Neural Classification of Malicious Scripts: A study with JavaScript and VBScript

Jack W. Stokes
Microsoft Research
Redmond, WA 98052, USA

Rakshit Agrawal
Department of Computer Science
University of California, Santa Cruz
Santa Cruz, CA 95064, USA

Geoff McDonald
Microsoft Corp.
Vancouver, BC, V6E 4M3, CA

Abstract
Malicious scripts are an important computer infection threat vector. Our analysis reveals that the two most prevalent types of malicious scripts include JavaScript and VBScript. The percentage of detected JavaScript attacks are on the rise. To address these threats, we investigate two deep recurrent models, LaMP (LSTM and Max Pooling) and CPoLS (Convoluted Partitioning of Long Sequences), which process JavaScript and VBScript as byte sequences. Lower layers capture the sequential nature of these byte sequences while higher layers classify the resulting embedding as malicious or benign. Unlike previously proposed solutions, our models are trained in an end-to-end fashion allowing discriminative training even for the sequential processing layers. Evaluating these models on a large corpus of 296,274 JavaScript files indicates that the best performing LaMP model has a 65.9% true positive rate (TPR) at a false positive rate (FPR) of 1.0%. Similarly, the best CPoLS model has a TPR of 45.3% at an FPR of 1.0%. LaMP and CPoLS yield a TPR of 69.3% and 67.9%, respectively, at an FPR of 1.0% on a collection of 240,504 VBScript files.

1. Introduction
Malicious scripts are widely abused by malware authors to infect users’ computers. In this paper, we show that in the current threat landscape, the two most prevalent types of script malware that Windows users encounter are JavaScript (JS) and VBScript (VBS). JavaScript is an interpreted scripting language developed by Netscape that is often included in webpages to provide additional dynamic functionality Mozilla. VBScript, or Microsoft Visual Basic Scripting Edition, is an active scripting language originally designed for Internet Explorer and the Microsoft Internet Information Service web server Microsoft.

Spearphishing attacks have been a key component of several recent large-scale data breaches (CRN; Snell). For example in Figure 1, a typical spearphishing attack involves a user being sent an email stating that they have an outstanding invoice. An archive is attached to the email, and inside the archive is a VBScript file called ”invoice.vbs”. If the user opens the VBScript file, it will be executed through the default file association using a native script execution host on Windows (in this example “wscript.exe”). Now that the
malicious script is running on the computer, these attacks commonly download and execute further malware such as ransomware (Corporation (2016)). Figure 2 presents examples of malicious JavaScript and VBScript content.

Figure 1: Example of an email-based social engineering attack using an attached VBScript file.

Figure 2: Example a) JavaScript file from the TrojanDownloader:JS/Swabfex malware family, and b) from a malicious VBScript file from the Worm:VBS/Jenxcus malware family.

While a wide range of different machine learning models have been proposed for detecting malicious executable files (Gandotra et al. (2014)), there has been little work in investigating malicious JavaScript, and even less research has been devoted to trying to detect malicious VBScript. Previous JavaScript solutions include those based on static analysis (Likarish et al. (2009); Maiorca et al. (2015); Shah (2016)), and both static and dynamic analysis (Corona et al. (2014)). Two previous solutions for VBScript are based
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on static analysis (Kim et al. (2006); Wael et al. (2017)). In addition, deep recurrent
models have recently been proposed detecting system API calls in PE files (Athiwaratkun and
Stokes (2017); Kolosnjaji et al. (2016); Pascanu et al. (2015)), JavaScript (Wang et al.
(2016)), and Powershell (Hendler et al. (2018)).

There are several challenges posed by trying to detect malicious JavaScript and VB-
Script. One main challenge is the lack of labeled data. While obtaining malicious samples
is challenging enough, creating a large benign set of script files is extremely difficult given
strict privacy email policies which prevent manual inspection of undetected email. Furthermore, malicious scripts include obfuscation to hide the malicious content, and often unpack or decrypt the underlying malicious script only upon execution. Complicating this
is the fact that the obfuscators, in some cases, are used by both benign and malware files.
Thus pure static analysis of the primary script often fails to detect some malicious activity.
Another problem is that anti-virus (AV) automation systems such as sandboxing environ-
ments are designed primarily to handle Windows Portable Executable (PE) files (e.g., .exe
and .dll). Accordingly, the number of labeled script files is typically much lower than for executable files.

In this paper, we propose ScriptNet, a deep recurrent neural classification system which
can be trained to detect either malicious JavaScript or VBScript using a combination of
both static and dynamic analysis. We first use a production anti-virus engine to dynamically
execute a script in a sandboxed environment inside of the engine. This allows the AV
engine to safely analyze any child scripts which are dropped during script execution without
infecting the computer.

We investigate two different models for the task of detecting malicious JavaScript and
VBScript. Both models encode sequential information using one or more long, short-term
memory (LSTM) layers. The LSTM and Max Pooling (LaMP) model follows a two-stage
approach where the first stage learns a language model for the individual characters in the
script content. Next, the second stage includes a, potentially deep, neural network for the
final classification of the script as malicious or benign. To allow the processing of longer
script files, we next investigate the Convoluted Partitioning of Long Sequences (CPoLS)
model which adds an additional layer consisting of a one-dimensional convolutional neural
network. LaMP is similar to the model proposed by Athiwaratkun and Stokes (2017) for
PE files, but differs in two respects. While Athiwaratkun’s model also has an LSTM-based
language model followed by a neural network classification stage, each component is trained
in isolation. The language model is first trained in an unsupervised fashion, and this trained
language model is then frozen and used to generate the embeddings for the classification
stage. Instead, LaMP is trained with end-to-end learning where all the model parameters,
including those in the language model and the classifier, are learned simultaneously directly
from the characters in the script content. Similarly, CPoLS is also trained in an end-to-
end manner. Second, LaMP extends the model in Athiwaratkun and Stokes (2017) to
allow for stacked (i.e., multiple) LSTM layers. Since our models operate directly on the
script content encoded as bytes, they do not require careful and potentially computationally
expensive feature engineering proposed by other solutions. The main contributions of this
paper include:

- We study the detection percentage and threat vectors of malicious JavaScript and
  VBScript from telemetry generated by a production anti-virus product.
We investigate two deep recurrent neural network models for the detection of malicious JavaScript and VBScript.

We evaluate these models on two large corpora of JavaScript and VBScript files.

2. Motivation

The detection of malicious JavaScript and VBScript is important for protecting users against modern malware attacks. With advances in browser and operating system security making browser exploit attacks more difficult, miscreants are instead relying on social engineering attacks. Figure 3 illustrates the percentage of malicious detected files by the Windows Defender anti-malware engine in the categories of JavaScript and VBScript attacks. The percentage of malicious JavaScript-based attacks has been rising recently, while the percentage of detected attacks involving VBScript have remained relatively constant since 2014. Figure 4 indicates the percentage of all, non-PE files detected in the Windows Defender telemetry. This figure indicates that JavaScript and VBScript are the two most prevalent types of detected scripts found in the telemetry data. Since the remaining 92.5% of the detections are for PE files, malicious scripts are still a small minority of the detected files in the wild.

Based on the identified arrival methods of malicious JavaScript and VBScript, Figure 5 illustrates the identified attack methods based on the telemetry data from 2017. Archive file detections, the most prevalent threat vector for JavaScript, are generated when the user extracts the script from within an archive and are often used in social-engineering attacks. Interestingly, removable drives (e.g., thumbdrives, external USB harddrives) were responsible for the second most JavaScript attacks. Only 11.1% of detected malicious JavaScript files were encountered from malicious email, and 3.8% of the files were directly downloaded from the internet.

The distribution of the attack sources for malicious VBScript tells a different story. The main threat vector of malicious VBScript is emails followed closely again by downloads. Archives and removable drives play a smaller role in VBScript attacks, but they are still important threat vectors.
3. Threat Model

It is necessary to specify the assumptions that we make about the attacker. The most important assumption is that the model is able to learn some deep embedding which is able to identify activity related to malware from the first $T$ bytes (e.g., 200, 1000) of the script. If the first $T$ bytes are randomly initialized, the models will fail to detect the activity that somehow captures malicious intent.

Another assumption is that the behavior which identifies an unknown malicious script is also found in labeled scripts in the training set. If the training set does not contain scripts which are somehow related to the unknown script being evaluated, the classifier may again fail to accurately predict the script type.

As part of the scanning process, the anti-malware engine emulates an unknown file and attempts to extract any child scripts. It may be possible that the anti-malware engine fails to successfully extract all the child scripts. In this case, the model may also fail to detect the malicious script if the parent script is predicted to be benign, and the child script which executes the malicious activity is not successfully extracted.

4. Data

Scripts: Building a dataset of malicious and benign scripts for training is a challenge. A sizable percentage of malicious scripts are delivered in email and for privacy reasons cannot be collected. For this research, samples were selected randomly from the files observed on users’ computers during June 2017 that had been successfully collected, with permission, by the Windows Defender backend. These samples are collected by many sources including users directly submitting suspicious files for analysis, files shared through sample exchanges such as VirusTotal, and scripts that were extracted from installer packages or archives.

Labels: Another challenge in training a classifier for detecting malicious scripts is obtaining enough labeled data. Since we are trying to predict if a script is malware or benign, we must obtain both types of labels.
A script is labeled as malware if it has been inspected by our AV partner’s analysts and determined to be malicious. In addition, the script is labeled as malicious if it has been detected by the company’s detection signatures. Finally, scripts are labeled as malware if eight or more other anti-virus vendors detect the script as malware.

Obtaining enough benign scripts is a challenge because labeling a script as benign often requires manual inspection. Thus, a script is labeled as benign by a number of methods. First, the script is considered benign if it has been labeled as benign by an analyst or has been collected by a trusted source such as being downloaded from a legitimate webpage. However, this does not provide enough labeled benign scripts so we augment this benign dataset with scripts which are not detected by any trusted scanner at least 15 days after our AV partner has first encountered it in the wild.

Datasets: Our anti-virus partners provided the first 1000 bytes of 296,274 JavaScript files which contained 166,179 malicious and 130,095 benign scripts. We randomly assigned these scripts into training, validation, and test sets containing 207,392, 29,627, and 59,255 samples, respectively. The validation set is a small dataset which is used for hyperparameter tuning during the training phase. By doing so, we are later able to make a fair assessment of the final model’s performance on the held-out test set. Similarly, our partners provided a VBScript dataset with 240,504 examples including 66,028 malicious scripts and 174,476 benign scripts. This dataset was then randomly split into 168,353 training scripts, 24,050 validation scripts, and 48,101 test scripts.

5. System

Figure 6 presents an overview of the proposed neural script classification system. The labeled collection of malicious and benign scripts (e.g., JavaScript or VBScript files), described in the previous section, are first scanned with the Windows Defender anti-malware engine. During this scanning operation, the script is emulated and unpacked and may drop one or more additional scripts. Each child script is also emulated and unpacked which may generate even more scripts. This process continues until all scripts have been extracted and scanned.

Figure 6: Overview of the neural script classification system.
These scripts are next normalized. All whitespace characters, except line breaks, are first removed. Next the text is standardized to lowercase and converted to the US-ASCII character set. Any characters which are not included in the US-ASCII character set, such as non-English language characters, are replaced by the constant character ‘?’. Figure 7 illustrates an example script before and after normalization.

![Example malicious packed JavaScript file from the TrojanDownloader:JS/Crimace.A malware family before (left), and after normalization (right).](image)

Before training the model, each normalized script is written to the file system. To avoid storing malicious content on the hard drive, the characters are next encoded by their numeric ASCII encoding (e.g., '97' for the character 'a') delimited by commas. This delimited, encoded sequence data is then used to train the neural script malware model.

To evaluate an unknown file, the system uses the trained model to produce a prediction which indicates the probability that the unknown script is malicious.

6. Models

Static and dynamic analysis of script files, like VBScript and JavaScript, allows our system to use information hidden in the script’s unpacked content to learn its malicious nature. In this section, we discuss our models which can capture the script files and learn malicious intent using neural classifier models and sequential learning.

**Translation to Sequences:** The raw scripts can be considered to be documents containing a limited vocabulary set. As such, the scripts are long ordered sequences of encoded characters. For normalized script files, we define our vocabulary as the set of all possible bytes (8-bits). This leads to a vocabulary of size 256. Each normalized script, therefore, is a sequence of these bytes.

**Sequential Learning:** In language models over document-like datasets, sequential learning is a commonly used learning methodology (Józefowicz et al. (2016); Sutskever et al. (2014)). Neural network-based models for sequential learning use Recurrent Neural Networks (RNNs), and their variants, to capture the ordered nature of elements, while learning generally over each individual item. In our models, we use a specific memory-based gated variant of RNNs, known as the Long Short-Term Memory (LSTM) model (Gers et al. (2000); Hochreiter and Schmidhuber (1997)). LSTMs are used extensively for processing long sequences of data. In speech and language models in particular, enhanced LSTMs de-
fine the state-of-the-art (Cho et al. (2014); Graves et al. (2013a b); Sutskever et al. (2014)). However, their general neural nature, along with the ability to learn using backpropagation through time (Werbos (1990)), makes them useful in many domains. For our byte sequences, we therefore use LSTMs as the primary element for the capturing sequential attributes of the data. LSTMs can often be implemented with minor variations in their structure. The implementation used in our models, at each timestep \( t \), is described by the following equations:

\[
\begin{align*}
i_t &= \sigma(W_{hi} h_{t-1} + W_{xi} x_t + b_i) \\
f_t &= \sigma(W_{hf} h_{t-1} + W_{xf} x_t + b_f) \\
o_t &= \sigma(W_{ho} h_{t-1} + W_{xo} x_t + b_o) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tanh(W_{hc} h_{t-1} + W_{xc} x_t + b_c) \\
h_t &= o_t \odot \tanh(c_t)
\end{align*}
\]  

where the nonlinearity defined by \( \sigma \) corresponds to the logistic sigmoid function. The variables \( i_t, f_t, o_t, c_t \) are the input gate, forget gate, output gate and cell activation, respectively. \( W_{hi} \) are the weight matrices for each gate corresponding to the recurrent input from the previous timestep, \( W_{xf} \) are the input weight matrices per gate, and \( b_i, b_f, b_o \) are the biases for each gate. The function \( \odot \) represents the pairwise product between two vectors.

The network takes input vector \( x_t \) at each timestep \( t \), and updates two properties of the LSTM. It updates the cell memory \( c_t \) using the gates as well as the cell memory \( c_{t-1} \) from the previous timestep. It then updates the hidden activation \( h_t \) for timestep \( t \) by using the gates and cell memory. The input vector provided to the LSTM cell can be of any structure depending on the data. In a categorical representation, it can be a one-hot encoded vector, while in the case of embeddings, it can be in the form of a dense vector. For sparse featured data, the input can simply be a sparse vector.

**Model Architectures:** In our experiments for sequential learning, we designed two neural model architectures. The primary difference in these two architectures is their resilience against very long length sequences. We will discuss these properties in detail below.

**LSTM and Max Pooling:** In the LSTM and Max Pooling (LaMP) architecture, illustrated in Figure 8, we first use an embedding layer, EMBEDDING, to process the input byte sequence \( B \). Since each element in \( B \) corresponds to a byte from the vocabulary, it is symbolic in nature. We use the embedding layer to transform each byte into a dense vector (i.e., an embedding) which captures relatedness among different bytes, thereby assisting the overall model in learning. The sequence of embeddings \( E \) is then passed through multiple LSTM layers stacked on top of each other. The LSTM generates representations for each element in the input sequence as \( H_L \). In order for us to perform classification on the sequence and identify its hidden malicious content, we transform the sequence \( H_L \) into a vector highlighting significant information, while reducing its dimensionality. For this purpose, we use a temporal, max pooling layer, MAXPOOL1D, as proposed by Pascanu et al. (2015). Given an input vector sequence \( S = [s_0, s_1, \ldots, s_{M-1}] \in S \) of length \( M \), where each vector \( s_i \in \mathbb{R}^k \) is a \( k \)-dimensional vector, MAXPOOL1D computes an output vector \( s_{MP} \in \mathbb{R}^k \) as \( s_{MP}(k) = \max(s_0(k), s_1(k), \ldots, s_{M-1}(k)) \).

We pass the sequence \( H_L \) through MAXPOOL1D to obtain vector \( h_L \). Next, \( h_L \) is passed through one or more dense neural layers employing a rectified linear (RELU) nonlinear
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activation function. This helps learn an additional layer of weights before performing the final prediction. The \texttt{ReLU} activated vector is finally used by a sigmoid layer to generate final probability $p_m$ indicating if the script is malicious or benign. We can formally define \texttt{LaMP} on an input byte sequence $B$ as:

$$
E = \text{Embedding}(B)\\
H_L = \text{LSTM}(E)\\
h_L = \text{MaxPool1d}(H_L)\\
h_{CL} = \text{ReLU}(W_L \ast h_L)\\
p_m = \sigma(W_D \ast h_{CL})
$$

(2)

where $W_L$ is the weight matrix for the dense \texttt{ReLU} hidden layer, and $W_D$ is the weight matrix for the final sigmoid classification layer.

While \texttt{LaMP} provides a simple model to capture sequences directly, it is limited by the length of the input sequences. As the length of input sequence $B$ increases, the model becomes both difficult to train and more memory-intensive. In the case of detecting malicious content, long sequences can often separate two or more bytes far from each other even when their combined presence is a cause of the malicious intent. When learning directly on a sequence, it is possible for the model to lose the context of an identified byte earlier in the sequence when processing a new byte at a larger distance. To cope with such problems in detection, we therefore, propose another architecture called \texttt{Convoluted Partitioning of Long Sequences (CPoLS)}.

\texttt{Convoluted Partitioning of Long Sequences (CPoLS)} is a neural model architecture designed specifically to extract classification information hidden deep within long sequences. In this model illustrated in Figure 9, we process the input sequence in parts by splitting it first into smaller pieces of fixed length. By performing this step, we generate a sequence of multiple partitions, each of which is a sequence in itself of a smaller length.

We use \texttt{Convolutional Neural Networks (CNNs)} LeCun and Bengio (1995) in this model, along with the other \texttt{LaMP} modules. CNNs are widely used in computer vision (Krizhevsky et al. (2012); Russakovsky et al. (2015)), and they have also recently shown success in sequential learning domains as well (Gehring et al. (2016, 2017)).

Given an input byte sequence $B$, the model first splits it into a partitioned list $C$ containing several small subsequences $c_i \in C$ where $i$ is the index of each partition in $C$. To translate the bytes in these sequences from symbols to dense vectors, we pass them through an embedding layer, \texttt{Embedding}, and obtain sequence $E$, where each element $e_i \in E$ corresponds to the sequence of embeddings for partition $c_i$ in $C$. Each of these partitions $e_i$, are now separately processed, while still maintaining their overall sequential nature. We call this method \texttt{ReCURRENTCONVOLUTIONS}. In this method, we pass each partition $e_i$ through the one-dimensional CNN, \texttt{Conv1D}, which applies multiple filters on the input sequence and generates tensor $e_i^\chi$ representing the convoluted output of vector sequence $e_i$. $\chi$ refers to the sequence with \texttt{Conv1D} performed on it. The combined list of these convolved partitions $e_i^\chi$ is referred to as $E^\chi$. In \texttt{ReCURRENTCONVOLUTIONS}, we then reduce the dimensionality of $e_i^\chi$ by performing a temporal max pooling \texttt{MaxPool1d}. \texttt{MaxPool1d} takes a tensor input $e_i^\chi$ and extracts a vector $e'_i$ from it. Similarly, we apply
Stokes et al.

**Figure 8:** LaMP model for detecting malicious JavaScript and VBScript files.

**RecurrenceConvolutions** on each partition $e_i$ to obtain the updated vectors $e'_i$. These vectors $e'_i$ are finally combined in the same order to create an updated sequence $E'$ of learned partition representations. With the help of partitioning, the length of $E'$ is also limited to a trainable length.

At this stage, the model uses sequence $E'$ as an input to the LaMP model and learns the probability $p_m$ that the script is malicious. Therefore, we use a combination of an LSTM, a second `MaxPool1D` layer, dense `ReLU` activations, and a final sigmoid layer for generating the prediction $p_m$ on the new input sequence $E'$. Formally, we define the CPoLS model as:

$$
C = \text{Partition}(B) \\
E = [\text{Embedding}(c_i) \ \forall c_i \in C] \\
E' = [\text{Conv1D}(e_i) \ \forall e_i \in E] \\
E' = [\text{MaxPool1D}(e'_i) \ \forall e'_i \in E'] \\
p_m = \text{LaMP}(E')
$$

(3)

Such a model is resilient to extremely long sequence lengths and can also find malicious objects hidden very late in the sequence.
Figure 9: Convoluted Partitioning of Long Sequences (CPoLS) model for detecting malicious JavaScript and VBScript files.

**End-to-End Learning:** To train the models described above, we perform an end-to-end learning process. Since the data available to us is in the form of a sequence and an associated binary label, we need to train the entire model, solely from this label. In end-to-end learning, we pass each sequence $B$ through all layers of our model to derive the probability $p_m$. Using this probability, with the true label $L \in \{0, 1\}$, we measure the cross-entropy loss $L$. This loss is used to compute the gradients required for updating the weights in each layer of the model. Therefore, we simultaneously learn all the parameters for the primary classification objective.

### 7. Experimental Results

We next evaluate the performance of the proposed neural malware script classifier models on JavaScript and VBScript files using the data described in Section 4. We first start by describing the experimental setup used to generate the results. Instead of training a single model to detect both JavaScript and VBScript, we train individual models for each...
script type since a specific model can better learn to identify the nuances of each particular scripting language. Accordingly, we first evaluate the LaMP and CPoLS models trained on JavaScript files and then repeat the evaluation for models trained on VBScript files.

**Experimental Setup:** All the experiments were performed using Keras (Chollet et al. (2015)) with the TensorFlow (Abadi et al. (2015)) backend. The models were trained and evaluated on a cluster of NVIDIA K40 graphical processing unit (GPU) cards. All models were trained with a maximum of 15 epochs, but early stopping was employed if the model fully converged before reaching the maximum number of epochs.

We did hyperparameter tuning of the various input parameters for both types of script models, and the results are summarized in Table 1. To do so, we first set the other hyperparameters to fixed values and then vary the hyperparameter under consideration. For example, to evaluate different minibatch sizes for the JavaScript LaMP classifier, we first set the LSTM’s hidden layer size $H_{JS,LaMP} = 1500$, the embedding dimension to $E_{JS,LaMP} = 128$, the number of LSTM layers $L_{JS,LaMP} = 1$ and the number of hidden layers in the classifier $C_{JS,LaMP} = 1$. With these settings, we evaluate the classification error rate on the validation set for the JavaScript dataset. Table 1 indicates the final hyperparameter settings used for the remainder of the experiments.

**JavaScript:** We evaluate the performance of the LaMP model on the JavaScript dataset in Figure 10a for several different combinations of LSTM stacked layers, $L_{JS,LaMP}$, and classifier hidden layers, $C_{JS,LaMP}$. Similarly, the CPoLS model is evaluated with the JavaScript files in Figure 10b. For LaMP, adding either another stacked LSTM layer or classifier hidden layer improves the detection results. On the other hand, the simplest CPoLS model with one LSTM layer and one neural network hidden layer performs best. For lower FPRs, LaMP offers significant performance advantages over CPoLS. This result indicates that sequential modeling of the individual characters in the JavaScript content captures the underlying behavior compared to a sequential model on the output of the convolutional processing of the subsequences in CPoLS.

| Script Type | Model | Parameter | Description          | Value  |
|-------------|-------|-----------|----------------------|--------|
| JavaScript  | LaMP  | $B_{JS,LaMP}$ | Minibatch Size       | 200    |
| JavaScript  | LaMP  | $H_{JS,LaMP}$ | LSTM Hidden Layer Size | 1500  |
| JavaScript  | LaMP  | $E_{JS,LaMP}$ | Embedding Layer Size  | 64     |
| JavaScript  | CPoLS | $B_{JS,CPoLS}$ | Minibatch Size       | 50     |
| JavaScript  | CPoLS | $H_{JS,CPoLS}$ | LSTM Hidden Layer Size | 1500  |
| JavaScript  | CPoLS | $E_{JS,CPoLS}$ | Embedding Layer Size  | 64     |
| JavaScript  | CPoLS | $W_{JS,CPoLS}$ | CNN Window Size      | 10     |
| JavaScript  | CPoLS | $S_{JS,CPoLS}$ | CNN Window Stride    | 5      |
| JavaScript  | CPoLS | $F_{JS,CPoLS}$ | Number of CNN Filters| 128    |
| VBScript    | LaMP  | $B_{VB,LaMP}$ | Minibatch Size       | 100    |
| VBScript    | LaMP  | $H_{VB,LaMP}$ | LSTM Hidden Layer Size | 1500  |
| VBScript    | LaMP  | $E_{VB,LaMP}$ | Embedding Layer Size  | 128    |
| VBScript    | CPoLS | $B_{VB,CPoLS}$ | Minibatch Size       | 100    |
| VBScript    | CPoLS | $H_{VB,CPoLS}$ | LSTM Hidden Layer Size | 1500  |
| VBScript    | CPoLS | $E_{VB,CPoLS}$ | Embedding Layer Size  | 128    |
| VBScript    | CPoLS | $W_{VB,CPoLS}$ | CNN Window Size      | 10     |
| VBScript    | CPoLS | $S_{VB,CPoLS}$ | CNN Window Stride    | 5      |
| VBScript    | CPoLS | $F_{VB,CPoLS}$ | Number of CNN Filters| 128    |

Table 1: Settings for the various model parameters.
At a false positive rate (FPR) of 1%, the best performing JavaScript LaMP model has a true positive rate of 67.2% with $L_\text{JS,LaMP} = 2$, $C_\text{JS,LaMP} = 1$. Similarly for CPoLS with $L_\text{JS,CPoLS} = 1$, $C_\text{JS,CPoLS} = 1$, the best performing model yields a TPR of 45.3% at an FPR of 1.0%

![ROC curves for different JavaScript models.](image)

(a) LaMP  
(b) CPoLS

Figure 10: ROC curves for different JavaScript models.

**VBScript**: Next we evaluate the LaMP and CPoLS models for VBScript in Figures 11a and Figure 11b, respectively. Similar to the JavaScript CPoLS model results, the simplest LaMP and CPoLS VBScript models with a single LSTM layer and classifier hidden layer offer the best, or nearly the best, performance compared to the more complex models. At an FPR of 1.0%, the TPR for the LaMP model is 69.3% with $L_\text{VBS,LaMP} = 1$, $C_\text{VBS,LaMP} = 1$. Similarly, CPoLS yields a TPR of 67.1% with $L_\text{VBS,CPoLS} = 1$, $C_\text{VBS,CPoLS} = 1$ at this FPR = 1.0%.

8. Discussion

In this section, we consider several limitations of the proposed ScriptNet neural malware script classification system. These include limitations due to the size of the GPU memory and adversarial learning-based attacks.

One limitation is the maximum sequence length, $T = 200$, employed by the LaMP models. This parameter value was primarily chosen because it allows the LaMP models to be trained in the 12 GB of SDRAM on the NVIDIA K40. If the length was increased much beyond this value, we could not train all the models investigated in this study. It may be possible that more advanced GPUs that are released in the future, and contain more GPU memory, might allow better performance if the maximum sequence length can be extended.

Attacks based on adversarial learning are another important concern. Both architectures used in this study include recurrent LSTM and possibly deep neural network (DNN) components. While researchers have not directly attacked LSTM structures using adversarial learning-based attacks, Papernot et al. (2016) have shown that standard RNN cells
9. Related Work

**JavaScript:** Maiorca et al. (2015) propose a static analysis-based system to detect malicious PDF files which use features constructed from both the content of the PDF, including JavaScript, as well as its structure. Once these features are extracted, the authors use a boosted decision tree trained with the AdaBoost algorithm to detect malicious PDFs. Cova et al. (2010) use the approach of anomaly detection for detecting malicious JavaScript code. They learn a model for representing normal (benign) JavaScript code, and then use it during the detection of anomalous code. They also present the learning of specific features that helps characterize intrinsic events of a drive-by download. Hallaraker and Vigna (2005) present an auditing system in Mozilla for JavaScript interpreters. They provide logging and monitoring on downloaded JavaScript, which can be integrated with intrusion detection systems for malicious behavior detection. In Likarish et al. (2009), they classify obfuscated malicious JavaScript using several different types of classifiers including Naive Bayes, an Alternating Decision Tree (ADTree), a Support Vector Machine (SVM) with using the Radial Basis Function (RBF) kernel, and the rule-based Ripper algorithm. In their static analysis-based study, the SVM performed best based on tokenized unigrams and bigrams chosen by feature selection. A PDF classifier proposed by Laskov and Šrndić (2011) uses a one-class SVM to detect malicious PDFs which contain JavaScript code. Laskov’s system is based solely on static analysis. The features are derived from lexical analysis of JavaScript
code extracted from the PDF files in their dataset. Corona et al. (2014), propose Lux0R, a system to select API references for the detection of malicious JavaScript in PDF documents. These references include JavaScript APIs as well as functions, methods, keywords, and constants. The authors propose a discriminant analysis feature selection method. The features are then classified with an SVM, a Decision Tree and a Random Forest model. Like ScriptNet, Lux0R performs both static and dynamic analysis. However, they do not use deep learning and require the extraction of the JavaScript API references. Wang et al. (2016) use deep learning models in combination with sparse random projections, and logistic regression. They also present feature extraction from JavaScript code using auto-encoders. While they use deep learning models, the feature extraction and model architectures limit the information extractability from JavaScript code. Shah (2016) propose using a statistical n-gram language model to detect malicious JavaScript. Our proposed system uses an LSTM neural model for the language model instead of the n-gram model proposed by Shah (2016). Other papers which investigate the detection of malicious JavaScript include Liu et al. (2014); Schütz et al. (2012); Wang et al. (2013); Xu et al. (2012, 2013).

**VBScript:** While more research has been devoted to detecting malicious JavaScript, partly because of its inclusion in malicious PDFs, only a few previous studies have considered malicious VBScript. In Kim et al. (2006), a conceptual graph is first computed for VBScript files, and new malware is detected by identifying graphs which are similar to those of known malicious VBScript files. The method is based on static analysis of the VBScripts. Wael et al. (2017) propose a number of different classifiers to detect malicious VBScript including Logistic Regression, a Support Vector Machine with an RBF kernel, a Random Forest, a Multilayer Perceptron, and a Decision Table. The features are created based on static analysis. The best performing classifier in their study is the SVM. In Zhao and Chen (2010), they detect malicious applets, JavaScript and VBScript based on a method which models immunoglobulin secretion.

**Other File Types:** A number of deep learning models have been proposed for detecting malicious PE files including Athiwaratkun and Stokes (2017); Dahl et al. (2013); Huang and Stokes (2016); Kolosnjaji et al. (2016); Pascaru et al. (2015). In particular, a character-level CNN has been proposed for detecting malicious PE files (Athiwaratkun and Stokes (2017)) and Powershell script files (Hendler et al. (2018)). Raff et al. (2017) discuss a model which is similar to CPOLS but noted it did not work for PE files. They did not provide any results for their model.

**10. Conclusions**

Malicious script classification is an important problem facing anti-virus companies. Failure to detect a malicious script may result in a successful spearphishing, ransomware, or drive-by download attack. Neural language models have shown promising results in the detection of malicious executable files. Similarly, we show that these types of models can also detect malicious JavaScript and VBScript files with relatively high true positive rates at low false positive rates. These results are even more remarkable because the best performing models only utilize the first 200 characters in the script, making them fast for large-scale production.

The performance results confirm that the LaMP and CPOLS architectures using LSTM and CNN neural models are able to learn and generate representations of byte sequences in
the scripts. In particular, the LaMP JavaScript malware script classification model using two LSTM layers and one dense neural network layer offers the best results, while for VBScript malware, the LaMP model with one LSTM and one hidden layer is significantly better than the competing models. The embeddings generated in these models, therefore, capture important sequential information from within the script file and help to predict their malicious nature through neural training over these embeddings.

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