Bridging the gap to real-world for network intrusion detection systems with data-centric approach

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Abstract

Most research using machine learning (ML) for network intrusion detection systems (NIDS) uses well-established datasets such as KDD-CUP99, NSL-KDD, UNSW-NB15, and CICIDS-2017. In this context, the possibilities of machine learning techniques are explored, aiming for metrics improvements compared to the published baselines (model-centric approach). However, those datasets present some limitations as aging that make it unfeasible to transpose those ML-based solutions to real-world applications. This paper presents a systematic data-centric approach to address the current limitations of NIDS research, specifically the datasets. This approach generates NIDS datasets composed of the most recent network traffic and attacks, with the labeling process integrated by design.

1 Introduction

There is an increase of connected devices nowadays as aggregated by the Internet of Things (IoT) paradigm and further with the rise of 5G [1][2]. This scenario results in a greater heterogeneity of devices and network architectures to make the solutions available, such as autonomous driving, remote surgery, connected infrastructures, among others. In this context, cybersecurity is one of the properties that must be in place to make these solutions available with trust.

To deal with the pace of increasing network agents, architectural changes, diversity of attacks, and the increasing amount of network traffic, the use of machine learning (ML) based network intrusion detection systems (NIDS) raises as a technical approach to deal with the evolving context bringing trust to these applications [3]. In contrast with the NIDS research trend, ML-based NIDS are still not prevalent in real-world applications [4]. Instead, most research uses well-established datasets like KDD-CUP99 [5], NSL-KDD [6], UNSW-NB15 [7], and CICIDS-2017 [8], that from a machine learning perspective, are good as baseline comparisons on different ML techniques. However, to derive these findings to real-world application, we claim that a data-centric approach must be in place to continuously generate datasets and re-train models, address the following limitations: evolving network traffic, aging of attacks, and capability to generalize for different network architectures.

The remaining of the paper presents the related works about the challenges faced by NIDS datasets in Section 2. Section 3 and 4 details our approach to generate NIDS datasets from a data-centric perspective. Section 5 presents the conclusion, next steps of our research, and open questions.
2 Challenge and Related Work

[4] reported the low performance of NIDS in the real-world environment as a research challenge. Some probable causes are using old datasets and not evaluating the proposed solutions considering a realistic environment. In addition, the authors report the lack of a systematic approach for dataset generation capable of being updated frequently. The challenges about datasets for NIDS research are also reported by [9]. It presents the inherent network traffic diversity characteristic and the difficulty for a dataset to cope with all possibilities. Furthermore, it is highlighted the difficulty of data availability (public datasets) and criticizes generalizing results obtained in small network architecture to larger networks. Regarding dataset aging, [9] reports that the most used datasets in 2010 were already one decade old (DARPA98, and KDD-CUP99). [10] [11] highlights the current trend for using a deep learning approach in the NIDS research but also points out the use of old datasets such as KDD-CUP99 and NSL-KDD. It also reports the lack of available datasets and low performance in a real-world environment. Next, [12] provides a survey about NIDS datasets and reports the outdated datasets in use by NIDS research as a challenge.

The survey by [13] reports the “perfect dataset” composed of up-to-date traffic, labeled, publicly available, with real network traffic and a multitude of attacks and normal traffic, spanning a long time frame. However, they are skeptical about the availability of datasets comprising all these properties, with the challenge for a labeled dataset containing long-time traffic. In this context of dataset aging for NIDS applications, it is important to clarify that the network traffic and attacks have a lifespan. In other words, the NIDS are susceptible to concept drift as reported by [14]. It reports a six-week of good performance of the trained models. This study indicates that a continuous update is required to address the evolving characteristics of the network traffic.

In summary, the related works present dataset aging and poor performance in a real-world environment as a research gap. Our proposition is a framework for dataset generation capable of generating NIDS datasets with the most recent network traffic and attack patterns shifting the current NIDS paradigm from model-centric to data-centric. The downside of our approach is the limited possibilities to benchmark ML solutions using the generated dataset with published baselines. Nevertheless, we envision this approach as a next step to the current NIDS solutions to bridge the gap to the real world. Thus, after performing the traditional NIDS research to obtain the best model, our approach must be part of an end-to-end pipeline to continuously re-train this model with a dataset composed of up-to-date traffic and network attacks. Another limitation is that we do not evaluate the use of commonality for NIDS features between our generated datasets and those publicly available [15].

3 Methodology

Our methodology starts with the generation of network traffic that represents the attack behavior. This step aims to overcome the current datasets’ challenges: not containing the most recent attacks, not reproducible, and not properly labeled [16]. For the attack traffic, we take advantage of virtualization and cloud infrastructure to generate this traffic on-demand. We use a Docker container with the base image of Kali Linux distribution (a well-known distribution for cybersecurity tasks). The use of Kali Linux is a common approach to generate attack traffic [17]. This container is responsible for generating all attack traffic against the cloud infrastructure that we manage. This container is a customized step that can include different attacks and targets through configuration files. Knowing the attacker instance and the targets in advance is crucial because this information supports the automation of the labeling process. For example, it is possible to construct a tuple with the attacker and target IP addresses to determine the attack traffic. To compose the NIDS dataset, we use a method known as salting [18]. This method merges the legit traffic data with the attack traffic generated on-demand. We obtain this legit traffic after removing the malicious traffic from open-data traffic providers as MAWILab [19], from other public NIDS datasets, or from the deployment environment that increases the effectiveness of the solution (better data). Using traffic from the deployment environment requires authorization of the IT infrastructure in conjunction with the network administrators to label the legit traffic correctly. This labeling process can make use of firewall rules to determine the legit traffic. The generation of the dataset becomes part of the overall process of NIDS development (Figure 1). This process considers the generation of up-to-date datasets from both attack and benign traffic perspectives to bridge the gap between research and the real-world application of ML-based NIDS.
We also ensure that the data generated is tidy [20], that is, has a rectangular structure composed of observations (rows) and variables (columns). Such an organization, popular among data scientists, enables the utilization of common tools for exploratory analysis, data manipulation, and model building [20]. Each packet in the dataset has its row (Table 1). Each column represents a packet feature that can be either context-aware ($X^C_1, \ldots, X^C_{n_c}$) that are common to multiple observations, such as source and destination IP addresses or context-free, that is, intrinsic of the packet ($X^P_1, \ldots, X^P_{n_p}$). One of the columns ($Y$) represents the variable that informs whether the packet is from benign traffic or an attack.

As a result, one can easily reshape the generated dataset to meet the requirements and aspects of the desired machine-learning task. For instance, in a stateless approach, one can discard all context-aware variables (Table 2a); while, in a stateful approach, one can use the consolidated summarizing operations in data science to aggregate rows (Table 2b). The common and consistent shape of the data also eases selection and filtering operations.

### 4 Results and Discussion

We created an environment using a cloud service provider to create a geographically distributed testbed. For the attacker instance, the container’s configuration file is available on our public repository. To support the labeling process, we set up a UDP daemon on each of the cloud instances that receive remote UDP commands from the attacker container to start and stop the network traffic capture using Tcpdump [1] on these cloud instances. The choice for the UDP protocol is because we focused on the TCP protocol, so there is no conflict between the command and control traffic and the one that makes

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1TCPdump: tcpcap.org
up our dataset. Figure 2 presents the overall picture of the process. From the UDP message starting
the recording, the source IP address (i.e., attacker address) is used to compose the Tcpdump filter to
capture only the traffic from the attacker to the target instance.

Hence, we generated a specific file containing the network traffic with a filename composed by the label name (e.g., attack type) and its start
timestamp for each attack. Finally, all network traffic files generated during the attack are re-
trieved from multiple cloud instances, processed to retrieve the network traffic, and merged into
a single dataset.

For the benign dataset, we use the up-to-date MAWILab dataset, which is a daily 15-minutes
network recording from trans-pacific backbone traffic between the USA and Japan. It has labels
for the following classes: anomalous and suspicious. Our rationale to obtain benign traffic is
to remove from the MAWILab dataset all the
traffic inferred as anomalous and suspicious by the MAWILab classifiers. Normally, MAWILab
traffic contains tens of millions of packets on each trace, so we introduced a step to random sample
packets from these filtered traces to work with a not too much-imbalanced dataset. It is important
to highlight that our current applications use a stateless approach (analysis of each packet without
the context), so for a stateful analysis (based on flow), the sampling step must retrieve packets that are
part of the same context. Figure 3 presents a summary of the process to obtain the benign dataset.

Our research focuses on the problem of the detection of port scanning attacks. This Attack attempts
to identify the system’s available services or characteristics, which is normally the first step of a cyber
attack. Thus, blocking port scanning stops an attack in its early stages, reducing the risks and the
resources to secure a system. We effortlessly generated a dataset for the port scanning problem with
this proposed framework for the Internet environment. The dataset comprises 22 classes (TCP port
scanning attacks) targeting 4 cloud instances, resulting in 455,503 correctly labeled attack samples.
For the benign samples, we obtained from MAWILab traffic from November 10
2020. After preprocessing the MAWILab traffic to remove the attack samples, we got a total of 380,438
samples (packets) of benign traffic, resulting in a dataset with 835,941 packets with the following
distribution: Benign = 46% and Attack = 54% in a tidy dataset with 41 features (packet-intrinsic
and context-aware). Furthermore, the NIDS is an inherently imbalanced problem (higher occurrences
of benign traffic); indeed, our solution provides a controlled approach over it, either by managing the
repetition of attacks, the number of target instances, or sampling benign traffic.

5 Conclusion

We presented the challenges for ML-based NIDS of aging datasets, the difficulty of coping with
the constantly evolving characteristics of network traffic, and bad performance in the real-world
environment. To address these gaps, we presented a systematic data-centric approach capable of
generating up-to-date NIDS datasets. The approach exploits the public and up-to-date MAWILab
dataset in conjunction with virtualization to generate the attack traffic. Then, it combines those two
sources in a salting process to generate labeled NIDS datasets. The reproducible source-code to
generate datasets as presented on this paper is available in our repository: https://github.com/
c2dc/AB-TRAP (steps A and B from [21]).

\(^2\)fukuda-lab.org/mawilab/v1.1/2020/11/10/20201110.html
\(^3\)fukuda-lab.org/mawilab/v1.1/2020/11/29/20201129.html
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