Identifying botnet IP address clusters using natural language processing techniques on honeypot command logs

Valentino Crespi    Wes Hardaker    Sami Abu-El-Haija    Aram Galstyan†

Abstract
Computer security has been plagued by increasing formidable, dynamic, hard-to-detect, hard-to-predict, and hard-to-characterize hacking techniques. Such techniques are very often deployed in self-propagating worms capable of automatically infecting vulnerable computer systems and then building large bot networks, which are then used to launch coordinated attacks on designated targets. In this work, we investigate novel applications of Natural Language Processing (NLP) methods to detect and correlate botnet behaviors through the analysis of honeypot data. In our approach we take observed behaviors in shell commands issued by intruders during captured internet sessions and reduce them to collections of stochastic processes that are, in turn, processed with machine learning techniques to build classifiers and predictors. Our technique results in a new ability to cluster botnet source IP address even in the face of their desire to obfuscate their penetration attempts through rapid or random permutation techniques.

1 Introduction
With the establishment of botnet technologies [5, 4, 12] the need for methods to understand the lethality of certain behaviors and anticipate future moves of attackers has become of paramount importance. The challenge for cyberdefenders is further exacerbated by the constant invention of new hard-to-detect and hard-to-track rapidly mutating hacking techniques. In such scenarios simple string-matching log searches to identify common threat actors is no longer a sufficient technique.

In this work we study intruder behaviors within data from a honeypot network to discover the latent characteristics of hacking agent groups. We base our work on the assumption that individual worms or automated hacking techniques that attack from different IP sources are likely to exhibit similar, but slightly varied, modes of operation. Our intuition is that grouping behaviors by similarity of the attack sequence may uncover botnets or coordinated agents, allowing security analysts to track their activity, and the evolution of their attack methodologies. Honeypots [11] as a service (HAAS) networks are large collections of Honeypots that aggregate reports consisting of a set of time-stamped, captured sessions of honeypot-shell or similar commands collected from intrusions of individual hackers (human or automated bot). We collect large amounts of real and unlabeled data (see Appendix A) and apply unsupervised NLP methods to learn statistics and cluster reports. To the best of our knowledge the application of such methods to the cyber domain is quite novel. Supervised NLP methods have been successfully applied to cluster tweets in social media [1], under the assumption that tweets from the same account contain stationary statistics and that different accounts would most probably correspond to different users. Here we make opposite assumptions insofar as large sets of bots are controlled by the same infrastructure and their individual behaviors can be periodic or evolve dynamically. Given the impossibility of performing automated model evaluation we chose to design two different classes of solutions (LDA and Deep Learning) with the idea of using one as a reference for the other.

2 Levels of attacker behaviors
Suppose that at time $t$ a hacker from source IP $ip$ succeeded in establishing a Secure Shell (SSH) [7] connection with one of the honeypot servers and a finite sequence of session commands $s$ is collected. The honeypot system captures the record $ip : (t, s)$, where $s$ is in turn a sequence of shell commands. Moreover, we observed that individual hackers intrude into multiple honeypots over time. Thus, for each hacker source IP $ip$, we observe a sequence of sessions: $ip : (t_1, s_1), (t_2, s_2), \ldots, (t_n, s_n)$, with $t_i < t_{i+1}$ for all $i$. We embed sessions into finite dimensional metric spaces in order to learn the behavior of individual hackers or of groups of “somewhat related” hackers (botnets) for classification and prediction purposes. To be precise, we are interested in two levels of analysis of hacking be-
haviors: L1) the statistics of lexical terms (commands and identifiers) occurring in its sessions and L2) given L1, the longitudinal statistical characteristics of session time series. Learning L1 behaviors allows us to characterize the fuzzy-signature shell techniques used by a hacker (§2.1). Learning L2 behaviors allows us to characterize the types of hacker activity over time, active during specific, potentially recurring, time periods observed in certain short subsequences of sessions (§2.2). Given the success of these techniques, we consider future directions and approaches in §3.

2.1 L1: learning statistics of lexical terms. We break the L1 task into three separate stages. First, we train a probabilistic model to capture the statistics of terms occurring in individual sessions (or in groups of sessions generated by the same hacker\(^4\)). Second, we exploit the model to embed sessions or groups of sessions into a finite dimensional metric space. Third, we cluster such embeddings with respect to the metric of the embedding space. The intuition behind this method is that two behaviors are syntactically similar if their embeddings are close in metric, namely they fall into the same cluster. Thus, this clustering identifies botnets on the basis of sharing similar technical sequences of commands in their generated sessions. For the first stage we consider two different embedding methods. In the first, we train a Latent Dirichlet Allocation (LDA) model (§2.1.1). In the second, we train a Deep Learning autoencoder and exploit the encoding component to map each session to a vector (§2.1.2). LDA and, more generally, topic modeling, provides an “explainable” interpretation of the embedding that is implicit in the Bayesian description of the documents. Par contre, our Deep Learning autoencoder captures the order of the commands and allows large scale processing of millions of sessions. Finally, we employ k-means [9] and vdgmm [2] to perform clustering.

2.1.1 LDA pipeline. LDA is a generative probabilistic model for collections of discrete data such as text corpora introduced in 2003 by Blei et al. [3] to solve problems of text classification. LDA models an individual document as a mixture of a finite number of topics where, in turn, each topic is a probability distribution over a potentially infinite vocabulary. An LDA model consists of a collection of K multinomial distributions \( p(w|j) \), for \( j = 1, 2, \ldots, K \), over \( \mathcal{V} \) called topics and a K-dimensional Dirichlet distribution \( q(\theta) \). Given an LDA model \( \mathcal{M} = \{p(w|j), q(\theta)\} \) a document of \( N \) words is generated in the following way. First, we sample a multinomial distribution \( \theta \sim q(\theta) \) over the K topics\(^2\). Then for each \( i = 1, 2, \ldots, N \) we sample a topic \( t_i \sim \theta(t_i) \) and the word \( w_i \sim p(w_i|t_i) \). One way of using LDA models is to apply Bayesian techniques [3] to learn \( p \) and \( q \) from a given corpus \( \mathcal{C} \) of documents and then, for each document \( w \in \mathcal{C} \), to infer \( \theta_w \in \mathbb{R}^K \) from the posterior distribution \( P_M(\theta|w) \) induced by the learned model \( \mathcal{M} \). The inferring of the multinomial distribution \( \theta_w \) from \( \mathcal{M} \) and \( w \) defines an embedding of the document \( w \) into a latent \( K \)-dimensional space. We process a HAAS honeypot dataset through the following pipeline (also shown in Figure 1) and cluster IP addresses exhibiting similar statistics of lexical terms used in their sessions.

1. Define documents: we aggregate sessions by source IP yielding a collection \( \mathcal{D}_1 \) of documents;

2. Build corpus: we tokenize documents in \( \mathcal{D}_1 \), build a vocabulary \( \mathcal{V}_1 \), and encode each document as a “bag of words” with respect to \( \mathcal{V}_1 \). This gives a corpus \( \mathcal{C}_1 \) of encoded documents;

3. LDA compress: we train an LDA model (gensim) with corpus \( \mathcal{C}_1 \) for a fixed number of topics \(^3\) (\( K = 200 \)) and we exploit the model to embed each document in \( \mathcal{C}_1 \) in the latent \( K \)-dimensional space;

4. Cluster: we employ k-means with \( k = 200 \) to cluster all the embedded documents in the latent space and group IPs by similarity of fuzzy signature.

2.1.2 Autoencoder pipeline. We also employ a second NLP method for comparison using applications of Deep Learning to unsupervised clustering (Deep

\(^4\)We use terms “bot” and “hacker” interchangeably throughout the text, as our technique applies to both.

\(^2\)Samples from a \( K \)-dimensional Dirichlet distribution are probability vectors of \( K \) elements that can represent a multinomial distribution over \( K \) labels.

\(^3\)A commonly chosen value in NLP.
Clustering), which proved effective in clustering unlabeled images [6, 13] and signals [10]. Our deep learning pipeline, detailed below, consists of two deep learning modules. First, we tokenize all sessions as before to build a vocabulary $V$ and then train a Word2Vec model [8]. This defines a map $W : V \rightarrow \mathbb{R}^h$, $h = 128$, that embeds each word into a $h$-dimensional metric space, and, by extension, each sequence of tokens $v_1 v_2 \cdots v_N$ into the $N \times h$ matrix $W(v_N') = [W(v_1); W(v_2); \ldots; W(v_N)] \in \mathbb{R}^{N \times h}$ (here, we have used the expression $v_i'$ to denote the sequence $v_i v_{i+1} \cdots v_j$, $\mathbb{R}^{N \times h}$ to denote the set of all $N \times h$ matrices of real numbers, and employed matlab syntax to describe matrices). Second, for a fixed value of $N$ (e.g., $N = 500$, sessions are either truncated or padded in order to have a fixed length in number of tokens) we train an ad hoc autoencoder $D \circ E : \mathbb{R}^{N \times h} \rightarrow \mathbb{R}^{N \times h}$, with $E : \mathbb{R}^{N \times h} \rightarrow \mathbb{R}^M$, $D : \mathbb{R}^M \rightarrow \mathbb{R}^{N \times h}$, and $D(E(W(s))) \approx W(s)$ for each (tokenized) session $s$.

We implemented a standard Word2Vec Skip-gram model \(^4\) with Negative Sampling (with a window size of 2 and a number of negative samples of 4) using tensorflow and experimentally established that $h = 128$ (with 4 epochs of training) was an optimal embedding dimension. We designed an autoencoder to capture the order of tokens in sessions. The Encoder consists of an upper LSTM layer built on top of a (maxpooled) convolutional lower layer, and the decoder consists of an upper deconvolution layer built on top of an upsampling layer. The intuition behind this architecture is that, while convolutional layers extract latent features, LSTMs capture the order of the sequence of the tokens in their latent representation. The output of the encoder $E(W(s)) \in \mathbb{R}^M$, $M = 200$, provides the embedding of session $s$ into an $M$-dimensional metric space. Unlike in [6] we did not jointly train a clustering layer together with the autoencoder because we were interested in also learning the number of session clusters. Thus, we clustered the embedded sessions employing a Bayesian nonparametric algorithm (VDGMM) that learns the parameters of a Gaussian Mixture Model (GMM) with an a priori unknown number of Gaussian components [2]. As before, we process the HAAS data with the following pipeline (see Figure 2) to discover clusters of “similar” sessions:

1. Define documents: we treat each session as a separate document and build collection $\mathcal{D}_2$ (with 192.0.2.1-4 we mean the 5\textsuperscript{th} recorded session from 192.0.2.1).

2. Build word embedding: we tokenize all the documents in $\mathcal{D}_2$ and build a vocabulary $V_2$. We then train a Word2Vec model and exploit it to encode each document as an $N \times h$ matrix. This gives a corpus $\mathcal{C}_2$ of encoded sessions;

3. Build session embedding: we use corpus $\mathcal{C}_2$ to train an autoencoder whose encoder component encodes inputs into vectors of $M$ reals, $M = 200$. We exploit the encoder to map each session in $\mathcal{C}_2$ to a vector in $\mathbb{R}^M$;

4. Cluster: we employ VDGMM to cluster embedded sessions recorded in a bounded period of time (a month in our experiments) and learn the number of different types of sessions.

2.1.3 L1 clustering results. The LDA pipeline groups documents according to a predefined number of clusters (200). A direct inspection of the output shows command list clusters that are visibly similar to a human eye. Despite the presence of outliers, the clusters seem quite homogeneous as seen, for example, in Fig. 3 which contains a small excerpt of text from one of the computed clusters. These results indicate that NLP text processing techniques can be successfully applied to command sequences, provided that we define an appropriate vocabulary (the tokenization method we deploy dictates the observable vocabulary features). The autoencoder pipeline identified 120 different clusters of sessions. Figure 4 shows one of the clusters whereas Fig-
Figure 4: One of the 120 autoencoder session clusters containing three sessions with their ID, epoch time stamp, and list of commands. To the human eye they appear as variations of a same mode.

Figure 5: 8 representative sessions from as many session clusters out of the 120 autoencoder session clusters.

Figure 6: Signals 220.133.96.132 (left) and 5.99.213.53 (right). Each point \((t, d)\) represents an embedded session \(y_t\) that occurred at time \(t\) with \(d\) the distance from the first signal session. Thus, similar sessions map to points with similar ordinate. While the converse is not necessarily true it is reasonable to hypothesize that the two signals share four fuzzy signatures. Moreover, they seem to exhibit a joint temporal pattern. This intuition is confirmed by the inspection of the corresponding raw sessions (bottom).

3 Conclusions and Future Work
We have demonstrated the potential of applying NLP methods to parse honeypot logs of shell commands and to characterize fuzzy signatures. We also discussed exploiting session embedding functions to study high-level, longitudinal botnet behaviors.

We are expanding this work in three directions: 1) developing fast algorithms to train and incrementally update word2vec models as suggested in [8]; 2) modifying the autoencoder to jointly train a classification layer as done in [13]; and 3) building probabilistic models (HMMs, HSMMs, LSTMs) to study longitudinal botnet behaviors (time series of encoded sessions) to predict future session clusters and to group source IPs exhibiting temporally coordinated behaviors.
A Appendix

All honeypot data were downloaded from https://haas.nic.cz/. Sessions are time-stamped. However, individual bash commands in each session are not. We tokenized bash commands with

```python
def tokenize(line):
    words = re.sub(r"(2>&1)|(>&)|(&>)|(>|>)|([012]>), \ "_r_ ", line)
    words = words.replace(">", " > ")
    words = words.replace("<", " < ")
    words = words.replace("=" " = ")
    words = words.replace("||","_P_ ")
    words = words.replace("|","_p_ ")
    words = words.replace("&&","_A_ ")
    words = words.replace("&","_a_ ")
    lwords = re.split("[;"\(\) ", words)
    return lwords
```

A.1 LDA (LSI) pipeline: We parsed sessions collected between 1/2018 and 2/2020 and aggregated them by source IP:

| Description                      | Value         |
|----------------------------------|---------------|
| Number of tokens                 | 331550        |
| Source IPs (documents)           | 248795        |
| Average document length          | 5347.61       |

Figure 7 shows the distribution of the lengths of the documents aggregated by IPs where we have removed few but very long documents for ease of display.

A.2 Autoencoder pipeline: full vocabulary: We parsed sessions collected between 1/2018 and 10/2020

![Distribution of document lengths](image.png)
and treated them as separate documents; different tokens were mapped to different indexes:

| Source IPs:                    | 420695 |
|-------------------------------|--------|
| Vocabulary size:              | 569665 |
| Number of sessions (documents): | 90063468 |
| Average session length:       | 15.7   |

Figure 8 shows the distribution of session lengths.

A.3 Autoencoder pipeline: vocabulary with tokens occurring only once mapped to single word: We parsed sessions collected between 1/2018 and 10/2020 and treated them as separate documents; tokens occurring only once were mapped to the same index:

| Source IPs:                    | 420695 |
|-------------------------------|--------|
| Vocabulary Size:              | 426439 |
| Number of sessions (documents): | 90063468 |
| Average session length:       | 15.7   |

Figure 8 shows the distribution of session lengths.

Figure 8: Distribution of session lengths.