain but based on current investigation; it may be due to how certain features are tracking information. While this isn't proven, it was merely an observation that was done by comparing the analytic result from DuckDuckGo tracking extension 4. For testing purposes, 5 websites were chosen from phish tank website to see if the model correctly classifies them as phishing. About 50 websites were chosen from the website and tested against the plugin manually, the success rate was 35/50 while the remaining websites were falsely reported to the website. Due to high number of tested website, only the 5 latest websites are listed. Website are listed below:

a. https://online-billing-llc.net/993a36dc7b50be416f3...

b. https://kundenservice-umstellung.live/

c. https://shortinieri-fast.life/HwfiG

d. https://allegro.pl-nowe-regulamini3758.cho274.pl/6...

e. http://superchange.site/

Conclusion

This research illustrates and explains the development of a phishing detection on URLs as an extension plugin on google chrome which aids in privacy matters as its implemented on a client side with the capability to detect phishing in efficient rapid manner for users to be notified before accessing potential phished websites or entering confidential information's. The implementing method of exporting Random Forest from python to JavaScript is the most essential part in this project as JavaScript for Random Forest had to be done natively with proper understanding of how the classifier works and performs. Many of past related work done by several other researchers often prefers to use website features with the aid of 3rd party services to provide a better accuracy measure when it comes to predicting phished websites. This won't be a viable option for us since it results in security measures regarding privacy of data browsing and also it will be dependent on latency of the networks. As our development extracts features through client side, this helps vastly in providing fast reliable detection together with the possibility of providing privacy towards users browsing. But it needs to be kept in motion that while not using all the features provided, the accuracy result gets effected minimally but it does increase the functionality of the extension being built. This is achieved by choosing specific subset of features on web-pages that can be used to implement without huge loss of accuracy from the client-side. Exporting the classifier from python to JavaScript for extension plugin development, with the development of Random Forest in JavaScript gave us a foundation to provide an efficient and quick detection plugin for phishing as the model was represented in JSON format, together with scripts for classification was development with the idea of the understanding of timing is most vital when it comes to providing awareness to users. With this development, it is possible to detect phishing websites before the page even loads, as this gives the awareness to users before they decide to provide any confidential information into the phished website. While it was noted that using minimal features to adapt to client side functionality will reduce the accuracy score of the model, but it wasn't severe to the point of many false positive results. Precision score that was calculated on the testing set is 0.8724385245901639. While the accuracy score is rather low, it didn't have much impact on true positive results for detecting phished websites. It was a trade-off between loss of accuracy against efficient and quick detection.

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References

1. Patil D, Patil J (2015) Survey on malicious web pages detection techniques. International Journal of u- and e-Service, Science and Technology 8(5): 195-206.
2. Wardman B, Shukla G, Warner G (2009) Identifying vulnerable websites by analysis of common strings in phishing URLs. IEEE pp. 1-15.
3. Hong J, Rose C, Xiang G, Cranor L (2011) Framework on identifying phishing websites using machine learning. ACM Transactions on Information and System Security 14(2): 1-28.
4. Akanbi O, Abunadi A, Zainal A (2013) Feature extraction process: A phishing detection approach. 13th International Conference on Intellient Systems Design and Applications.
5. Aydin M, Baykal N (2015) Feature extraction and classification phishing websites based on URL. IEEE Conference on Communications and Network Security (CNS).
6. Nappa D, Wang X, Abu Nimeh S, Nair S (2007) A comparison of machine learning techniques for phishing detection. Proceedings of the Anti-Phishing Working Groups 2nd Annual eCrime Researchers Summit on–eCrime '07. pp. 60-69.
7. Sandhya L, James J, Thomas C (2013) Detection of phishing URLs using machine learning techniques. International Conference on Control Communication and Computing (ICCC).
8. Chang Y, Chen T, Laih C, Hou Y, Chen C (2010) Malicious web content detection by machine learning. Expert Systems with Applications 37(1): 55-60.
9. Lu G, Debray S (2012) Automatic simplification of obfuscated javascript code: A semantics based approach. IEEE Sixth International Conference on Software Security and Reliability.
10. Benjamin L, Benjamin Z, Curtsinger C, Christian S (2011) Zozzle: Fast and precise in-browser javascript malware detection.

11. Aldwairi M, Alsalman R (2012) Malurls: A lightweight malicious website classification based on URL features. Journal of Emerging Technologies in Web Intelligence 4(2): 128-133.

12. What is multithreading?-definition from techopedia_2019.