DDoS attack detection and defense in SDN based on machine learning

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***Abstract*—Distributed Denial of Service (DDoS) attack is one of the most dangerous threats in computer networks. Hence, DDoS attack detection is one of the key defense mechanisms. In this paper, we propose a DDoS detection and defense approach in Software Defined Network (SDN) systems based on machine learning (ML) and deep neural network (DNN) models. The combination of ML and DNN classifiers with the centralized factors of SDN can efficiently mitigate the harmful effect of DDoS to the network system. Besides, we conducted two types of attack scenarios, one is from inside and one is from outside of the network system.**

***Index Terms*—DDoS, Machine Learning, SDN**

I. Introduction

DDoS attack is the fatal and widespread threat on today's Internet. Massive DDoS attacks appear more frequently. In 2016, the world's largest DDoS attack was recorded at that time. The Dyn, a DNS service provider company, experienced a massive DDoS, at its peek, the system received incoming traffic at a rate of 1.2Tbps [1]. This particular attack was based on a botnet (Mirai) on unsecured IoT devices which were allowed non-authorized attackers remotely accessing. In 2018, Github experienced the largest DDoS attack in history, at 1.35Tbps. The attackers launched an amplification based on exploiting the unsecured memcached servers [2]. Moreover, with the combination of multiple attack vectors, the conventional statistical based methods show their weakness to identify abnormal traffic. An attack with small volume can even be seen as a normal one in the early stages, therefore, statistical based methods were not efficient to low-rate attacks. Besides, machine learning methods identify DDoS based on statistical features performed better than statistical traffic approaches.

SDN is the promising network architecture which allows logical programming with abstraction level behind the network's operation. SDN commonly includes three parts, the OpenFlow switch, the host, and the controller. Most important part in SDN is the controller. It is responsible for generation, delivery, maintenance of the network forwarding flow table. The OpenFlow switch is another core component and mainly responsible for routing and forwarding data packets [3].

Our work proposed a DDoS classifier based on machine learning and deep neural network to interact with our conducted SDN controller to intermediately drop the harmful flows from both inbound and outbound traffic. Moreover, we also indicate the gap from theoretical results to the reality experiments.

The rest of this paper is constructed as follows: Section II discusses some related works, section III describes our proposal approach and experiment results, the conclusion is shown in section IV.

II. Related works

A. Statistical approaches to DDoS detection

Statistical approaches to DDoS detection are the conventional methods, which are based on monitoring the entropy variations of header fields in packets. In the early 2000s, this approach has been proposed with the expectation that during a volumetric attack, the randomness of traffic features is subject to sudden variations [4]. The bandwidth attacks are defined by a large set of compromised devices which send high volume of traffic to one or multiple victims. As a result, these traffics caused a rise (or a drop) in distribution of some attributes in packets' header, eg. the decreasing of target IP and the increasing of source IP. Therefore, DDoS is usually identified based on the average of threshold values on these distribution indicators.

Feinstein et al. [5] proposed the earliest method to detect DDoS based on Chi-square distribution and computation of source IP address entropy. The authors indicated that the variation of source IP and Chi-square statistics in abnormal traffic was massively larger than that one in legitimate traffic. Similarity to this, P.Bojovic et al. [6] observed the bandwidth of traffic entropy variation to detect high-rate DDoS attack.

A common limitation of these approaches is that entropy-based techniques need to adopt exact threshold value. In different network systems, the deviation of traffic volume is completely different that leads to a challenge to find out adaptive methods, which could generate a high appropriate threshold to minimize the both false positive and negative detection. Kumar et al. [7], proposed an adaptive technique to dynamically adjust the threshold in different network systems.

B. Machine and deep learning approaches to DDoS detection

Several datasets related to DDoS fields have been proposed. Before 2012, most of the datasets were small and not diverse in attack methods. Some of them are DARPA [8], KDD CUP 99 [9], NSL-KDD [10], or a private dataset - Booster [11]. However, after 2012, Canadian Institute for Cybersercurity in University of New Brunswick released three large-scale datasets in computer security in 2012, 2017, 2018 called ISCXIDS2012 [12], CIC-IDS2017 [13], and CSE-CIC-IDS2018 on AWS [14] respectively. CSE-CIC-IDS2018 on AWS (CICIDS2018) is the newest and largest network security dataset at this time. It was conducted on a simulation network created on AWS clouds which includes hundreds of computer, server, and network devices.

Most machine learning based approaches used popular algorithms such as Support Vector Machine (SVM), Linear Regression (LR), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), etc. Among these methods, SVM with linear kernel always showed the high accuracy and stability on different datasets and network systems. He et al. [15], used nine machine learning algorithms including LR, SVM (linear, RBF, Polynomial kernel), DT, NB, RF, K-means, Gaussian EM. In the experiment, Linear SVM produced the best accuracy (99.7%) with the lowest false cases (¡0.07%). Similarly, R.Doshi et el [16] applied many ML algorithms to detect DDoS from the origin of attacks in IoT systems. The authors mainly observed the high volumetric traffic when the IoT network was intruded. As a result, Linear SVM model also reported achieving the high accuracy at 99.1%.

Some research using deep learning showed the potential of earlier detection of DDoS. DL approaches commonly rely on two basic model architectures are CNN and RNN. Some of them rely on the abilities of learning from time-series data of RNN and others based the sliding-window technique in CNN to extract the features of traffic. In the research [17], [18], [19] the authors used RNN models. Yuan et al. [17], used both RNN (LSTM, GRU) and the combination of CNN and RNN and trained on the dataset ISCXIDS2012. They reported an extremely high result compared to the common ML algorithms Random forest. Meanwhile, [4], [20] used CNN models. R. Doriguzzi-Corin et al [4] realized a limitation of RNN architecture is high computation cost, therefore they used Convolution1D and MaxPooling layers in CNN to simplify the architecture but still keep the accuracy. Basnet et al [21] tried to measure the performance of different deep learning frameworks on a deep neural network to detect DDoS. The authors train the model on the dataset CICIDS2018 with many DL frameworks such as Theano, Tensorflow, FastML, etc.

III. DDoS defense in SDN

In SDN, several methods were proposed to detect and mitigate the effect of DDoS attacks.

Kim et al [22] proposed a technique to predict harmful bandwidth based on threshold of flow. The author applied Cisco's NetFlow Technology to detect network traffic by the extracted flow features and pre-defined thresholds.

Manso et al [23] apply an open-source intrusion detection system (IDS) called SNORT to early notify attacks to SDN controllers by setting a combination of rules. The main idea of the authors is to detect the DDoS from the source of attacks.

Niyar et al [24] proposed a deep neural network model based on Stacked Autoencoder to detect and mitigate DDoS in SDN. Firstly, the authors conducted a simulation of SDN to collect samples of legitimate and malicious traffic to build a dataset. Their dataset included most common attacks such as SYN flood, UDP flood, TCP flood, etc. The goal of the authors is to detect multi-vector attacks. In the experiment, the result was reported higher than 90% in most scenarios and up to 99% in binary classification.

Li et al [3] applied the RNN models in [17] to extract traffic features. They conducted a multi-module defense system. The traffic features are stored and weighted in a statistical module, and when these features meet a pre-set threshold, a notification module will fire a command to the SDN controller to drop the flow between two IPs.

IV. Proposal approach

In this section, first of all, we conduct the machine learning classifier with Linear Support Vector Machine (LSVM), Decision Tree, Random Forest, and Naive Bayes algorithms on the data set CSE-CIC-IDS2018. In addition, we also build a deep neural network based classifier to compare with above conventional ML methods. Secondly, we conduct a DDoS detection software called IDS-DDoS that collects the network packets to generate and classify flow, and announce the malicious to SDN controller. Thirdly, we built a SDN controller that received abnormal flow identification to generate dropping rules in forwarding flow tables on OpenFlow switches. Finally, we experiment two attack scenarios on a simulation network.

A. Machine learning and deep neural network classifier

1) Dataset: We trained our models on the dataset CICIDS2018. This dataset was produced with an open-source software called CICFlowMeter [25] on a series of large size PCAP files. CICFlowMeter produced 84 statistical attributes of traffic flow for example source IP, destination IP, flow duration, max, min, mean, standard deviation values of packets' size, etc. We choose the parts in the dataset containing DDoS traffic only. The DDoS traffic was conducted by well-known DDoS attack tools such as Hulk, Golden-Eyes, HOIC, etc.

There are some error data points such as containing NaN values, negative values, therefore we have to remove these records in the dataset. Finally, the dataset remains more than 11 million data points. After that, we split the dataset into 2 sets, one for training and another for testing called IDS-Train and IDS-Test respectively.

Finally, we applied feature selection with Chi-square test to find the best features for training on IDS-Train. After all, we kept 67 features in total. Top 5 of features are "No. packets have data in forward flow", "Total length of forward packets", "Total backward packets per second", "Window bytes of initial forward flow", "Average segmentation size in forward flow".

Before training, we normalize the IDS-Train using L2-norm. We did not scale the training set, which could lead to overfitting.

2) Machine Learning and Deep Neural Network models: We applied four machine learning models including Linear SVM, Naive Bayes, Decision Tree, and Random Forest.

To find the best Deep neural network model. First of all, we build a series of models from 2 to 6 hidden fully connected layers, with 32 units each layer. After that, we increased the number of units in each layer of the 6-layer model from 32 to 64 and 128 units. After achieving the highest accuracy, we started reducing the number of hidden layers from 6 to 2. Finally, we got the simplest model with best accuracy shows in figure 1.

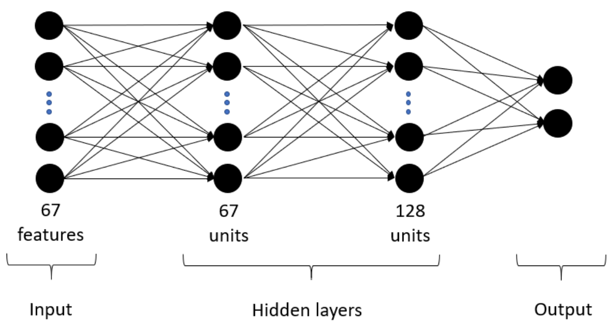

Fig. 1. DNN model

B. Result on IDS-Test

We assessed the models with 4 conventional assessment indicators including accuracy, precision, recall, and f1-score. We used binary-classification with malicious flow as Positive and legitimate flow as Negative. The formula of above indicators is as follows:

Accuracy:

$$Acc = \frac{TP + TN}{Total}$$

Precision (hay Positive predictive value):

$$Pre = \frac{TP}{TP + FP}$$

Recall:

$$Rec = \frac{TP}{TP + FN}$$

F1-score:

$$F1 = 2\frac{Pre \cdot Rec}{Pre + Rec}$$

The testing result is shown on the table I. Decision Tree is an algorithm with a naive and simple approach, however it performed the best result among these models, even higher than the most complex model DNN. It showed that the more complex architecture might not ensure more accuracy.

TABLE I
RESULT ON IDS-TEST

Model	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
LSVM	95.67	88.05	86.91	87.48
NB	67.69	34.92	99.31	51.67
DT	**99.97**	**99.91**	**99.94**	**99.92**
RF	99.83	99.11	99.94	99.52
DNN	99.22	97.91	97.58	97.74

C. IDS-DDoS

In this section, we applied our models in the previous section to conduct a software which has the ability to capture, collect packets to generate traffic flow, and furthermore could classify the traffic flow as malicious or legitimate, called IDS-DDoS.

We conduct the software with Python programming language. On the capturing and collecting packets part we use the library called Scapy. To generate traffic flow, we referred to the source code of CICFlowMeter which was written in Java. The workflow of IDs-DDoS is shown in figure 2. The socket server in this scenario is a SDN controller.

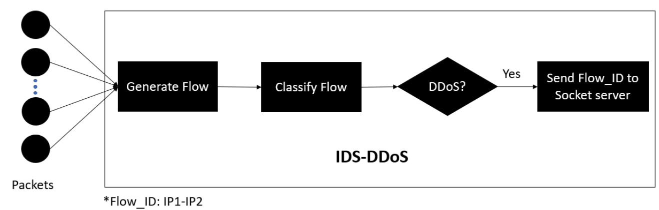

Fig. 2. IDS-DDoS workflow

D. SDN controller

We used Ryu framework to conduct a SDN controller. Our controller had 2 different tasks, one is normal SDN to control and monitor the network and one is a defense layer. The workflow of this SDN is shown in figure 3. At this time, we applied the simplest threshold which indicates a traffic flow as malicious flow when it is sent from IDS-DDoS N times within T seconds.

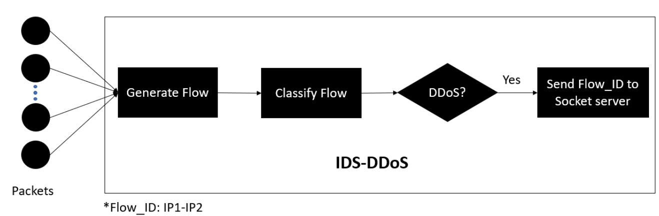

Fig. 3. SDN controller workflow

To show the traffic monitor in SDN, we conduct a visual graphic interface as in figure 4. Y-axis indicates number of packets, X-axis indicates timestamp, the blue line indicates number of received packets, and the green line indicates number of transferred packets. Below the graph is "Blocking history" containing a list of blocked Flow_ID.

E. Experiment on simulation network

1) Simulation network: The simulation network is shown in figure 5.

There are 3 virtual machines "Inner network machine", "Outer attacker", and "Outer Webserver". These machines are connected together via a "Host Only" of Virtualbox

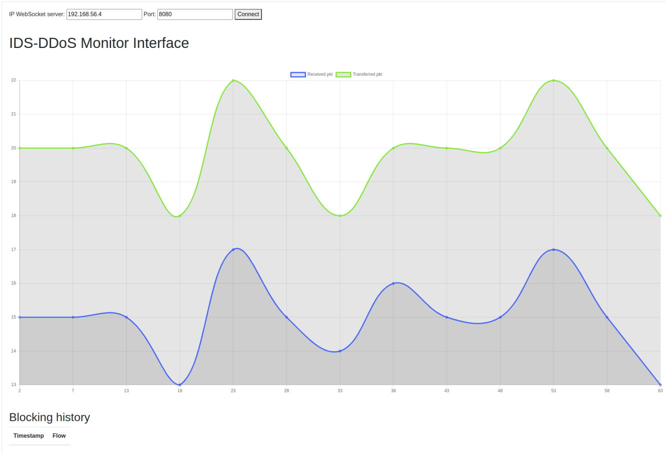

Fig. 4. SDN monitor GUI

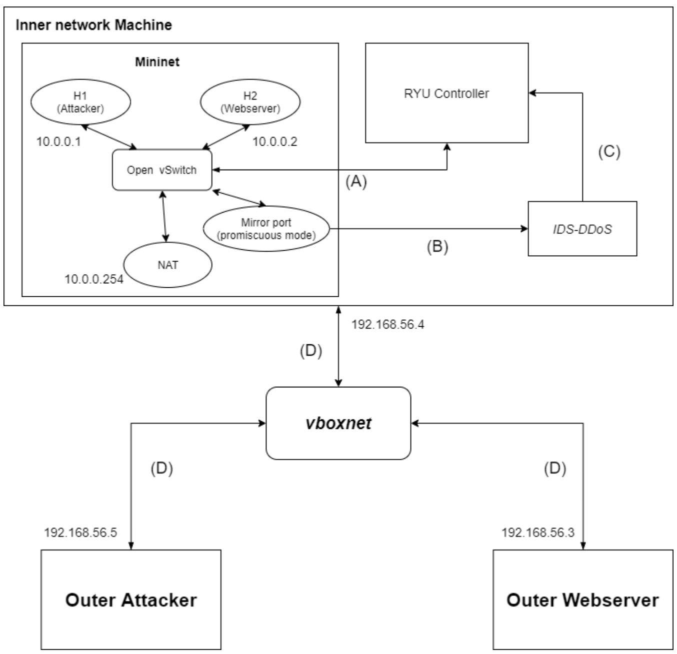

Fig. 5. SDN monitor GUI

called "vboxnet". The vboxnet represents for the Internet, the outer attacker, and the outer webserver represents for random attackers and webservers on the Internet respectively, and the inner network machine represents for our local network. Inner network machine contains 3 parts, the first is SDN controller, the second is IDS-DDoS software, and the third is a simulation of SDN created with Mininet. The simulation SDN contains 2 machines called H1 and H2. These machines communicate with the outside world through a NAT device. H1, H2 represents the inner attacker and inner webserver respectively.

2) Experiment results: To launch the experiment, we proposed 2 scripts of attack scenarios. The first one is that our SDN is attacked by a random attacker on the Internet. The second is that our local network was intruded, and the devices in SDN become a part of a botnet attacking a random webserver on the Internet.

For the first script, we used the HOIC attack tool on the outer attacker to attack H2. For the second one, we used the Hulk attack tool on H1 to attack the outer webserver. In these scripts, we set the threshold as "appearing 10 times within 1 minute".

The model we used to classify the flow was Linear SVM. Theoretically, Decision Tree and Random Forest achieved an extreme accuracy, however, on experiment, they could barely recognize the malicious flows. Meanwhile, DNN and Linear SVM recognized the abnormal flows quite well. However, Linear SVM ran faster than DNN more than 80 times. Therefore, we used Linear SVM instead of DNN.

a) Script 1: The figure 6 shows the state of the SDN before, during and after the attack. Before the attack began, the network's state was completely stable, but when the attack was launched, the number of received and transferred packets suddenly increased. However, after a while, when the IDS-DDoS classified enough flow as malicious ones, and the SDN controller matched the Flow_ID with defined threshold and dropped the flow, the number of transferred packets dropped dramatically.

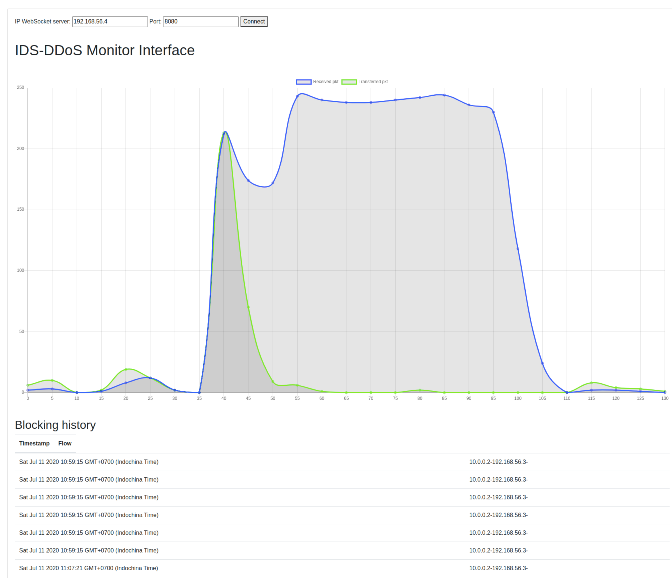

Fig. 6. Script 1

b) Script 2: The figure 7 shows the state of the SDN before, during and after the attack. Similarly to the previous script, after about 1 minute, the system recognized and dropped the flow. However, on script 1, after the flow was dropped, the number of received packets still increased meanwhile the number of transferred packets decreased dramatically. Meanwhile on script 2, the number of both received and transferred networks dropped dramatically. The reason was, on script 1, when the SDN prevented the communication between outer attacker and H2, the attacker still sent new packets going through the monitor, meanwhile, on script 2, all packets sent from H1 was dropped before it went through the monitor.

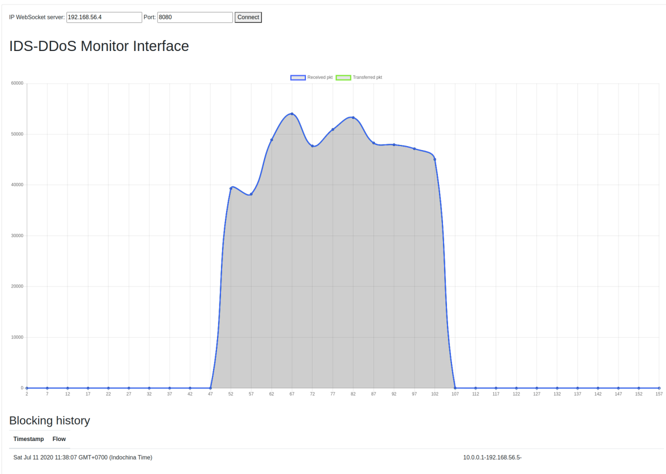

Fig. 7. Script 1

V. Conclusion

- Decision Tree and Random Forest are the best model on simulation, but in practice, the Linear SVM and DNN are outperforming. There is a need for further research to fill the gap between theory and practice. Through the experiments, we observe that the more complex DDoS detection system might not produce more accuracy results than the simple one.
- Our proposed models are sensitive to the new attacks, because it is trained by the dataset collected from 8 different attacks only. However, with the simple architecture of SVM, the system can easily learn and classify any new attacks.

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