An Unsupervised Method for Detection of XSS Attack

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Abstract

Cross-site scripting (XSS) is a code injection attack that allows an attacker to execute malicious script in another user’s browser. Once the attacker gains control over the Website vulnerable to XSS attack, it can perform actions like cookie-stealing, malware-spreading, session-hijacking and malicious redirection. Malicious JavaScripts are the most conventional ways of performing XSS attacks. Although several approaches have been proposed, XSS is still a live problem since it is very easy to implement, but difficult to detect. In this paper, we propose an effective approach for XSS attack detection. Our method focuses on balancing the load between client and the server. Our method performs an initial checking in the client side for vulnerability using divergence measure. If the suspicion level exceeds beyond a threshold value, then the request is discarded. Otherwise, it is forwarded to the proxy for further processing. In our approach we introduce an attribute clustering method supported by rank aggregation technique to detect confounded JavaScripts. The approach is validated using real life data.

Keywords: Attribute Clustering; Divergence; Malicious Script; Proxy; XSS

1 Introduction

Cross-site Scripting (XSS) is one of the most common application layer hacking techniques. It allows an attacker to embed malicious JavaScript, VBScript, ActiveX, HTML or Flash into a vulnerable dynamic page to fool the user, executing the script on his/her machine in order to gather data [17]. Most common way of stealing cookies or hijacking session is to embed a JavaScript encoded with browser supported HTML encoding technique. XSS attacks are categorized into three types [10]: reflected XSS, stored XSS and Document Object Model or DOM-based XSS attack.

As the Internet applications are becoming more and more dynamic, the possibilities of such attacks have become more prominent. The number of vectors which are used to carry out such attacks are increasing with the increase in interactiveness of an application. Severeness of XSS attack can easily be predicted as it is ranked in top positions in recent security related surveys. For example, XSS is ranked third in the “OWASP Top 10 Application Security Risks-2013” [32].

Most of the existing intrusion detection systems which are designed to detect the XSS attack consider that, XSS attack is substantially caused by the failure of a Web application to check the contents for malicious codes before running it in the user’s browser. The existing approaches can be categorized into three basic types [27]: dynamic approach, static approach, and hybrid approach. Static analysis includes various methods such as taint propagation analysis [20], string analysis [31], software testing techniques [28], etc. Taint propagation analysis includes construction of a control flow graph, where each node contains a label. An Web page is considered vulnerable, if the input node of the control flow graph for a certain variable has an edge leading to the output node. In string analysis, the program generated string values contain formal language expressions, such as Context Free Grammar (CFG) with labels. Minamide’s method [24] of string tainting, which is an example of string analysis approximates string output of a program with a CFG. Software based testing techniques such as fault injection, penetration testing are used to infer the existence of vulnerabilities. Dynamic analysis includes proxy based solutions [21], browser enforced embedded policies [19], etc. In proxy based solutions, requests from the client side are intercepted in the proxy and based on the rules of the proxy the required actions are taken. On the other hand, in browser enforced embedded policies client is provided with a list of benign scripts by the Web application
and only these scripts are run. Although the static and dynamic solutions are effective in various cases, but in some situations the combination of both the approaches is much needed. Hence, the hybrid approaches are introduced. Sanar [3] is such a tool which combines static and dynamic approaches. In static analysis, it models the data input methods to indicate sanitization process. On the other hand, the code irresponsible for sanitization is reconstructed by dynamic analysis approach.

Machine learning based approaches use statically and dynamically extracted characteristic features from both malicious and benign samples and build classification tools [4].

1.1 Motivation

Although several methods have been introduced so far to mitigate XSS attack, it is still a live problem. The attack instances are increasing continuously and intruders are introducing more complex ways for embedding their scripts to trick users. Motivation behind choosing JavaScripts is that, now a days most of the web applications use JavaScripts extensively and the XSS attacks reported so far are in maximum cases found to be executed using JavaScripts. Moreover, already existing incremental approaches show a high false alarm rate and are not scalable [5]. Taking the whole scenario into consideration we are motivated to introduce a faster, stable and cost effective detection mechanism which will ensure high detection accuracy. Our aim is to reduce the false alarm rate and to increase the scalability.

1.2 Contributions

The two major contributions of this work are:

- A load balanced Client-Server based architecture to support XSS attack detection.
- An attribute clustering technique to support feature-level unsupervised grouping of attack and normal scripts over relevant and optimal feature space.

The remainder of this paper is organized as follows. The background of XSS attacks and a brief discussion on why we have concentrated mainly on reflected XSS attack is discussed in Section 2. Section 3 gives an overview of related works. Section 4 introduces our proposed method which is followed by experimental results in Section 5. Finally, we conclude our paper in Section 6.

2 Background and Related Work

In this section, we discuss the basics of XSS attacks, their categories and characteristics.

2.1 Basics of XSS Attacks

XSS attack mainly occurs due to the improper sanitization and validation of the user inputs given in the form of scripts. Figure 1 depicts a typical scenario of XSS attack. It shows, how an attacker can easily generate an XSS attack by sending a mail to the user containing a malicious URL. In the first step, attacker crafts a URL containing the malicious script and e-mail it to the victim. In Step 2, user clicks on the link send by the attacker and on clicking the link, the script is sent to the web server as the user request as shown in Step 3. In Step 4, the server reflects back the request to the user and the script is executed in the user’s browser. Once the script is executed, sensitive data like session cookies are sent to the attacker in Step 6. Then attacker gets control over the user’s session and can access the Web server on behalf of the user. The methods through which one can execute an XSS attack can be categorized into the following three types.

2.1.1 Persistent or Stored XSS Attack

Persistent or Stored XSS attack is server database related and it can affect a numerous number of users visiting the server which contains the malicious script in its database injected by the attacker. This type of attack mainly occurs due to the improper validation of the user inputs. Let us take an example to clarify the statement. A guestbook, which is a visitors log through which they can post their query or just leave a comment or give feedback for some services provided by a Website can be an easy victim of persistent XSS attack. Suppose a malicious user crafts a special script for cookie stealing and posted that script as a comment in the guest-book. This malicious link may be a link to provoke the user for getting free recharge by posting a link with the tagline “Hey check this link. I got free Recharge!!!”. If the server is not able to sanitize the input properly then this comment is saved to the server database. Now the visitors visiting that particular Webpage will execute that javascript in their browser unknowingly. The attacker will thus get the cookies of the user’s browser and thus will get the control over the user’s session.

2.1.2 Non-Persistent or Reflected XSS Attack

Recently, non-persistent or reflected XSS attacks have been found as a common type of XSS attack. Here, victim’s request itself contains the malicious string. The server then responds with an HTML page that contains the script and thus the script is executed in the user’s browser. Let us consider the following scenarios.

Scenario 1: Email is one of the most common ways of tricking a user to click on a malicious script. The attacker can send a link to the user via an email crafting a link which contains the malicious link. As and when the link is clicked by the user, the script which is hidden either in the link itself or in a script...
which the attacker refers to is executed and users credentials such as session cookies, are sent to the attacker. The attacker can easily get access to the site which the legitimate user is surfing. Figure 2(a) shows the scenario of this attack.

Scenario 2: We can consider yet another scenario of XSS attack. Here, the attacker acts as an intermediary agent. The attacker can be the host of a legitimate Website. When the user visits the attacker’s Website, then the attacker prompts with a specially crafted link. When the user clicks on the link, it redirects the user to another Website to which the user have access to. This reflected message can contain a script, which is then executed in the user’s browser and the attacker can get the browser info this way. The link may contain a page which actually doesn’t exist on the requested server. Then the server sends back a message to the user saying that page not found.

This scenario is depicted in Figure 2(b).

### 2.1.3 DOM-based XSS Attack

DOM-based XSS attack is the type of XSS attack that occurs in the Document Object Model (DOM) of an HTML page in lieu of the part of an HTML page. Here, since the changes occur to the DOM environment, so the HTTP response code runs in a different manner. DOM XSS attack can be carried out with a numerous DOM objects as mentioned below.

- User name or password part of a location or URL:
  Here the payload is received by the server in the authentication header.
- Portion where the query part is located in the URL:
  Here the payload is received by the server as URL part of HTTP request.
- Fragment part of an URL: This part basically contains the portion of the URL separated by ‘#’ symbol from the rest of the URL. Here payload is not received by the server.
- HTML DOM referrer object: The referrer object is the document.referrer, which represents currently loaded document’s URL. Here the payload is received by the server at the referrer header.

A report by Trustwave’s Spiderlabs says that the number of applications that are vulnerable to XSS attack are 82% of the total Web applications (2013)\(^1\). Again, according to WhiteHat Security XSS stood first in the most common vulnerability category (2014)\(^2\). XSS also tops the list of most frequently occurring vulnerability in the survey carried out by Cenzic (2014)\(^3\). CWE by MITRE \[^8\] also warns by saying that XSS is one of the most prevalent, obstinate and dangerous vulnerability in Web application. Among the XSS vulnerabilities, the most frequent one is the reflected XSS attack.

2.2 Related Work

Javascript has become an unavoidable part of most Web applications due to the necessity of increased interactivity between the user and the Web applications. So the idea of detection of malicious JavaScript is not new. A brief summary of the work done so far, that are thoroughly studied to understand the present scenario in this field, are mentioned in Table 1.

In [22], Likarish et al. propose a classification based approach for detecting obfuscated malicious JavaScript detection. They propose features that can identify obfuscation, since obfuscation is a well known method of bypassing security filters. Based on the recommendation of various classifiers, the designed malicious JavaScript detector either passes or discards the request.

In [21], Kirda et al. propose a tool Noxes. This is a client side solution to mitigate XSS-attack. It uses both manual and auto generated rules to mitigate XSS-attacks. Since we are focusing on designing a solution which balances the loads among server and the client, so it is very important for us to study the existing client based and server based approaches. Noxes identifies all the links either as statically embedded or dynamic links. Dynamic links are considered vulnerable to XSS attack, since attacker can embed their code in a dynamic link.

In [33], Wurzinger et al. propose a tool Secure Web Application Proxy (SWAP), which is a server-side solution for mitigating XSS attack. SWAP consists of a reverse proxy. It interprets the HTML responses and the modified web browser detects the script contents.

In [23], Di Lucca et al. propose an approach, which is a combination of both static and dynamic approach. Static analysis is used to determine whether a server page is vulnerable to XSS attack. Dynamic approach verifies whether the determined vulnerable web application by static approach is actually vulnerable or not. This approach uses a control flow graph (CFG) to determine the vulnerability in a Web application.

In [28], Salas et al. propose an approach which uses security testing methods like penetration testing and fault injection for detection of XSS attack. Depending upon the results of penetration testing by a user utility referred to as soapUI and interpretation of HTTP status codes in the header of SOAP message, they develop 8 rules. On the basis of which they determine the existence of vulnerability in Web services. Fault injection phase is carried out with WSInject, which is placed as proxy between client and server and intercept the messages sent by soapUI before passing it to the server. Faults are injected during this phase. By intercepting the HTTP messages sent by the SOAP request message, they use the previously defined vulnerability analysis rules to determine the injection.

In [2], Athanasopoulos et al. present a tool called xHunter, which checks the JavaScript parse tree depth. If the depth is beyond some threshold value, it considers the URL as suspicious.

In [1], Adi et al. propose a design for a proxy named Wines that monitors the browser requests sent to a server. Depending upon the patterns of malicious strings kept in different cells of Wines, the requests are categorized as either harmful or harmless. Harmless strings are forwarded to the server and harmful strings are blocked. All the terms used by the method are biological term since the work is inspired by Human Immune System.
Table 1: Comparison among existing methods

<table>
<thead>
<tr>
<th>Referred Work</th>
<th>Year</th>
<th>Description</th>
<th>Dataset (R/S)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Likarish et al. [22]</td>
<td>2009</td>
<td>This technique propose a method to suppress potentially malicious JavaScripts based on the recommendation of classifiers.</td>
<td>S</td>
</tr>
<tr>
<td>Kirda et al. [21]</td>
<td>2006</td>
<td>This is a rule based client side solution to mitigate XSS attack.</td>
<td>R</td>
</tr>
<tr>
<td>Wurzinger et al. [33]</td>
<td>2009</td>
<td>This server side solution intercepts all HTML responses, and uses a modified Web browser which is utilized to detect script content.</td>
<td>R</td>
</tr>
<tr>
<td>Di Lucca et al. [23]</td>
<td>2004</td>
<td>This approach is a combination of static and dynamic approach for detecting XSS attack.</td>
<td>R</td>
</tr>
<tr>
<td>Salas et al. [28]</td>
<td>2014</td>
<td>This method is to analyze the robustness of web services by fault injection with WSInject.</td>
<td>R</td>
</tr>
<tr>
<td>Athanasopoulos et al. [2]</td>
<td>2010</td>
<td>Proposes a method called xHunter to detect XSS exploits from web trace.</td>
<td>R</td>
</tr>
<tr>
<td>Shar et al. [29]</td>
<td>2013</td>
<td>Hybrid model for XSS and SQL injection attack detection</td>
<td>S</td>
</tr>
<tr>
<td>Adi et al. [1]</td>
<td>2012</td>
<td>Proposes a method called Wines to detect mutated attack strings.</td>
<td>R</td>
</tr>
<tr>
<td>Chun et al. [9]</td>
<td>2016</td>
<td>XSS Attack Detection Method based on Skip List</td>
<td>S</td>
</tr>
</tbody>
</table>

R=Real life, S=Synthetic

Gupta et al. [12] proposed a method called XSS-SAFE for XSS attack detection and prevention based on automated feature injection statements and placement of sanitizers in the injected code of JavaScript. The main advantage of this method is that it can detect XSS attacks without any modification to client- and server-side commodities.

Our approach is a Client-Server based approach, which focuses on balancing the load between client and the server. The detection mechanism in the proxy includes an ensemble based feature selection approach followed by an attribute clustering method to distinguish the malicious traffic from the benign traffic.

3 Proposed Method

The following definitions and theorem provide the theoretical basis of our work. The symbols/notations used to describe our work are reported in Table 2.

**Definition 1. Attribute Rank:** The rank of an attribute $D_{a_i}$ is defined as the relevance of the attribute $a_i$ for a given class (attack or normal) in a dataset $D$.

**Definition 2. Attribute Cluster:** An attribute cluster $C_k^i$ of an attribute $D_{a_i}$ is defined as a subset of objects of a given dataset $D$ (i.e., $C_k^i \subseteq D_{a_i}$) which has high intra-cluster similarity over the attribute $D_{a_i}$.

**Definition 3. Cluster:** A cluster $C_A$ is a subset of objects of a given dataset $D$ (i.e., $C_A \subseteq D$) which is obtained by considering the common objects $C_A$ over a selected subset of relevant attributes $S$. In other words,

$$C_A = C^1_A \cap C^2_A \cap ... C^S_A, \quad S \leq n$$

**Theorem 1.** If $SD_{attrib\_clus()}$ assigns an instance/object $O_j$ to attack group $C_A$, it cannot be in the normal group of a relevant attribute cluster, w.r.t predefined attribute rank or relevance, i.e., $O_j \notin C^i_N, \forall i = 1, ..., S$.

**Proof:** It can be proved by contradiction. Let an object $O_j \in C_A$ as given by $SD_{attrib\_clus()}$ and also let $O_j \in C^i_N$, i.e., a normal group for a given relevant attribute.

Now, as per definition, the attack group, i.e., $C_A$ given by $SD_{attrib\_clus()}$ is the intersection of all those attribute clusters $C^i_A$ which,
• have high relevance for attack class over selected subset of relevant features and
• have high compactness.

So if $O_j \in C_N$, none of the above two conditions are fulfilled. Hence the proof.

3.1 Proposed Framework

The proposed framework for the detection of XSS attack is shown in Figure 3. We have proposed a proxy based approach, where it is attempted to balance the load in both the client and the server. A majority of the detection task is carried out in the proxy. An initial checking for vulnerability is done in the client side.

A. Client-based Processing: An initial checking for the vulnerability is carried out at the client machine. Though one of our objects is to balance the work load between the client and the server, considering the possible low computational ability of a client, we maintain minimum overhead in the client machine. We assign three tasks to the client, i.e., preprocessing, feature extraction of the captured data and $\alpha-$divergence test. The client machine also maintains the profiles of attack and normal instances provided by the detection module in the proxy for reference. When the client sends a request to the server, it is handled by the client for preprocessing, feature extraction and $\alpha-$divergence test with reference to the attack/normal profile. If the value exceeds a pre-defined threshold value then the request is not further processed. It is dropped in the client side only. Otherwise, the request is forwarded to the proxy for further processing.

B. Proxy-level Processing: The majority of the detection tasks are carried out in the proxy server to keep the load in the main server minimum. This includes a step-by-step method to detect the attack using an unsupervised approach. The method follows four steps in sequence, viz., (a) data gathering, (b) preprocessing and feature extraction, (c) feature selection using an ensemble approach and (d) attack detection using attribute clustering over an optimal subset of relevant features. The steps are discussed in detail next.

B.1 Data Gathering: A major brainstorming task of this proxy level processing is to find the Websites for gathering the attack scripts. Since most of the Websites remove the scripts as they are no longer in use once detected, so finding such scripts are difficult. We have collected most of the attack scripts from [6]. Similarly, we gather the normal scripts using a testbed in our institution.

B.2 Preprocessing and Feature Extraction: This step involves finding out a number of features to describe the gathered data. We have found a total of 15 features relevant to our problem as also can be found in [22]. After extracting the features a 16 dimensional dataset (including the class label) is prepared. But since all the features in the dataset are not equally weighted and the ranges vary by a large margin, we have normalized the dataset using min-max normalization method.

B.3 Feature Selection Using Rank Aggregation: At this step, the features which are least relevant are excluded and only a subset of optimal relevant features is taken. Rank aggregation algorithm available in R package selects an optimal subset of attributes (say $S$) from total number of attributes $n$. Rank aggregation framework consists of a number of steps as shown in Figure 4. The prerequisite for the algorithm is a dataset with class labels which is given to different ranking based feature selection algorithms such as infogain [26], correlation based feature selection [14], gain Ratio [25], symmetric uncertainty [13], chi-square [18], mutual information [16] and reliefF [30]. The rankings given by these algorithm are input to a rank aggregation algorithm for the final subset of relevant features generation as shown in the Figure 5.

B.4 Attribute Clustering: Our proposed attribute clustering clusters the instances using the algorithm shown in Algorithm 1. Attribute clustering algorithm is based on the kmeans [15] clustering algorithm. Here each feature is clustered individually applying kmeans. The kmeans algorithm refers the parameters,
The experiments were carried out in both Windows 7 and Linux environment. The machine used was a 64-bit machine with 2 GB RAM. Matlab 2010 was used to performing attribute clustering. WEKA 3.7.11 was used to run the individual ranking algorithm on the labeled dataset. R package was used to run the rank aggregation algorithm over the rank lists given by the individual rankers. All the experiments carried out can be subdivided into the following sections.

4.1 Dataset Preparation

Dataset preparation involves several steps as described below.

4.1.1 Data Gathering

The first step of dataset generation is the collection of data from the Internet. Since the malicious scripts are immediately removed after detection from the Web applications, so it is very hard to collect live scripts. We have collected attack scripts from [6] and the benign JavaScripts from various Websites, which are using rich JavaScript contents. Figure 6 and Figure 7 are the example of collected attack and normal script respectively.
4.1.2 Feature Extraction

After gathering the data, the second major phase is to extract the features that are relevant to our problem. After performing a thorough study of existing works [22] and the gathered data we finally picked up fifteen features as described in Table 3.

4.1.3 Modules

After extraction of the fifteen features a total of seventeen dimensional dataset (including the Sl. no. and class label) is prepared. However, while attribute clustering is performed only the first 15 features are considered as shown in Figure 8. The values of the instances for the 16th feature in most cases are found to be zero. The dataset consists of 71 instances as of now and is flexible. That is, at any point of time if we find a new attack script or normal script we can add that instance to the existing dataset.

Different procedures written in C and their functions are described below.

1) extract_script(): This function extract only the codes included within the script begin tag <script> and the script end tag </script>. All the codes other than this are discarded as they are not executed as JavaScript. The function also calls all the remaining methods.

2) compute_length(): Calculates the total number of characters in the script.

3) no_of_lines(): Calculates the total number of lines in the script.

4) no_of_strings(): This function outputs the total number of lines in the script.

5) avg_characters(): It calculates average number of characters per line in the script.

6) percentage_whitespace(): This method gives the percentage of whitespace characters with respect to the total number of characters in the script.

7) avg_string_length(): It calculates average length of the strings in terms of number of characters present in the string.

8) no_of_comments(): This method gives the number of comment lines present in the script.

9) avg_comments_per_line(): It calculates the average number of comments per line of the script.

10) no_of_words(): Calculates the total number of words in the script.

11) percentage_of_not_commented_words(): This method calculates the percentage of words that are not commented over the total number of words present in the script.

12) count_hex_octal(): It outputs the total number of hexadecimal numbers and octal numbers present in the script.

13) human_readability(): It gives the output in boolean form i.e., either 'Y'(Yes) or 'N'(No). If a script is human readable then it gives the output as 'Y', otherwise 'N'. Human readability is determined with the help of the following methods.
4.1.4 Increase in the Population Density of the Dataset

After collecting the attack and normal scripts, with the help of the modules described in the previous subsection we created a dataset consisting of 71 attack and normal instances in the ratio 1:2 respectively. Now with the help of a module written in C, we increase the number of instances of the dataset to 1078 instances with the same ratio 1:2, respectively. This dataset is used to perform all the operations performed in the following sections.

4.1.5 Normalization of the Dataset

In many pragmatic scenarios, a dataset may consist of attributes or features having values with different ranges. It generally tends to create problem while the some of the values of some attributes are relatively much larger then that of the other attributes. This is because, larger values have a greater impact on the proximity measures like Euclidean distance. Since the base of our proposed attribute clustering algorithm is kmeans, which uses Euclidean distance measure, so it is very important for us to normalize the dataset. Figure 8 displays a part of the original dataset, whereas Figure 9 shows a part of the dataset after normalization. We have used min-max normalization to normalize the dataset. The formula for which is given next.

\[
X_n = \frac{(X - X_{\text{min}})}{(X_{\text{max}} - X_{\text{min}})}. 
\]

Where, \(X_n\) = Normalized value between 0 and 1, \(X\) = Original value, \(X_{\text{max}}\) = Maximum value of the attribute, \(X_{\text{min}}\) = Minimum value of the attribute.

4.2 Results

In this section, we have shown the true positive rate, false positive rate, and accuracy in identifying the groups of attack and normal scripts. An ROC curve is plotted as shown in Figure 10 to demonstrate the detection performance.

4.2.1 ROC Curve

Receiver Operating Curve (ROC) for our dataset is the curve of True Positive Rate (TPR) vs False Positive rate (FPR) of the clusters given by different subset of the attributes or features. Table 4 shows the value of the TPR, FPR, and accuracy of the clusters given by the attribute selection algorithm based on the feature subsets. The feature subsets contains the feature values according to the rank given by the ensemble feature selection algorithm.
Steps involved in calculating the True Positive (TP) and False Positive (FP) values of a cluster given by the attribute clustering algorithm are as follows:

- The attribute rank subset given by rank aggregation is taken and SD\_attrib\_clus() algorithm is applied on the whole dataset according to the given feature rank.
- The cluster which is more compact is considered as the attack cluster and the cluster instances are stored in a matrix.
- Now from the actual labeled dataset the attack instances are determined and intersection of these instances with the previously stored cluster instances are found. Thus we get the TP value. And the instances, that are excluded are counted as the FP value.
- The TPR and FPR are calculated from these TP and FP values with the help of the following formulas:

\[
\text{True Positive Rate (TPR)} = \frac{\sum \text{True Positive}}{\sum \text{Condition Positive}}
\]

\[
\text{False Positive Rate (FPR)} = \frac{\sum \text{False Positive}}{\sum \text{Condition Negative}}
\]

\[
\text{Accuracy (ACC)} = \frac{\sum \text{True Positive} + \sum \text{True Negative}}{\sum \text{Total Instances}}
\]

4.3 Comparison with Other Methods

In this section, we compare our method with other competing methods of XSS detection.

- Like [22], our method is also established on feature dataset generated based on the extracted features from attack and normal scripts.
- Like [7, 29], we also evaluate our method in terms of detection accuracy and the performance of our method is highly satisfactory.
- Unlike [7, 22], our method uses unsupervised attribute clustering technique to group the JavaScripts into legitimate and malicious.
- Unlike most other methods [21, 33], our approach attempts to balance the load between the client and server.
Table 3: Description of extracted features

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Feature Label</th>
<th>Feature Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>Number of characters in the script</td>
</tr>
<tr>
<td>2</td>
<td>B</td>
<td>Number of lines in the script</td>
</tr>
<tr>
<td>3</td>
<td>C</td>
<td>Number of strings in the script</td>
</tr>
<tr>
<td>4</td>
<td>D</td>
<td>Average characters per line</td>
</tr>
<tr>
<td>5</td>
<td>E</td>
<td>Percentage of whitespace in the script</td>
</tr>
<tr>
<td>6</td>
<td>F</td>
<td>Average string length</td>
</tr>
<tr>
<td>7</td>
<td>G</td>
<td>Number of comments in the script</td>
</tr>
<tr>
<td>8</td>
<td>H</td>
<td>Average comments per line</td>
</tr>
<tr>
<td>9</td>
<td>I</td>
<td>Total number of words</td>
</tr>
<tr>
<td>10</td>
<td>J</td>
<td>Percentage of words that are not commented</td>
</tr>
<tr>
<td>11</td>
<td>K</td>
<td>Number of octal numbers</td>
</tr>
<tr>
<td>12</td>
<td>L</td>
<td>Human readability in terms of yes or no. checking criteria are:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>a) Percentage of words which are &gt;70% alphabetical &gt;=45%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>b) Percentage of words, where 20% &lt; vowels &lt;60% &gt;=40%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>c) Percentage of words which are less than 15 characters long &gt;=70%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>d) Percentage of words containing &lt; 3 repetition of the same letter in a row &gt;=80%</td>
</tr>
<tr>
<td>13</td>
<td>M</td>
<td>Number of methods called</td>
</tr>
<tr>
<td>14</td>
<td>N</td>
<td>Average argument length</td>
</tr>
<tr>
<td>15</td>
<td>O</td>
<td>Number of unicode symbols</td>
</tr>
<tr>
<td>16</td>
<td>P</td>
<td>Number of HEX numbers</td>
</tr>
</tbody>
</table>

Figure 8: A portion of the original dataset
Table 4: Accuracy of the classes based on the feature subset

<table>
<thead>
<tr>
<th>Feature Subset</th>
<th>True Positive Rate (TPR)</th>
<th>False Positive Rate (FPR)</th>
<th>Accuracy</th>
</tr>
</thead>
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<td>12,2,7,13,5,3,1,9,4,8,11,14,15,6,10</td>
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<td>0.7449</td>
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<tr>
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<td>0.978</td>
<td>0.006</td>
<td>0.9889</td>
</tr>
<tr>
<td>12,2,7,13,5,3,1,9,4,8,11,14,15,6,10</td>
<td>0.983</td>
<td>0.006</td>
<td>0.9907</td>
</tr>
<tr>
<td>12,2,7,13,5,3,1,9,4,8,11,14,15,6,10</td>
<td>0.983</td>
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<tr>
<td>12,2,7,13,5,3,1,9,4,8,11,14,15,6,10</td>
<td>0.983</td>
<td>0.007</td>
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<tr>
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<td>0.008</td>
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<td>0.008</td>
<td>0.9889</td>
</tr>
</tbody>
</table>

Figure 9: A portion of the normalized dataset
Data: $D = \text{Dataset}, D_{ai} = i^{th}$ attribute of $D$, $\forall i = 1, 2, ..., n$  
$K = \text{No. of clusters}$  
Result: $C_A = \text{Attack cluster}$  
Function $\text{SD}_\text{attribclus}()$

```
foreach attribute $D_{ai} \in D$ do
    [indexMatrix, sumd] = kmeans($D_{ai}$, $K$)
    foreach Cluster $C_i^k, k = 1, 2$ do
        $\text{CP}_k^i = \frac{\text{sumd}}{\text{No. of objects in } C_i^k}$
    end
    if $\text{CP}_k^i < \text{CP}_{k+1}^i$, $k = 1$ then
        foreach Object $O_{i}^j \in D_{ai}$ do
            if $\text{indexMatrix}(O_{i}^j) == k$ then
                $C_A \leftarrow O_{i}^j$
            end
        end
    else
        $C_N \leftarrow O_{i}^j$
    end
    end
end
```

// Find the common objects of the attributes in the order given by rank aggregation method
$C_A = \cap C_i^k, \forall i = 1, 2, ..., S, S \leq n$

Algorithm 1: Attribute clustering algorithm

5 Discussion and Conclusion

Based on the results we got from the attribute clustering algorithm, proceeded by rank aggregation using cross entropy monte carlo algorithm, shows us a way how we can use unsupervised techniques in clustering the malicious and benign scripts into two classes with high accuracy. The computation overhead also decreases significantly in the proxy as our proposed method distributes the task between the client and the server. The detection mechanism in the proxy is easy to implement and requires a little knowledge to detect an attack with high accuracy.

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References

Biography

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