Towards Reliable Intrusion Detection in High Speed Networks

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Abstract. *Existing machine learning solutions for network-based intrusion detection cannot maintain their reliability over time in production environments. In such context, detection schemes must be able to detect intrusion attempts at a high network bandwidth, besides having to deal with the lack of realistic training/testing data, changes in network traffic behavior, unreliable classifications over time and adversarial settings. In this work a new intrusion detection model, namely reliable intrusion detection, is introduced, whose main characteristic is the usage of both batch and stream learning algorithms coupled together. The proposed model advances the state-of-the-art in intrusion detection, providing reliable detection even in the presence of network traffic behavior changes and lack of model updates. The work relevance was recognized in the publication of 5 international top-tier journals, 6 international and national conference papers, and 1 registered patent.*

1. Introduction

According to a CISCO network forecast report, the worldwide network traffic in 2016 was 96 EB/month, and, it is expected to reach 278 EB/month in 2021 [CISCO, 2017]. Current network devices can reach a bandwidth of 100 Gbps, and there are plans to support 400 Gbps in a near future [P802.3cd, 2017]. Moreover, current network-based cyber-attacks are also significantly increasing their capabilities. Thereby, operators need access to solutions to enable the real-time measurement and analysis of such malicious content over those massive network attacks.

To this end, over the last years, several works have applied machine learning (ML) techniques, mostly through pattern recognition schemes, for the detection of network-based attacks. In a pattern recognition scheme, the classification of intrusion attempts is, in general, achieved through a two-phase process: training and testing [R. Sommer and V. Paxson, 2010]. In the training phase, the classifier learns the environment behavior, as present in the training dataset, producing a model. Afterwards, in the testing phase, the model is evaluated regarding its accuracy using a test dataset, which is expected to represent the production environment behavior [C. Gates and C. Taylor, 2010].

However, on the other side, the network traffic behavior changes in a daily-basis, either due to the discovery of new attacks [R. Sommer and V. Paxson, 2010], or due to the offering of new services [E. K. Viegas et al. 2017-1]. In such context, due to the evolving behavior of such environment [E. K. Viegas et al. 2017-2], and the high network throughput [E. K. Viegas et al. 2019], the identification of network attacks becomes a challenging task, in which a designed detection mechanism can become out-of-date before they are even deployed in real-world (production) environments [E. K. Viegas et al. 2019]. This because network-based intrusion detection field presents several challenges to ML techniques when compared to other fields [E. K. Viegas et al. 2017-1]. Thereby, when a new ML-based approach is under development it must undergo through a more comprehensive evaluation. However, in general, the majority of works employs a traditional evaluation approach [E. K. Viegas et al. 2017-3], in which the accuracy rates measured in a single test dataset are assumed to be evidenced in production [E. K. Viegas et al. 2017-1], despite the challenges that networked environments present. In such a case, a ML-based scheme must be able to detect intrusion attempts at a ***high network bandwidth***, besides having to deal with the ***lack of realistic training/testing data, not generalization capable models, changes in network behavior, unreliable classifications over time, and adversarial attack setting.***

1.1. Objective and Contributions

This work was motivated by the need of a reliable intrusion detection model able to deal with the aforementioned challenges of production environments. To tackle these challenges, this work introduced a new intrusion detection model, namely reliable intrusion detection, whose main characteristic is the usage of both batch and stream learning algorithms coupled together. The model exploits the characteristics of each type of learner in a cascade pipeline to overcome the challenges of high-speed networks. Batch learning schemes are designed in such a way, that they provide reliable classifications over time and are able to generalize the behavior from the training dataset in the model. On the other hand, the used stream learning detection schemes are built to be resilient to adversarial attacks to hinder attacks over the designed system. Finally, batch and stream learning algorithm are coupled together to provide classification reliability over time, while also reliably adapting to network traffic behavior changes.

The research advanced the state-of-the-art by providing the following contributions: (i) An approach named BigFlow, which performs reliable and near real-time network traffic measurement (feature extraction) and classification in the Big Data context; (ii) A tool-based method that produces real and valid network traffic in a controlled and reproducible environment for creating intrusion datasets. The datasets built through such method aim at evaluating both batch and stream learning intrusion detection schemes; (iii) An intrusion dataset with real and labeled network traffic, based on MAWI database, built by analyzing over 10 years of real network traces, composed by more than 30 TB of data and 30 billion network flows. The built dataset aims at evaluating stream learning intrusion detection schemes; (iv) A new and fine-grained evaluation method specific for batch learning intrusion detection schemes; (v) A new multi-objective feature selection method aiming to improve the generalization capacity of batch learning schemes, by considering the network properties in intrusion detection; (vi) A new rejection method that provides classification reliability even when facing

unknown network traffic behavior; (vii) A new approach to reliably deal with evolving network data streams to perform anomaly-based intrusion detection, in the presence of an adversary; (viii) A new classification reliability assessment method through a conformal evaluator module. It aims at providing a reliability degree while facing new network traffic behavior even in the absence of model updates. The conformal evaluator assesses the classifier confidence according to the behavior seen in the training dataset; (ix) A new reliable intrusion detection mechanism made of both batch and stream learning algorithms, providing classification reliability and ongoing updated classification models with minimal human assistance.

1.2. Publications

The impact of this work can be evidenced in the achieved publications. The design of the reliable intrusion detection model has resulted in the following journals publications:

1. Eduardo Viegas; Altair Santin; Alysson Bessani; Nuno Neves. *BigFlow: Real-time and reliable anomaly-based intrusion detection for high-speed networks*. ***Elsevier Future Generation Computer Systems***, 2019. Qualis A2. IF 4.639;
2. Eduardo Viegas; Altair Santin; Luiz Oliveira; André França; Ricardo Jasinski; Volnei Pedroni. *A reliable and energy-efficient classifier combination scheme for intrusion detection in embedded systems*. ***Elsevier Computers & Security***, 2018. Qualis A2. IF 2.650;
3. Eduardo Viegas; Altair Santin; Luiz Oliveira. *Toward a reliable anomaly-based intrusion detection in real-world environments*. **Elsevier Computer Networks**, 2017. Qualis A1. IF 2.522;
4. Eduardo Viegas; Altair Santin; André França; Ricardo Jasinski; Volnei Pedroni; Luiz Oliveira. *Towards an Energy-Efficient Anomaly-Based Intrusion Detection Engine for Embedded Systems*. **IEEE Transactions on Computers**, 2017. Qualis A1. IF 3.052;
5. Cleverton Vicentini; Altair Santin; Eduardo Viegas; Vilmar Abreu. *SDN-based and multitenant-aware resource provisioning mechanism for cloud-based big data streaming*. ***Elsevier Journal of Network and Computer Applications***, 2019. Qualis A2. IF 3.991;

Besides the aforementioned journals, this work has also resulted in the following conferences publications:

1. Eduardo Viegas; Altair Santin; Vilmar Abreu; Luiz Oliveira. *Enabling Anomaly-based Intrusion Detection Through Model Generalization*. ***IEEE Symposium on Computers and Communications***, 2018. Qualis A2;
2. Eduardo Viegas; Altair Santin; Nuno Neves; Alysson Bessani; Vilmar Abreu. *A Resilient Stream Learning Intrusion Detection Mechanism for Real-Time Analysis of Network Traffic*. ***IEEE Global Communications Conference (GLOBECOM),*** 2017. Qualis A1;
3. Eduardo Viegas; Altair Santin; Vilmar Abreu; Luiz Oliveira. *Detecção de Intrusão Através de Aprendizagem de Fluxo no Ambiente do Adversário*. ***Simpósio Brasileiro de Segurança da Informação e de Sistemas Computacionais (SBSeg)***, 2017. Qualis B3;
4. Eduardo Viegas; Altair Santin; Vilmar Abreu; Luiz Oliveira. *Stream learning and anomaly-based intrusion detection in the adversarial settings*. ***IEEE Symposium on Computers and Communications***, 2017. Qualis A2;
5. Vilmar Abreu; Altair Santin; Eduardo Viegas; Maicon Stihler. *A multi-domain role activation model*. ***IEEE International Conference on Communications (ICC)***, 2017. Qualis A1;
6. Cleverton Vicentini; Altair Santin; Eduardo Viegas; Vilmar Abreu. *A Machine Learning Auditing Model for Detection of Multi-Tenancy Issues Within Tenant Domain*. IEEE/ACM International Symposium on Cluster, Cloud, and Grid Computing (CCGRID), 2018. Qualis A1;

A patent was also registered regarding the reliable intrusion detection model as a product, including all of the listed contributions registered as:

- Eduardo Viegas; Altair Santin. *MECANISMO DE DETECÇÃO DE INTRUSÃO CONFIÁVEL BASEADA EM MACHINE LEARNING EM REDES DE ALTA VELOCIDADE*. 2018, Brazil. Patent. Register Number: BR10201801101;

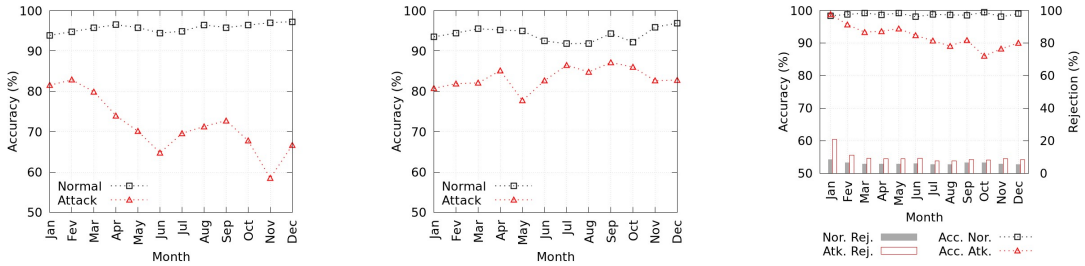
The main impact of this work is the in-depth evaluation and design of novel intrusion detection models aiming the reliability of classifications. In this work, the reliability of current intrusion detection techniques is extensively evaluated, and the

results shows that the state-of-the-art is unable to provide reliable intrusion detection. In the next section, one of the main results obtained in this work is presented, regarding the reliability and detection of network attacks over time in the intrusion detection field.

2. Dealing with network traffic behavior changes in high-speed networks

The behavior of network traffic changes over time, either due to new types of malicious actions or alterations in the transmitted content (e.g., due to the offering of new services [E. K. Viegas et al. 2017-1]), the attack models require constant revision. Consequently, the model's accuracy observed on the training dataset might not be evidenced on unseen data. In such a case, the intrusion detection engine will no longer be trusted by the operator given that the alarms are not generated as expected [E. K. Viegas et al. 2018].

In this work, we have assessed this accuracy loss experimentally, using a real network traffic dataset spanning a year and several ML classifiers. Figure 1-a shows that the accuracy of a Random Forest classifier trained in the beginning of the year can decrease by up to 23% during the year. In addition, when model updates are performed weekly using the same classifier, the accuracy does not significantly drops, as shown in Figure 1-b. However, to perform such updates periodically is not a feasible task in high-speed networks.



(a) *No-update* random forest classifier

(b) *Weekly-update* random forest classifier

(c) BigFlow with OzaBoosting with verifier module

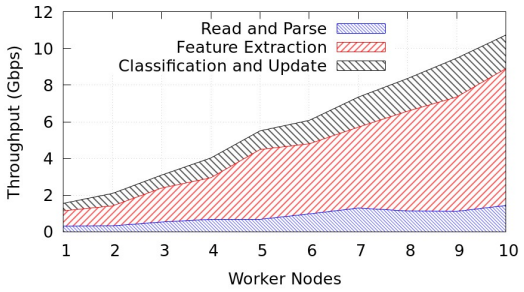
Figure 1. (a) Random Forest classifier accuracy behavior over time without model updates; (b) Random Forest classifier accuracy behavior over time with weekly model updates; (c) Proposed technique accuracy behavior over time.

Therefore, to address network traffic behavior changes in high-speed networks, this work have designed BigFlow, a system for reliable real-time network traffic classification in high-speed networks. The proposal is based on two main insights. First, BigFlow determines whether the classification outcome should be accepted or not, in contrast to traditional approaches, which always classify events as normal or attack. The purpose is to make the administrator aware that a possible change has occurred in the network traffic behavior. In this sense, when an event is rejected, there is a high probability that a new network traffic behavior is taking place. Although classification rejection has been used in other areas (e.g., for optical character recognition (OCR) or medical diagnosis), in these areas contextual information can help to identify pattern deviations; however, in the high-speed network traffic field, such a task is challenging. The main challenge that is not present in other areas relates to rejections based on the classifier confidence. This is because a classifier may become unreliable when facing unseen network traffic behavior, thereby committing classification mistakes with high confidence. The second insight relates to the fact that BigFlow employs stream learning

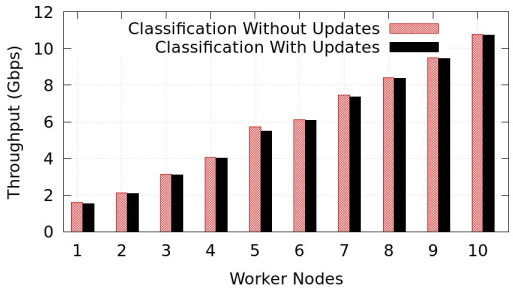
techniques to analyze traffic in near real time. Such techniques support incremental model updates based on the rejected instances. The expectation is that after a period (e.g., within one week), the rejected event is properly classified by an expert or a tool (e.g. signature-based network-based intrusion detection system - NIDS) based on public information (e.g., new indicators of compromise). A major advantage of this approach is that the incremental model updates, that incorporates new knowledge into the model, is based only on correctly classified events. This decreases the risk of inaccurate detections, which may lead to a high rate of false positives when processing further packets. Moreover, incremental model updates significantly decrease training time because the current model is not discarded, which is advantageous for high-speed networks.

Rejecting low-confidence classifications in an NIDS – the key idea of BigFlow – has lead to two important benefits: better detection accuracy (i.e., fewer misclassifications) and the identification of new characteristics of the evolving traffic, which are then used to incrementally update the classifier model. These benefits improve BigFlow reliability over time, even if the network's traffic behavior changes, as shown in Figure 1-c.

In addition, at the same time BigFlow significantly decreases the amount of computational and storage resources needed to operate the system. In combination, these techniques make BigFlow scalable with the number of nodes employed in the system (with a network traffic processing capacity of up to 10 Gbps in our experiments), without losing accuracy over time, as shown in Figure 2.



(a) *BigFlow* throughput performance according to the number of worker nodes.



(b) *BigFlow* throughput comparison with and without updates.

Figure 2. BigFlow scalability tests.

3. Conclusion

This work has addressed each of the challenges of building reliable intrusion detection schemes by the means of machine learning techniques for production usage. To this end, the approach proposed in this work, namely reliable intrusion detection model, relies in the use of both batch and stream learning algorithms coped together, in which, each learner overcomes a specific challenge. In such a case, batch learning algorithms were designed and evaluated to deal with the ***lack of realistic training/testing data, not generalization capable models,*** and ***unreliable classifications over time.*** On the other hand, stream learning algorithms were used to address ***high network bandwidth***, ***changes in network behavior*** and ***adversarial attack setting***.

Therefore, this work significantly advanced the state-of-the-art in intrusion detection. The knowledge produced in this work shows that current approaches for

intrusion detection are unreliable. Nonetheless, the datasets created are being openly shared to the scientific community. As a consequence, this work resulted in the publication of 5 international top-tier journals, 6 international and national conference papers, and 1 registered patent. Besides that, other three international journal papers, obtained as a result of this work, are also currently under review. A preview of this summary was also published in SBRC.

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