Improving Botnet Detection with Recurrent Neural Network and Transfer Learning

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Abstract—Botnet detection is a critical step in stopping the spread of botnets and preventing malicious activities. However, reliable detection is still a challenging task, due to a wide variety of botnets involving ever-increasing types of devices and attack vectors. Recent approaches employing machine learning (ML) showed improved performance than earlier ones, but these ML-based approaches still have significant limitations. For example, most ML approaches cannot incorporate sequential pattern analysis techniques key to detect some classes of botnets. Another common shortcoming of ML-based approaches is the need to retrain neural networks in order to detect the evolving botnets; however, the training process is time-consuming and requires significant efforts to label the training data. For fast-evolving botnets, it might take too long to create sufficient training samples before the botnets have changed again. To address these challenges, we propose a novel botnet detection method, built upon Recurrent Variational Autoencoder (RVAE) that effectively captures sequential characteristics of botnet activities. In the experiment, this semi-supervised learning method achieves better detection accuracy than similar learning methods, especially on hard to detect classes. Additionally, we devise a transfer learning framework to learn from a well-curated source data set and transfer the knowledge to a target problem domain not seen before. Tests show that the true-positive rate (TPR) with transfer learning is higher than the RVAE semi-supervised learning method trained using the target data set (91.8% vs. 68.3%).

Index Terms—Anomaly Detection System, Botnet Detection, Network Security, Recurrent Neural Network, Variational Autoencoder, Transfer Learning

I. INTRODUCTION

Botnet is one of the most significant threats to the cybersecurity as they are the source of many malicious activities [1]. The compromised machines in a botnet are typically hijacked without the owner’s knowledge. These machines (also known as “bots”) are then commanded to act together to attack targeted servers or find more valuable zombie candidates. In fact, the botnet is frequently used to perform a variety of attacks, including distributed denial-of-service attacks (DDoS), click-fraud, spamming and crypto-mining. Botnets also harbor malware and ransomware for delivery to additional victims. A critical task of cybersecurity research is to detect botnets and stop their attacks.

It is challenging to identify botnets due to following reasons. First, the malicious software that infects a victim host and operates the botnet is evolving to evade detection. For example, botnets may use a combination of communication protocols, such as Internet Relay Chat (IRC), peer-to-peer (P2P), and HTTP, rather than relying on one protocol [2]. Second, newly introduced botnets are capable of utilizing diverse types of computing devices and attack vectors. For example, in 2016 the Mirai botnet controlled hundreds of thousands of Internet of Things (IoT) devices to conduct a high-profile DDoS attack [3], and in 2018 another sophisticated botnet system called Smominru started crypto-mining. These fast-evolving characteristics significantly reduce the effectiveness of the traditional detection approaches.

The existing botnet detection approaches fall into two broad categories: honeypots and Intrusion Detection Systems (IDS). Honeypot is a computer system used as a trap to draw the attention of attackers [3]. This approach has several limitations in scale and detection capability [4]. IDS monitors network systems to uncover malicious activities based on either pattern matching using predefined rulesets (“signature-based”) or behavioral analysis to discriminate anomalies from normal actions (“anomaly-based”). The signature-based method is configured with a set of rules or signatures to classify types of network traffics. This approach often requires a relatively small amount of computation (e.g., using a customized pattern machine engine for faster look-up), and work in real-time without slowing down normal network operations. The effectiveness of the signature-based detection has widely been studied, but it is only able to identify well-known botnets [4], [5].

An anomaly-based approach identifies network traffic anomalies, such as high network latency, high volumes of traffic, and unusual system behavior, to detect malicious actions [4]. A common strategy is to model normal behavior of network traffic and then declare significant statistical deviations as potential threats [6]. Many statistical techniques and heuristics have been proposed to characterize botnet anomalies [7], [8]. Recently, a number of machine learning (ML) techniques have shown to be very effective, even possible to detect previously unseen types of botnet attacks [2], [9]–[12].

While attractive, there are several limitations with the existing ML-based botnet detection algorithms. One of the critical limitations is that these algorithms did not pay much attention to sequential patterns within network data, even though botnet traffic shows repeated patterns due to the nature of the pre-programmed activities [13]. There are studies considered sequential characteristics by the same source IP addresses, which may not be generalized to other IP addresses [14], [15]. In addition, existing studies only consider specific types of network activities, such as IRC, P2P, and HTTP traffic,
while active botnets are utilizing a combination of different protocols [14]–[17].

Another limitation of the existing approaches is the need of labeled training datasets. The learning process requiring labeled training data is commonly known as supervised learning. So far, anomaly detection based on supervised learning has achieved a high accuracy for detecting botnets [10], [18], [19]. The key drawback of supervised learning is the labeled training data is often unavailable in practice, especially, the malicious samples. The semi-supervised learning approach addresses this difficulty by requiring only one type of samples, typically, normal samples, for training. Popular semi-supervised learning algorithms include autoencoders (AEs) [20], Variational Autoencoder (VAEs) [16], [17], [21], one-class support vector machines (OSVMs) [17], and so on.

Another possible solution to address the shortage of the labeled data is transfer learning, which utilizes labeled data available in one domain ("source domain") for the domain of interest ("target domain"). When there is insufficient labeled data in the target domain, transfer learning allows us to construct a learning model without the expensive data-labeling effort [22]. So far, transfer learning has been successfully applied to text classification, speech recognition, and image classification [23]–[26]. There are also examples of applying transfer learning for botnet detection [27], [28]. However, these techniques require high computational costs and only achieve lower performance compared to supervised and semi-supervised techniques.

This work has two main goals. First, we propose an ML method capable to represent sequential patterns within network data, by utilizing Recurrent Variational Autoencoder (RVAE). From published literature, we know that sequential patterns of activities are critical for detecting many botnets [14], [15]. The proposed method also includes a new anomaly scoring function that allows on-line detection of botnets. Second, we introduce a new training framework based on transfer learning to facilitate the deployment of our botnet detection method without first collecting and labeling all possible anomalies in the target domain.

The main contributions of this paper can be summarized as follows:

- We present a new ML model for botnet detection built on Recurrent Variational Autoencoder (RVAE) to capture sequential patterns. This is a semi-supervised approach that learns from the normal data and detects potential anomalies that may vary over time.
- We devise a scoring strategy that allows us to identify anomalies in real-time. This scoring approach utilizes the probability density function of reconstruction errors from the RVAE network.
- We verify that our approach could detect changing botnets by splitting the popular test data set CTU-13 into training and testing sets with different types of botnets. Tests show that we are able to detect botnets effectively when previously unseen types of botnets appear in testing but not in training.
- We propose a transfer learning framework to construct a learning model without the labeled training samples from the target domain.

**II. RELATED WORK**

Following a broad introduction in the previous section, we next provide more details on a number of related works that lead to the unique combinations of techniques to be described in Section 3.

**A. ML Methodology**

**Variational Autoencoder (VAE).** Given an input $x$, the autoencoder neural network structure consists of an encoder network and a decoder network used together, where the encoder extracts the latent variable $z$ and the decoder reconstructs the input $x$ from $z$. VAE use reparameterization trick to allow this autoencoder structure to follow the variational Bayesian inference theory [29].

Throughout this paper, we use $\theta$ to denote parameters of the encoder of VAE and $F$ to represent the encoder, $\phi$ to denote parameters of the decoder of VAE and $G$ to represent the decoder. Let $x_n$ denote the $n$th input data record, we use $\hat{x}_n$ to denote the output produced by the decoder $G$. The loss function as follows:

$$J(x) = -E_{q_\phi(z|x)}[logp_\theta(x|z)] + \beta * D_{KL}[q_\phi(z|x)||p_\theta(z)] \quad (1)$$

$p$ represents the encoder, and $q$ represents the decoder.

**Gated Recurrent Unit (GRU).** GRU is a Recurrent Neural Network (RNN) structure containing directed cycles for representing sequential patterns. GRU is capable of remember longer sequences, which allows it to extract features across time [30].

**Recurrent Variational Autoencoder (RVAE).** RVAE is a structure that combines sequence-to-sequence model (seq2seq) with a VAE. The encoder and decoder of VAE consists of an auto-regressive model. As it utilizes RNN instead of multilayer perceptron (MLP) as the decoder, it takes the current input as well as its neighborhood into account to generate sequential outputs. The more detailed discussion of Recurrent VAE is available in literature [31], [32]. Based on published literature on extracting patterns from text and music, RVAE is very
effective for extract sequential patterns. We expect this neural
network structure could effectively extract sequential patterns
critical for detect anomalies in network traffic as well.

Transfer Learning. Transfer learning trains a model in one
problem domain, named the source domain, with plenty of
training data, and then apply the model to another application
domain, named the target domain, where there is limited or
insufficient amount of train data [22]. This model could be
either classification or regression. The transfer learning can be
divided into three categories according to the label existence
in the source/target domains and the types of tasks.

Inductive transfer learning involves the same source and tar-
get domain, but different tasks. Transductive transfer learning
involves different source and target domains, but, the same task
in source and target domain. Typically, the source domain and
the target domain are closely related.Unsupervised transfer
learning involves different source and target domains as well
different tasks. The technique to be described later is a
transductive transfer learning techniques.

B. Botnet Detection Methodology using ML

Many methods have been developed for botnet detection. Here,
we briefly describe a number of commonly used
signature-based methods and ML techniques(VAE, RNN) to
provide a more detailed context for our work.

Signature-based Network Intrusion Detection System.
Signature-based network IDS methods has been widely stud-
ied [4]–[8], [33]. In [6], the authors design a botnet decision
device engine that determines any divergence or statistical deviations,
which are based on normal network behaviors, over network
traffic data. Among this class of methods, Zeek is one of
the most popular Network Intrusion Detection System (IDS),
which is a monitoring system for detecting network intruders
in real-time by passively monitoring a network link over which
the intruder’s traffic transits [33]. Zeek analyzes packet traces
(PCAP) by utilizing libpcap, the packet-capture library. The
system is divided into event engine, which reduces a stream
of packets to a stream of higher-level network events, and
Policy Script Interpreter, which logs real-time notifications
and records data to disk. Even though Zeek is not built for
detecting botnet, we found that certain features it detects is
highly correlated with many classes of botnets and plan to
use these features to measure the detection performance of
transfer learning method when we have no labels on the data
records.

Botnet Detection Using Variational Autoencoder. [16] intro-
duced VAE as an unsupervised method for detecting anomalies
and proposed to explain anomalies with a gradient-based
fingerprinting technique. However, they assumed that they
already knew the ratio of anomaly and it did not consider
sequential patterns that can increase the performance of de-
tection. Nicolau et al. [17] proposed a revised VAE structure,
called as Dirac Delta VAE, for better anomaly detection
performance. It narrowed down the range of latent space that
makes classifiers detect anomaly easier. However, Dirac Delta
VAE cannot be trained end-to-end because it separates the
classifier and the feature extractor. Furthermore, the authors
conducted experiments using only one type of botnets for
training and testing. There are various of studies utilizing
VAE for anomaly detection of network traffic [21], [34], most
of them overlooked sequential characteristics within network
traffic.

Botnet Detection Using Recurrent Neural Network. RNN is
well-known for capturing sequential characteristics of network
traffic data. For example, Sinha et al. [14] proposed a sup-
ervised approach to detect botnet hosts by tracking the network
activities over time and extract graph-based features from
NetFlow data for botnet detection. However, their technique
only extracted features for each host IP address separately.
In addition, the method is trained and tested on the restricted
botnet scenarios. Torres et al. [15] assigned symbols to features
such as port number and packet size, and embed these symbols
in a distributed representation similar to word embedding.
Their work demonstrated the potential of using RNN for
botnet detection, but their tests showed poor performance
when the classes of different traffics are highly imbalanced.
Ongun et al. [18] utilized text output from IDS as input to
RNN, however, their RNN was specific designed for text
data. While many of these methods showed improved detection
performance compared earlier generations of tools. However,
most of them are not able to perform on-line anomaly detection
because they need to collect every traffic related to the host IP
addresses in order to distinguish whether they are malicious or
not. In addition, existing ML-based methods usually require
fully labeled data set that are hard to obtain due to lack of
labeled data on changing network traffic.

Botnet Detection Using Other Machine Learning Ap-

proach. Besides VAE and RNN, many recent studies have
attempted to make use of various ML approach to reduce the
dependence for human heuristics. Du et al. regard every feature
as sentence and embed the features. With embedded features,
classifier can be trained to detect malicious botnets [19]. Singh
et al. introduce the framework for P2P botnet detection using
Random Forest (RF) [10]. Furthermore, Ongun et al. present
how to extract features that are good for ML model. The
authors use a statistics aggregated feature processing method
and validate the method with RF and Gradient Boosting [18].

Botnet Detection Using Transfer Learning. Some studies
suggested making use of transfer learning on botnet detection
[27], [34], [38]. However, the method that is suggested by
Althoman et al. depends on naive techniques such as
calculating similarity between each instance in the source
and the target domain, which requires high computation cost [27].
Moreover, Jiang et al. use clustering technique and naive rule
methods and only focus on the botnet using Command and
Control channel [38]. These methods are limited in that they
cannot provide end-to-end learning manner while the proposed
method can. Furthermore, contrary to transfer learning studies
in other area that use Deep Neural Networks structure [23]–
[25], the studies on botnet detection utilize relatively simple
methods.

A few methods use Neural Networks in transfer learning
[35]–[37]. The authors treat network traffic features as
an image in [35], [36]. By bringing pre-trained Convolutional
Neural Network (CNN) model that is suitable for image
In this section, we first present our botnet detection method, which consists of three steps: data pre-processing, anomaly scoring, and anomaly detection. We then introduce our transfer learning mechanism for botnet detection, with/without the use of labeled data set in the target domain.

### A. Botnet Detection Method

In order to identify botnets, we propose a novel flow-based botnet detection system coping with sequential nature of traffic flows. The overall procedure is shown in Fig. 1, which consists of three steps as follows:

- **Data pre-processing:** The data instances are grouped based on a predefined time interval (e.g., 60-second time window), and they are aggregated by host IP addresses. This process also calculates statistical features and normalizes numerical values.

- **Anomaly scoring:** At every time window, anomaly scores of every aggregated flow are calculated, which provides a measure of deviation from normal for each individual connection. It is possible to use many different scoring functions. In this work, we assign scores by comparing the input \( x \) with the output from RVAE \( \tilde{x} \).

- **Anomaly detection:** Based on the calculated anomaly scores, the anomaly detection function classifies individual connections into either Malicious or Non-malicious. In particular, our method does not rely on threshold; rather, it utilizes a couple of probability density function (PDF) that are estimated by normal and botnet instances in training data, respectively.

Fig. 2 shows a snapshot of the process for the data pre-processing and anomaly scoring. In the phase of data processing, every flow sorted in chronological order is aggregated to obtain statistic features within the windows. These flow-based features are used as input to RVAE, and are input in the order of time. In the botnet detection system, the encoder distills the common characteristics within the sequential data into latent variable \( z \). The decoder reconstructs sequential inputs from \( z \). In the end, reconstruction loss is used as the anomaly scoring.

1) **Anomaly Scores from Recurrent Variational Autoencoder:** Notations used in this paper are summarized in Table I.

We first input network traffic data, which are pre-processed, to GRU structure. To obtain mean and variance of Gaussian distribution, we use \( h_{E,T} \) multiplied by trainable \( W_\mu \) and \( W_\sigma \), respectively. With \( \mu \) and \( \sigma \), \( z \) can be obtained, and the \( z \) is used as initial hidden state for the decoder.

\[
\mu(x) = W_\mu h_{E,T} \tag{2}
\]
\[
\sigma(x) = W_\sigma h_{E,T} \tag{3}
\]
\[
z = \mu(x) + \sigma(x) * \epsilon, \epsilon \sim N(0, 1) \tag{4}
\]

The second hidden state of decoder follows as:

\[
h_{D,2} = \text{sigmoid}(W^{hh}z + W^{hx}x_1) \tag{5}
\]

The first input of the decoder \( x_1 \) is zero-padded. Finally, the outputs we obtain from RVAE is formulated:

\[
y_t = \text{sigmoid}(W^s h_{D,1}) \tag{6}
\]

We train \( W \) to get minimized the loss function which is defined in [1]. We train the model with only non-malicious instances, and in evaluation phase, we calculate reconstruction errors and use it as anomaly scores using both non-malicious and malicious instances. As we use binary cross entropy as error function, the anomaly score is formulated:

\[
L = \sum_{n=1}^{N} (1 - y_{tn})\log(1 - \hat{y}_{tn}) + y_{tn}\log\hat{y}_{tn} \tag{7}
\]

Each time window, we can obtain the anomaly scores of every aggregated flow that belong to the time window. In other words, if the traffic connection can be considered malicious or not is indicated by the outputs \( L \) of the anomaly detection system. In the following section, we present how to detect botnets with anomaly scores.
2) Anomaly Detection: In many studies, threshold of anomaly scores is used to distinguish whether the source IP addresses in the time window is malicious or not in anomaly detection methods \[16\], \[20\], \[21\]. The threshold can be set in many ways. It is a simple and intuitive method; however, some global information about the dataset is required, for example, the ratio of botnets or at least approximate values of anomaly scores of botnet samples. Unfortunately, such global information about the traffic data is not known in advance. Therefore, this approach can not be used for on-line anomaly detection.

Instead, we suggest a more efficient method using the estimated probability distribution of reconstruction errors, which enables the method be applied in an on-line manner. In training phase, we collect reconstruction errors from normal and abnormal instances. Then, we find the distribution and its parameters to represent the distribution of reconstruction errors of abnormal and normal, respectively, by exploring various types of distributions and selecting the minimum sum of squared estimate errors (SSE). We call the distribution with the smallest SSE as the best-fit PDF. We search for the best-fit PDF among many different candidates such as gamma distribution, generalized logistic distribution, fold cauchy distribution, Mielke distribution and beta distribution, among others. In testing phase, the estimated PDF can be utilized to obtain likelihood to belong to each distribution. Comparing the likelihood values of the two different distributions, we assume that each sample of the test data set belongs to the distribution showing the higher likelihood. Using best-fit PDFs does not require global information about the data set and could be used for on-line botnet detection.

### B. Transfer Learning for Botnet Detection

We further propose a novel transfer learning technique for botnet detection. Unlike the semi-supervised RVAE method we present in the previous section \[III-A\] requiring labeled data on the domain of interest, the training framework lets the botnet detection system perform well on partially labeled or even unlabeled datasets in the target domains. Both the ML structure that produces anomaly scores and the anomaly detection method utilizing reconstruction errors maintain in the transfer learning framework. The only different thing is the way to train the RVAE: each minibatch sample from a source and a target domain is used for training, respectively and sequentially.

We follow the procedure of transfer anomaly detection method proposed in \[34\], and adapt it to the characteristics of network traffic data. Since it is hard to obtain labeled data for training, we further develop the method to be trained without label information on the target domain. Namely, we consider two cases of training data on botnet detection: labeled dataset on the target domain (with label) and unlabeled dataset on the target domain (without label). In the both methods, normal and anomalous instances in a source domain are used for training RVAE at first. After calculating the gradients with a minibatch of samples of the source domain and updating the parameters of the decoder and the encoder, we use a minibatch of samples of the target domain for training. Then, we calculate and update the gradients in the same manner.

\[X_s^+\] is a set of anomalous instances in a source domain \((x_s^+ \in X_s^+)\). \(X_s^-\) is a set of normal instances in a source domain \((x_s^- \in X_s^-)\). \(X_t^+\) is a set of anomalous instances in a target domain \((x_t^+ \in X_t^+)\). \(X_t^-\) is a set of normal instances in a target domain \((x_t^- \in X_t^-)\). \(N_t^+, N_s^-\) is the number of...
instances of anomalous and normal on the source domain.

We use the objective function of the source domain in [34]:

$$s_{\phi, \theta}(x|z) = \sum_{n=1}^{N} (1 - x_n) \log(1 - \tilde{x}_n) + x_n \log \tilde{x}_n$$  (8)

$$L_s(\theta, \phi|z) = \frac{1}{N_s} \sum_{n=1}^{N^-} s_{\phi, \theta}(x^-_n|z)$$

$$- \frac{\lambda}{N^- N^+} \sum_{n,m=1}^{N^-} f(s_{\phi, \theta}(x^+_m|z) - s_{\phi, \theta}(x^-_n|z))$$

$$L_s(\phi, \theta) = \mathbb{E}_{q_s(z|x)}[L_s(\theta, \phi|z)] + \beta D_{KL}(q_s(z|X^-)\|p(z))$$  (10)

We do not use latent domain vectors that is denoted as $z$ in [34] as there is only one domain for each source and target domain. Since we utilize VAE contrary to AE, $z$ represents the latent variable in the proposed method [29].

The proposed method can be categorized into two based on whether the labeled dataset on the target domain is used or not. The overall process is identical, but transfer learning with the unlabeled data set on the target domain is different from the method using the labeled data set on the target domain. It uses entire instances in the target domain for training. On the other hand, only normal instances in the target domain are made use of for training on with_label method. Therefore, there is a slight difference in the objective function of the target domain of the two methods, which you can find in the next subsection. In the case of the source domain, the objective functions on both methods are equal to Equation 10.

1) Using labeled data set in a target domain: In this case, we use only normal instances for training likewise other semi-supervised learning methods [17], [20]. The difference from the semi-supervised learning is that we utilize transferred knowledge from the source domain in order to classify instances of the target domain. Therefore, we can expect better results than semi-supervised learning methods. Furthermore, even if there is not enough labeled data, it might be possible to obtain comparable performance to other semi-supervised learning methods. The objective function for the target domain in with_label method is formulated as in [34]:

$$L_t(\phi, \theta) = \mathbb{E}_{q_t(z|x)} \left[ \frac{1}{N^-} \sum_{n=1}^{N^-} s_{\phi, \theta}(x^-_n|z) \right] + \beta D_{KL}(q_t(z|X^-)\|p(z))$$  (11)

The overall process of the method is shown in Algorithm 1.

\[\textbf{Algorithm 1: The Procedure of Training Transfer Anomaly Detection with_label Method}\]

\[\text{Input:}\] instances of source domain $x^-_i \in X^-_s$ and instances of target domain $x^-_t \in X^-_t$

\[\text{Output:}\] $G_\theta, F_\phi$

\[\text{for number of epochs do}\]

\[\text{Sample minibatches from } X^+_s, X^-_s, \text{ and } X^-_t\]

\[\text{for } x^+_s \in B^+_s \text{ do}\]

\[\tilde{x}^-_s = G_\theta(F_\phi(x^-_s))\]

\[\text{end}\]

\[\text{for } x^-_s \in B^-_s \text{ do}\]

\[\tilde{x}^-_s = G_\theta(F_\phi(x^-_s))\]

\[\text{end}\]

\[\text{Update the Encoder and the Decoder by}\]

\[\text{descending its stochastic gradient:}\]

\[\nabla_{\phi, \theta}(L_s(\phi, \theta))\]

\[\text{end}\]

\[\text{for } x^-_t \in B^+_t \text{ do}\]

\[\tilde{x}^-_t = G_\theta(F_\phi(x^-_t))\]

\[\text{end}\]

\[\text{Update the Encoder and the Decoder by}\]

\[\text{descending its stochastic gradient:}\]

\[\nabla_{\phi, \theta}(L_t(\phi, \theta))\]

\[\text{end}\]

2) using unlabeled data set in a target domain: In this method, we assume the situation where there is no labeled data set on the target domain. That means we cannot distinguish between normal and abnormal examples. To deal with such a case, we use an entire instance of the dataset in the target domain only for the first several epochs ($E$). From the very next sequence after $E$ epochs, we collect instances that show lower reconstruction errors in each minibatch. Given characteristics of datasets that the number of normal samples is much higher than the number of anomalies, it is inferred that the lower instance of reconstruction errors is more likely to be normal. In order to give weight to the estimated normal instances, we use the instances more than once in the following minibatch training.

To do this, we sort the instances by the size of reconstruction errors every minibatch. We then select instances of the bottom $r\%$ of reconstruction errors in minibatch as the estimated normal samples and add the instances to the following minibatch training samples. In other words, the sample used in the next step of training consists of the next step minibatch and the part of the previous samples with lower reconstruction error. By selecting samples this way, we can train the anomaly detector effectively even with an unlabeled dataset on the target domain.

$M_t$ is the number of the increased samples due to selection, and varies depending on the ratio$(r)$. $w_{x_i}$ is weight on each instance now that instances with lower reconstruction errors
Algorithm 2: The Procedure of Training Transfer Anomaly Detection without label Method

Input: instances of source domain $x_s^{-} \in X_s^{-}$ and instances of target domain $x_t^+ \in X_t^+$

Output: $G_\theta, F_\phi$

for the number of epochs do
  Sample minibatches from $X_s^+, X_s^-$ and $X_t$
  $(B_{x_s^+} \subset X_s^+, B_{x_s^-} \subset X_s^-, B_{x_t} \subset X_t)$
  for $B_{x_s^+}, B_{x_s^-}, B_{x_t}, (a = 1, \ldots, A, c = 1, \ldots, C, e = 1, \ldots, E)$ do
    forall $x_s^+ \in B_{x_s^+}$ do
      $\tilde{x}_s^- = G_\theta(F_\phi(x_s^-))$
      forall $x_s^- \in B_{x_s^-}$ do
        $\tilde{x}_s^+ = G_\theta(F_\phi(x_s^+))$
        Update the Encoder and the Decoder by descending its stochastic gradient:
        $\nabla G_{\theta, \phi}(L_s(\phi, \theta))$
      end
    end
    forall $x_t \in B_{x_t}^c$ and the previous samples do
      $\tilde{x}_t = G_\theta(F_\phi(x_t))$
    end
    Update the Encoder and the Decoder by descending its stochastic gradient:
    $\nabla G_{\theta, \phi}(L_t(\phi, \theta))$
    Add instances of the bottom $r\%$ reconstruction errors to the following minibatch training samples.
  end
end

are used more than once. The objective function for target domain in without_label method is formulated:

$$\mathbb{L}_t(\phi, \theta) = \mathbb{E}_{q_{\phi}(z|x)} \left[ \frac{w_{x_t}}{M_t} \sum_{n=1}^{M_t} s_{\phi, \theta}(x_t | z) \right] + \beta D_{KL}(q_{\phi}(z|x_t) | p(z))$$

IV. EXPERIMENTS

We have experimented several ways to validate reliability of the proposed method in different aspects. The first is to show that the proposed RVAE structure has better performance than both Random Forest and the standard VAE, which we call as MLP-VAE in this paper. Second, we explain how the reconstruction errors are distributed and how to utilize it in detecting botnets. Third, we demonstrate the effectiveness of the transfer learning framework using two different network traffic datasets.

We use the 5 different evaluation metrics to validate our performance when we show compare the RVAE with the other semi-supervised learning method and the supervised learning method; Area Under the Receiver Operating Characteristic (AUROC), Area Under the Precision-Recall Curve (AUPRC), Precision, Recall and F1 score. We present the results from the model showing the best value of AUPRC in 5-fold cross validation sets. When we evaluate the transfer learning framework, we use AUROC, True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR) and False Negative Rate (FNR). In this case, we present the results from the model showing the best value of AUROC in validation set to avoid over-fitting. We use the mean of outputs each metric on the five identical experiments. The source code is written with the PyTorch\(^{1}\) library.

A. Evaluation Datasets

We utilize two different datasets to test the performance of the proposed model.

1) Dataset used for Evaluating RVAE: We use CTU-13 dataset widely used in the studies of botnet detection [15–21, 39]. In this dataset, a botnet scenario is a particular infection of the virtual machines using a specific malware. Thirteen of these scenarios were created, and each of them was designed to be representative of some malware behavior [39]. To compare the results of MLP-VAE and Random Forest, we reproduced nearly the same experimental settings reported in [16] and [18]. In [16] and [18] that proposes VAE and Random Forest structures respectively that we select as the baseline, they prove the robustness of their methods on scenario 1, 2 and 9 of CTU-13 dataset, which consists of only botnet called Neris. The Neris is the IRC based bot infecting other machines by Spam and Click Fraud. In our experiments, all methods show the similar performance in every metrics, as shown in Table III. Especially, Random Forest performs very well on the testing dataset because botnet families in the testing dataset are already used for training. In other words, Random Forest method is able to capture dominant features to classify anomalies.

To test the cases where the training data might be different from testing data, we plan to separate the CTU-13 dataset as suggested by [39]. The idea is to separate the data set so that none of the botnet families used in the training and cross-validation datasets should be used in the testing dataset. A method that achieves high accuracy in this case is likely to detect new behaviors. By splitting of CTU-13 data this way, we also mimic the real situation where the operations of botnet changes over time in terms of protocols and attack types. Compared to the restricted dataset (scenario 1, 2, 9), various types of botnets that have IRC-based, P2P-based and HTTP-based communication methods and conduct attacks such as Spam, Click Fraud, Port Scan, DDoS and FastFlux are included in the dataset that we use for the experiments. The datasets describing which scenarios are included are in Table II.

2) Dataset used for Evaluating Transfer Learning Framework: In transfer learning framework, data are required in source domains and target domains, respectively. The existing studies on transfer learning usually use the same dataset for target domains and source domains [34–38, 41]. However, we want to detect suspicious botnet connections on a new network monitoring dataset (target domain). In this case, we cannot help using the target domain that is different from the

\(^{1}\)https://pytorch.org
source domain since the data on the target domain cannot be labeled. Therefore, we need two different datasets to test transfer learning framework.

For the dataset in the source domain, we use CTU-13 dataset that is used to test RVAE model. CTU-13 dataset is labeled network traffic data. In this experiment, we only focus on botnet called Neris, which is used in scenario 1, 2, and 9 in CTU-13 dataset, to reduce complications. We use whole data instances rather than separating Normal labels from background labels. The scenario 1, 2, and 9 were collected for three days. On the other hand, for the dataset in the target domain, we use a network monitoring data set from a large research institute (called dataset K). The dataset is collected using a Zeek server connected at the network border. The Zeek server was installed all-in-one and used a default policy. We use the data collected for one day among seven days to balance the size of the target domain data with the source domain data. The network monitoring data is not labeled.

In order to use transfer learning framework, each dataset in the source/target domain should be related. Therefore, even though every study that uses CTU-13 dataset utilizes Netflow type of data that is provided in [39], we utilize CTU-13 data from Zeek software as dataset K, as obtained from Zeek as well. In our experimental setting, the source domains and the target domain are different but related as we utilize two dataset generated on different environment but collected from Zeek. To sum up, we utilize CTU-13 Zeek dataset as a source domain, and use dataset K as a target domain.

B. Labeling method

Both dataset K and CTU-13 Zeek data have no labels. To quantify the accuracy of transfer learning, we need a way to assign labels to these data sets. We present the new labeling method that can be applied to both CTU-13 and dataset K. Zeek’s event engine records weird activities that can indicate malformed connections, malfunctioning or misconfigured hardware, or an attacker attempting to avoid/confuse a sensor. Also, Zeek provides specified type indication the reason why the connections provoke weird flags. Those suspicious connection are logged in a file named weird.log. However, we find that weird.log no clear correlation with botnet label in CTU-13 Netflow dataset. Many of the connections logged in weird.log might be made by misconfigured hardware or malformed connections, not related to botnet. Most connections that are made by botnet in Netflow are even not detected as "weird" activity in Zeek.

On closer examination, we find that botnet called Neris accounts for 84% of connections representing irc_line_too_short in weird.log among data from 13 scenarios. We infer that most connections in the weird.log representing irc_line_too_short and irc_invalid_line are given by Neris.

Therefore, we decide to use the indication information from weird.log, and label the host IP address with irc_line_too_short and irc_invalid_line as malicious. With the collected host IP addresses that are malicious, we can use network log features from conn.log composed of source/destination IP addresses, ports, time, protocol, duration, number of packets, number of bytes, state, and service. As both CTU-13 Zeek dataset and dataset K are produced by Zeek, the labeling method can be applied commonly to the two different datasets.

C. Data Pre-processing

We use the same data pre-processing method for CTU-13 dataset and dataset K. The data are composed of source and destination IP addresses and ports, time, protocol, duration, number of packets, number of bytes, state, and service. We process the data to use the aggregated flows statistic, which is the way many existing works adopt in order to obtain flow-based features [15], [18], [20], [21]. For the data collected from Zeek, we add to use missed bytes and include more types of service such as mysql, imap and ftp compared to the original CTU-13 dataset. We group the connections at every time interval of \( T \), and aggregate features within every group based on the source IP addresses to generate flow-based features.

With the processing method, we can detect IP address showing the malicious behavior in a particular time window. Many existing works experimentally find the most appropriate time window \( T \), which is crucial, while too small time window might not capture traffic characteristics over a longer period of time, too large time window cannot provide timely detection in waiting for the end of the window [2], [15], [16], [18], [20], [21], [39]. We experimented changing the duration of windows to find the ideal value for the statistical aggregation. We then sort the entire data within the time window by the time of the source IP connection group, because the RNN model is sensitive to the order of the inputs. For RVAE, we use the network traffic connections collected within \( N \) windows as the sequential inputs to the model. You can see it in the data processing part of Fig. 2. In the case of Fig. 2 60-second duration of three windows are used.

In terms of source/destination ports and destination IP addresses, we count the number of unique records with connected source IP addresses in the time window. In addition, for the source IP addresses, we count the number of connections with the source IP addresses in the time window. For service, state, and protocol, we count the number of different values in each category with the source IP addresses in the time window. Finally, we normalize the numerical values to be between 0 and 1 using min-max normalization. As a result, the number of features used in this experiment is smaller compared to the number of features used in [18] and [16].

| Scenario | CTU-13 Dataset |
|----------|----------------|
| Training&Validation | 3,4,5,7,10,11,12,13 |
| Testing   | 1,2,6,8,9     |

TABLE II

CTU-13 Dataset
TABLE III
RESULTS COMPARISON: TRAINED AND TESTED ON DIFFERENT DATASET

| Dataset          | Model    | Recall | Precision | F1    | AUPRC  | AUROC  |
|------------------|----------|--------|-----------|-------|--------|--------|
| Scenario 1, 2, 9 | RVAE     | 0.964  | 0.914     | 0.938 | 0.966  | 0.971  |
|                  | MLP-VAE  | 0.963  | 0.922     | 0.941 | 0.954  | 0.965  |
|                  | Random Forest | 0.996 | 1.000     | 0.998 | 0.999  | 0.999  |
| Scenario 1-13    | RVAE     | 0.970  | 0.871     | 0.918 | 0.976  | 0.979  |
|                  | MLP-VAE  | 0.941  | 0.936     | 0.938 | 0.967  | 0.963  |
|                  | Random Forest | 0.696 | 0.997     | 0.820 | 0.921  | 0.936  |

Fig. 3. Distribution of reconstruction errors of normal and botnet samples with different duration of window

D. Experimental Configuration

The architecture of MLP-VAE, which is used as an anomaly detector, follows the one from [16]. [# of features → 512 → 512 → 1024 → 100]. For RNN architecture, we use 2-layer bidirectional GRU. We use the 512 hidden states, and 100 latent variable as MLP-VAE. We also apply ReLU activation [41] to MLP-VAE as well as RVAE. The Kullback-Leibler annealing method is set so that the weight (β) multiplied to KLD increases linearly for 500 gradient updates for RVAE. We train for 500 epochs with Adam optimizer and 128 batch-size. Also, the learning rate is set as 0.01 for both VAE models.

E. Comparison Methods

There are two experiments in this paper. First, we compare the experimental results of the proposed model, RVAE, to the results of MLP-VAE and Random Forest. In terms of MLP-VAE, the experimental results are based on the same data processing method with the same optimizer, learning rate and the size of latent variable from our experiment. Second, in order to evaluate that the anomaly detector performs well on the dataset K, we compared the transfer learning results to the semi-supervised learning. For both cases, RVAE structure is used as an anomaly detector.

V. RESULTS AND DISCUSSION

We now report our experimental results. We first discuss the performance of anomaly detection based on RVAE semi-supervised learning with other methods using a set of different metrics. Then we compare the performance of RVAE transfer learning method with RVAE semi-supervised learning on different measures.

A. RVAE semi-supervised learning

For a quantitative evaluation, we compare the performance of our method with others on different metrics. For qualitative evaluation, we plot the distribution of the reconstruction errors of the normal and botnet cases. Moreover, we plot estimated the best-fit PDF described in the section III-A2. To compare methods with the same processing and detection method, we reproduce MLP-VAE and RF in [16] and [18], respectively. While the value in the literature [16] is 0.936, our reproduced value of AUROC with MLP-VAE is 0.963. Even if there may be a slightly different experimental setup, the reproduced results show that our implementation is still valid according to a bit higher result than the result of the original paper.

Performance comparison among methods. In Table III, the RF method shows the nearly perfect performance in every metric, even though VAE models show the comparable performance. This is because the training/testing datasets are based on scenario 1, 2 and 9 share the same characteristics. RF is effective in finding dominant features in these restricted datasets. However, as we mention in the section IV-A1 we want to evaluate the cases where the training and testing data sets are different. In Table III, we show the results from the training and testing on the whole dataset that we mentioned in the section IV-A1. In this experiment, we pre-processed our data by using 60-second duration of window and using three windows. While both restricted training and testing dataset(Scenario 1, 2 and 9) consist of only Neris, the entire testing and training dataset(Scenario 1-13) consist of each different botnets: Rbot, Virut, Sogou, and NESIS.ay are used for training, and Neris, Menti, and Murio are used for testing. Because each botnet shows different characteristics, there is an overall performance degrade with RF that is affected by the dominant features of the training dataset. Nonetheless,
TABLE IV
RESULTS COMPARISON ON DIFFERENT SCENARIOS

| Dataset | Model   | Recall | Precision | F1    | AUPRC | AUROC |
|---------|---------|--------|-----------|-------|-------|-------|
| Scenario 1 | RVAE   | 0.979  | 0.709     | 0.826 | 0.888 | 0.969 |
|          | MLP-VAE | 0.968  | 0.729     | 0.832 | 0.729 | 0.938 |
| Scenario 2 | RVAE   | 0.941  | 0.970     | 0.955 | 0.967 | 0.967 |
|          | MLP-VAE | 0.936  | 0.974     | 0.955 | 0.968 | 0.964 |
| Scenario 6 | RVAE   | 0.943  | 0.612     | 0.742 | 0.728 | 0.867 |
|          | MLP-VAE | 0.689  | 0.646     | 0.666 | 0.679 | 0.769 |
| Scenario 8 | RVAE   | 0.973  | 0.937     | 0.954 | 0.980 | 0.981 |
|          | MLP-VAE | 0.921  | 0.974     | 0.947 | 0.971 | 0.959 |
| Scenario 9 | RVAE   | 0.957  | 0.989     | 0.973 | 0.991 | 0.976 |
|          | MLP-VAE | 0.961  | 0.986     | 0.973 | 0.990 | 0.976 |

VAE methods validate its reliability by showing the robust performance with the generalized dataset. In addition, we find that RVAE method outperforms MLP-VAE method overall based on the same features and the same size of latent variables on both datasets, as you see in Table III. It can be concluded that the botnets of network traffic flow data should be detected utilizing sequential and periodic patterns.

Probability density function of reconstruction errors. As shown in Fig. 4, the distribution of the reconstruction errors of botnet samples can be distinguished from the distribution of the normal sample reconstruction errors. As we only use non-malicious samples for training, we expect that the reconstruction errors of malicious samples are larger than that of the non-malicious samples. Comparing medians of those two distributions, we can notice that the median of the distribution of non-malicious reconstruction errors is larger than the median of the distribution of botnet reconstruction errors.

Especially, you can find a group of botnet samples that have the smaller reconstruction errors compared to the other botnet samples in Fig. 3b. We focus on the samples whose reconstruction errors are smaller than 4. We find that 66% of the samples of the scenario 6 labeled as botnet show the reconstruction errors less than 4, while only 0%~4% of samples in the other scenario show reconstruction errors less than 4. The scenario 6 utilizes proprietary command control channels unlike other scenarios most of which use IRC, HTTP and P2P communication methods [39]. The samples of the group having small reconstruction errors show low values for DNS, smtp, ssl, the number of IP addresses, the number of ports, and the number of different IP addresses in window. These characteristics mainly represent non-malicious other than the botnet. We conclude that the general nature of the scenario 6 makes dozens of samples obtain the smaller reconstruction errors.

Results on each scenario. In Table IV, you can find the experiment results tested on each scenario. Overall, RVAE shows better performance than MLP-VAE. What stands out is that there exists a tendency that the MLP-VAE performs better than the RVAE on the precision, and the RVAE performs better than the MLP-VAE on the recall, as you can also find the same aspect in Table III. While the performance difference between the two methods is not very clear on the botnet called Neris (Scenario 1,2,9), it is clear that the RVAE surpasses the MLP-VAE, especially in Scenario 6. Although in terms of scenario 6, which consists of botnet called Menti, both RVAE and MLP-VAE shows somehow lower performance than other scenarios, RVAE is much more superior to MLP-VAE compared to other scenarios. As we mentioned above, botnet characteristics of scenario 6 are unlikely to be distinguished from normal instances. The AUROC of RVAE is 12% higher than that of MLP-VAE in the scenario 6, while the difference between RVAE and MLP-VAE in others is about 0.0%~3.0%. We can interpret that in the situation where botnet characteristics of the individual connections are not distinct, the method utilizing sequential properties of input helps the anomaly detector to detect botnet.

Duration of window. In order to propose the right duration of window, our experiments have been done with changing the duration of window to 5 seconds, 60 seconds and 300 seconds in Table V. In general, the performance of 60-second duration of window are higher than those of other duration lengths. We infer that as we use a long duration, the number of source IP addresses that belongs to the same time window increases, which aggravates the vanishing gradients problem in a long-term sequence. On the other hand, too short duration cannot provide efficient length to represent the patterns of the time windows with statistically aggregated values. From our experiments, 60-second duration is the most suitable, as you can find in Table V quantitatively and Fig. 3 qualitatively.

B. RVAE transfer learning

Now that we have validated the effectiveness of using RVAE structure as an botnet detector in [V-A], we conducted experiments to show that transfer learning framework allow the botnet detector working on the new dataset K. To present its possibility, we compare the performance of RVAE transfer learning method with RVAE semi-supervised learning on different measures.

t-SNE plot of each dataset. We plot t-SNE [42] of each instance of two datasets to justify to use transfer learning. To use transfer learning, two domains should be related and share common characteristics. We reduce dimension of features of data from 48 to 2 in order to visualize its distribution. The source domain dataset and the target domain dataset are not generated in the same environment. The source dataset, CTU-13 is made for the purpose of research for botnet detection in the environment where attacks of botnet are controlled. On the
other hand, the target domain dataset K is network monitoring data that is collected using a Zeek server connected to the switch between the Internet and the local network. Therefore, the two distributions cannot be completely overlapping, as you can see in Fig. 4. However, because both data share common characteristics generated from Zeek, the two distributions are not completely separated. As a result, transfer learning, especially the application of transductive transfer learning, can show the improved performance over semi-supervised learning.

**Performance comparison with semi-supervised method.**

We validate the proposed method by comparing with semi-supervised learning that uses RVAE method. We find that our proposed method with label outperforms RVAE, semi-supervised learning, as you can see in Table VII. We highlight TPR among other metrics since the purpose of using the proposed model is to detect botnet. TPR, which is also called detection rate, of with label method is 0.918 while TPR of RVAE method is 0.683 in Table VII. Even we obtain higher detection rate with without label method ($r_s=0.1$) (0.899). This output indicates that the effectiveness of using transfer learning as we use the same RVAE model and set the same hyper-parameters for training. Moreover, even without label method that does not use label information on the target domain shows higher performance than RVAE on TPR and FNR metrics. Overall, these results demonstrate that the proposed method detects suspicious botnet better on the target domain as using transferred knowledge that is obtained on the related domain (source domain) can provide useful information for the target domain lack of training data.

**Performance comparison with varying $r_s$ on without label method.**

We perform experiments to find the optimal $r_s$ on without label method. We change ratio of samples that are used again for the next batch training. In the case of dataset K, it has about 5% botnet samples in total. We change $r_s$ from 3% to 50% for experiments. Setting the ratio as 50% means that large portion of samples are used as normal samples for the next batch training. It leads to high TPR and low FNR as large portion of samples are re-used for training that makes reconstruction error distribution of normal samples biased to small reconstruction errors. It can have many samples predicted as botnet. Also, using high ratio causes low TNR and high FPR because of the same reason. On the other hand, when $r_s$ is 5%, we obtain higher TNR and low FPR, comparatively. It is because we use the small portion of samples, which has little impact on distinguishing botnet from normal samples. Therefore, setting the ratio appropriately is a key factor on using without label method. We propose empirical methodology of setting ratio by doing several experiments changing $r_s$ in this paper. For the purpose of practical use, the ratio should be determined by which measure is important.

**VI. Conclusion**

This paper focuses on improving botnet detection performance with the consideration of two challenges: characterization of botnet traffic (showing sequential patterns) and the shortage of labeled datasets essentially required for constructing learning models. We first presented the RVAE anomaly detection method taking into account for the sequential and periodic nature for the network traffic flow data. The study is of significance to providing the applicable solution for the botnet detection system, especially in an online manner. To validate RVAE method, we apply the proposed method with the CTU-13 dataset, a widely used dataset for botnet detection studies, and show that the proposed method can detect previously unseen botnets more effectively by utilizing sequential patterns of the network traffic compared to the methodology without using sequential pattern as AUROC is 0.979 higher than 0.963 of MLP-VAE. As the proposed method is validated on various scenarios of botnet operation, including the botnets that are not used for training, it can be concluded that the proposed method is robust in detecting previously unseen botnets.

We also presented a framework for transfer learning, to overcome the challenge of the unavailability of labeled datasets. Transfer learning can learn on the old data with labels and then apply the learning model on new data records as well as data records collected differently without labels. The ability of working with unlabeled data is particularly useful for the network security applications because security issues such as botnets continue to evolve. In our evaluation of the transfer...
learning framework, we use CTU-13 dataset as the source domain for training and a fresh set of network monitoring data as the target domain. Tests show that the proposed transfer learning method is able to detect botnets better than a semi-supervised learning method trained on the target domain data. We observe that True Positive Rate (TPR) is 0.918 for transfer learning and 0.683 for directly using RVAE on the target domain data. This indicates that the transfer learning could reliably identify anomalies.

For future studies, we plan to study some improvements in the proposed method. From the perspective of RVAE structure, fuzzy logic can be adapted to improve the anomaly detector utilizing PDF. It can provide more logical and systematic way of using PDFs for anomaly detection than comparing likelihoods from two distributions. In addition, it is potential to improve performance of the anomaly detector if the method to cope with some cases of botnets having the small reconstruction errors from the normal cases is developed. The common characteristics of the cases of botnets, which use a proprietary protocol, can be utilized to develop such a method. Moreover, the various VAE or RVAE architectures can be adapted to improve their anomaly detection performance. From the view of the transfer learning, while we propose an empirical manner of using transfer anomaly detection method without labels on a target domain, future research will be required to propose more systematic method beyond empirical ways to improve without_label method. In addition, it is potential to improve performance of the anomaly detector in the FPR measure as it shows the weak performance relatively.

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**TABLE VI**

| Model            | TNR  | TPR  | FNR  | FPR  |
|------------------|------|------|------|------|
| RVAE with_label  | 0.784| 0.683| 0.317| 0.215|
| without_label(0.05)| 0.649| 0.885| 0.115| 0.351|
| without_label(0.1)| 0.716| 0.899| 0.101| 0.284|
| without_label(0.5)| 0.632| 0.923| 0.077| 0.368|
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