Web Application Attack Detection using Deep Learning

Tikam Alma and Manik Lal Das

DA-IICT
Gandhinagar, India
Email: {201601030, maniklal_das}@daiict.ac.in

Abstract

Modern web applications are dominated by HTTP/HTTPS messages that consist of one or more headers, where most of the exploits and payloads can be injected by attackers. According to the OWASP, the 80 percent of the web attacks are done through HTTP/HTTPS requests queries. In this paper, we present a deep learning based web application attacks detection model. The model uses auto-encoder that can learn from the sequences of word and weight each word or character according to them. The classification engine is trained on ECML-KDD dataset for classification of anomaly queries with respect to specific attack type. The proposed web application detection engine is trained with anomaly and benign web queries to achieve the accuracy of receiver operating characteristic curve of 1. The experimental results show that the proposed model can detect web applications attack successfully with low false positive rate.

Keywords: Web Application; Web Security; Machine Learning; Deep Learning.

1 Introduction

Web application attacks are found one of the most targets by attackers. Symantec Internet security [9] reported an interesting statistics that 1 in 10 URLs are identified as being malicious. Web applications typically use the HTTP/HTTPS protocols supported by other backend and frontend interfaces. According to Imperva Web Application Vulnerability Report [9], high severity attacks are injection attacks, which are being exploited through injecting payloads in HTTP/HTTPS web queries by using GET, POST and PUT methods. CSRF (Cross Site Request Forgery) attack, SQL injection attack, XSS (Cross Site Scripts) attacks, and widely used vulnerable JS libraries, which account for 51 percent, 27 percent, 33 percent and 36 percent, respectively. This paper focuses on the most frequent types of web-based injection attacks, which includes SQL injection, XSS (Cross Site Script), RFI (Remote File Inclusion), XXE (XML External
Entity), CSRF (Cross Site Request Forgery), and SSRF (Server Side Request Forgery).

Network Intrusion Detection System (NIDS) monitors the network traffic in web applications. Web IDS acts as intermediate between web application and users, as it analyzes web traffics to detect any anomaly or malicious activity [2]. Generally, there are two types of detection approaches: anomaly-based detection and signature-based detection. The signature-based IDS system uses a signature concept, more like antivirus detects the virus, when the antivirus database has that specific kind of virus signature. If attackers create new virus, the antivirus is of no use if the signature/pattern is not present. Anomaly-based detection is based on detection unique behavior pattern recognition or any activity that differs from previous data or information is fed. When comparing signature-based detection method with anomaly-based detection method, the performance of anomaly based detection found high to detect the unknown attacks, but it comes with a cost that it has problem with false positive alarm rates. After detection of an anomaly it is stored in the database it becomes a “signature”, and furthermore, there are two detection methods which come under anomaly detection which is adaptive detection and constant detection [3]. An adaptive detection algorithm analyzes the network traffic of port 80 of web network that is HTTP traffic, which continuously gets the input of traffic and analyzes in a timely manner, while constant based detection method analyzes stores incoming traffic or use to analyze the logs of collected traffic.

The conventional patching approach to mitigating most network layer vulnerabilities does not work well in web application vulnerabilities such as SQLi, RCE, or XSS. The reason behind all these attacks is that modern web applications are poorly designed with insecure coding. One can follow the OWASP’s secure coding guidelines to prevent most of the attacks. Adaptive detection model is effective to detect anomalies and classify them which type of attack it is, so that the developer at backend can fix that patch or prevent it (e.g., Django uses CSRF Tokens in the framework to prevent CSRF) attacks which account for 51 percent of the web attack. At the same time, the model should learn the patterns over time to detect unknown web attacks and identify which type of attack vectors are being exploited. Anomaly based detection approaches [2] usually rely on an adaptive model to identify anomalous web requests, but with a high degree of false positive rate. In this paper, we come up with a solution to handle false positive where IDS monitor a system based on their behavior pattern. There are several reasons why a conventional IDS or web application firewall does not work, as follows:

- Limited Dataset: To collect and capture a large amount of anomalous data, one has to set-up a system or an automated system that captures the attack requests and classify them whether they are anomalous or normal requests. This is more like a attack-defense simulation system, but smart enough to classify, that does not need to be labeled manually and it could save lots of time.
- High False Positive: Conventional system uses unsupervised learning algorithms such as PCA [5] and SVM [7] to detect web attacks, these approaches require manual selection of attack specific features [6]. These conventional methods may achieve acceptable performance, but they face high false positive rates.

- Labeled Dataset: Conventional IDS uses rule-based or conditional strategies or supervised algorithms like support vector machines or decision trees to classify normal traffic requests from attack requests, which requires large database to get the accurate results [6].

In this paper, we present a web application attacks detection model, SWAD, based on deep learning technique that detects web application attacks autonomously in real-time. The model uses auto-encoder that can learn from the sequences of word and weight each word or character according to them. The classification engine is trained on ECML-KDD dataset for classification of anomaly queries with respect to specific attack type. We have implemented the model on sequence to sequence model, which consists of encoder and decoder, that sets its target values equal to its input values. The proposed SWAD model first uses 40,000 web requests, both anomaly and benign nature, for training and then 20,000 anomaly web requests and responses for training the model. The experimental results of the proposed model show that it can detect web applications attack with true positive rate is 1 and low false positive rate.

The paper is organized as follows: Section II summarizes the background and related works. Section III describes the system design. Section IV evaluates the performance of the proposed model. Section V concludes the paper.

2 Background and Related work

2.1 Deep Learning for Web Attack Detection

There are two categories of Machine Learning approaches for detecting web attacks: unsupervised and supervised learning. Supervised learning is the learning approach feeds mapped labeled data which then outputs the expected data, which is simply mapping of input functions to dataset and expecting new input with learned labels at the output. For the classification of data, the most common algorithm is supervised learning, which is used to learn the machine learning model to train and identify the data using the labels which are mapped. The concept of the algorithm is to learn the mapping function of a given input to the output, where the output is defined by variable $Y$ and input is defined by variable $x$.

$$Y = f(X)$$

If web attacks labeled dataset is trained using supervised algorithms such as SVM (Support Vector Machine) [11] and Naive Bayes [8], then it classifies
anomalous to normal web attack requests. However, the model cannot handle new types of attack requests and it requires a large amount of labeled dataset. Unsupervised learning is used mainly with unlabeled dataset. The model supported by this learning finds patterns from previous sequence or dataset and identifies or predicts the next one. For exploratory analysis, the unsupervised learning method is used to automate the identification pattern of data structures. Using an unsupervised method, one can reduce the dimensions used to represent data for fewer columns and features. To sort the eigenvectors, Principal Component Analysis (PCA) \[11\] is used to compute the eigenvectors of the co-variance matrix that is “principal axes”. To get the dimensionality reduction, the centered data were projected into principal axes. Principal component (PC) scores are a group of score that are obtained from PCA. To create equal number of new imaginary variables or principle components the relationship between a batch or group of those PC scores are analyzed. The optimized and maximally correlated with all of the original group of variables is the first created imaginary variables, then the next created imaginary variable is less correlated and next is lesser than the previous and it goes on until the point when the principal components scores predicts any variable from the first created group.

PCA Reconstruction = PC Score × EigenVectors(t) + Mean

The condition of perfect reconstruction of the data or input and the there will be no dimentionality reduction is when all the \(p\) eigenvectors are used and \(VV^t\) is the identity matrix. When using large dataset features, whether it is image, text or video data, one cannot use any machine-learning algorithms directly. In order to reduce the training time, preprocess steps are required to clean the dataset. It is noted that PCA is restricted to a linear map. Autoencoders \[10\] can have non linear encoder/decoders. A single layer autoencoder with linear function is nearly equivalent to PCA. We use sequence-to-sequence autoencoder in our proposed detection model.

![Autoencoder basic architecture](image)

Figure 1: Autoencoder basic architecture

The condition to make the autoencoder equivalent to principal component analysis is that if normalized inputs are used with the linear decoder, linear encoder and square error loss function, then autoencoders are not restricted to linear maps. The proposed model is optimized and trained to minimize and
reduce the loss between the input and the output layer. We have used non-
linear functions with encoders to get more accuracy when reconstruction of
data is processing. The activation functions used in autoencoders are ReLu and
sigmoid, which are non-linear in nature.

\[ \Phi : \chi \rightarrow F \]  
\[ \Psi : F \rightarrow \chi \]  
\[ \Phi, \Psi = \arg\min_{\Phi, \Psi} ||X = (\Phi * \Psi)X||^2 \]  

The encoder function, denoted by \( \Phi \), maps the original data \( X \) to a la
tent space \( F \). The decoder function, denoted by \( \Psi \), maps the latent spa
te \( F \) to the output. We basically recreate the original image after some genera
lized non-linear compression. The encoding network can be represented by the standard
neural network function passed through an activation function, where \( z \) is the
hidden dimension. The output works the same as the input.

\[ Z = \sigma(Wx + b) \]  
With slight different weight, bias and activation function, the output function
or the decoder network is represented in the same way.

\[ X' = \sigma'(W'z + b') \]  
To train the model for getting optimized results and the loss function in the
equation, the model is trained with back-propagation method.

\[ L(x, x') = ||x - x'|| = ||x - \sigma'(W'(\sigma(Wx + b)) + b')||^2 \]  
To reconstruct the input data or input characters, the autoencoders select the
encoder and decoder function for optimization, so that it requires the minimal
information to encode the input data for reconstructing the output.

3 The Proposed Model

The proposed detection engine uses an autoencoder model based on sequence
to sequence architecture that is made up of LSTM (Long Short Term Memory)
cells. LSTM networks are complex neural networks that are used to train
ordered sequences of inputs to remember it and re-create it. The proposed
model devises the LSTM neural network model, which feeds sequenced inputs.
After completing the reading input processes, the output is given by an internal
learned representation of the fed input sequences as a fixed-length vector. Then,
output vector is fed inputs that interprets the input sequence by sequence at
each step and the output is generated.

The proposed detection and classification model works in synchronization as follows:
Figure 2: The Proposed System Architecture

1. For the training purpose, large amounts of unlabeled normal HTTP requests are collected from open-source Vulnbank organization, which contains 40k normal HTTP (GET, POST and PUT) methods requests.

2. For the auto-encoder’s (Encoder-Decoder) architecture, the hyper-parameters are trained by setting the problem as a grid search problem. Each hyper-parameter combination requires training the neuron weights for the hidden layer(s), which results in increasing computational complexity with an increase in the number of layers and number of nodes within each layer. To deal with these critical parameters and training issues, stacked auto-encoder concepts have been proposed that trains each layer separately to get pre-trained weights. Then the model is fine-tuned using the obtained weights. This approach significantly improves the training performance.
over the conventional mode of training. For implementation of the proposed model, we consider the following parameters.

- Batch Size = 128
- Embed Size = 64
- Hidden Size = 64
- Number of Layers = 2
- Dropout Rate = 0.7

3. Reconstruction of requests are done by the decoder \( X' = \sigma'(W' + b') \), which perfectly reconstructs the given input and evaluates loss function and accuracy.

4. When a new requests is given as input to the trained autoencoder, it decodes and encodes the requests vector and calculates the reconstruction or loss error. If loss error is larger than the learned threshold \( \theta \), it categorizes as anomalous requests. If loss error is smaller than \( \theta \), it categorizes as normal requests.

5. After categorizing requests into normal and anomalous requests, normal requests are sent to the database for retraining or re-learning, so that over time the detection model learns new type of requests patterns. Anomalous requests are sent to the classification model which further categorizes the anomalous requests into which type of attack it was exploited through requests like SQLi, XSS or CSRF.

6. The classification model is trained on larger number of labeled attack vectors HTTP requests. It contains 7 class of attacks which are Os-Commanding, PathTraversal, SQLi, X-PathInjection, LDAPInjection, SSI, and XSS.

We use LSTM layers to train the classification model and fine-tune the model with hyperparametrs. Every LSTM layer is accompanied by a dropout layer, which helps to prevent over-fitting by ignoring randomly selected neurons during training, and hence, reduces the sensitivity to the specific weights of individual neurons.

The image in Figure-3 is the raw anomaly HTTP requests with XSS attack vector. In data pre-processing step, the raw HTTP data is converted to a single string and parsed as input to the LSTM cell, which is the passed to the training phase to train the model.
4 Experimental Results and Evaluation

We have experimented the proposed model with 40,000 web requests followed by 20,000 anomaly web requests and responses. The classification engine is trained on ECML-KDD dataset for classification of anomaly queries with respect to specific attack type. We have evaluated the proposed model on ROC curve. An ROC curve is a graph showing the performance of a classification model at all classification thresholds. The ROC curve plots two parameters - true positive rate and false positive rate. A false positive (FP) or false alarm, which refers to the detection of benign traffic as an attack. A false negative (FN) refers to detecting attack traffic as benign traffic. A key goal of an intrusion detection system is to minimize both the FP rate and FN rate. We use the following parameters to evaluate the proposed model’s performance:

- True Positive (TP): the number of observations correctly assigned to the positive class.

- False Positive (FP): the number of observations assigned by the model to the positive class.

- True Positive Rate (TPR) reflects the classifier’s ability to detect members of the positive class

\[
TPR = \frac{TP}{TP + FN}
\]

- False Positive Rate (FPR) reflects the frequency with which the classifier makes a mistake by classifying normal state as pathological

\[
FPR = \frac{FP}{FP + TN}
\]

An ROC curve plots TPR versus FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, and thus, increasing both false positives and true positives.
As defining normality with a descriptive feature set is difficult, anomalies raised by systems can sometime be detected with false alarms (false positives) or missed alerts (false negatives). With the ROC curve, the closer the graph is to the top and left-hand borders, the more accurate the test. Similarly, the closer the graph to the diagonal, the less accurate the test. The experimental results obtained on the proposed model are as follows:

- Precision: 0.9979
- Recall: 1.00
- Number of True Positive: 1097
- Number of Samples: 1097
- True Positive Rate: 1.00
- Number of False Positive: 7
- Number of samples: 2200
- False Positive Rate: 0.0032

5 Conclusion

We discussed an intrusion detection model using deep learning. The proposed model detects web application attacks autonomously in real-time. The model uses auto-encoder that can learn from the sequences of word and weight each word or character according to them. The experimental results show that the proposed model can detect web applications attack with low false positive rate and true positive rate is 1. Because of less volume of labeled categorized anomalous dataset, the proposed classification engine is not 100 percent accurate; however, the classification can be improved with optimized training with a large volume of dataset, which is left as the future scope of the work.
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