LITERATURE REVIEW

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Abstract

Malware is one of the fastest growing cybersecurity threats that individuals and organization face on a regular basis. The constant evolution of malware proves to be an ongoing issue for solutions that attempt to stop its attacks, as relying on human-based analysis proves to be more infeasible day by day. In this paper, we analyze literature for the state of the art for detecting malware on a network, and on a host respectively using machine learning for future work in developing a hybrid malware detection scheme using machine learning. Our findings for the state of the art suggest that most approaches are limited in scope, utilizing only features present in network traffic, or are only present on a host, which limit the potential for detecting the most variants of malware. For example, some approaches work by detecting DNS subdomains and determining malicious payloads in encrypted traffic, but do not consider host-based features that would help in detecting malware, as a third of ransomware do not create network traffic in their execution.

Introduction

The present state of detecting malware through network-based and host-based methods through machine learning is well-developed, but is lacking in hybridization. With a majority of malware payloads taking place through the network and/or through the compromised host, it is important to consider both types of levels when implementing a malware detection scheme, because a lot of information is missed when only considering one level in developing a solution, which may be crucial in identifying that a malware attack is underway or has occurred, as well as estimating the damage done by the attack. Additionally, the number of recent disruptive ransomware attacks is growing significantly (Cook, 2021). Symantec claims to have found over

186,000 new ransomware variants in 2018 alone (Symantec, 2018, 38). One notable victim of these malware attacks was the NHS, which cost them over $100 million in damages (Brunau, 2018). This was because it failed to detect the malware traversing the network, and the encryption it did on the host. In 2020, the average cost for a destructive malware breach was $4.52 million, and the average cost for a ransomware breach was $4.44 million (IBM, 2021). Our proposed method is to create a hybrid malware detection scheme using machine learning, by utilizing features present in a malware's network traffic or operating system/file changes. As the number of malware variants keeps increasing, and in such a large amount, utilizing machine learning will prove to be the most effective method of detecting malware. To this end, the purpose of this paper is to analyze current literature to establish a state of the art of methods used to detect malware in host-based and network-based environments using machine learning.

Literature Review

Malware detection has traditionally been classified in static and dynamic analysis. Static analysis looks at the source code of the malware in isolation. Signature based detection is one of the main approaches to detect malware in this manner, while it can be fast and efficient for known malware it is ineffective for novel attacks and is susceptible to obfuscation attempts, like making changes to the source code or encrypting the file (Aslan and Samet, 2020, 6253). Dynamic analysis, on the other hand looks how the malware behaves, e.g., what system call it makes or how it changes the filesystem. While network analysis can be considered a subset of dynamic analysis, Manzano, Meneses and Leger (2020, 1) instead propose to classify detection methods as host-based and network-based contexts.

In the literature, we noticed one certain common limitation between a majority of our papers. That limitation was that each paper or model was good at detecting one certain characteristic of a malware, however, they were poor at detecting other characteristics, or omit them entirely. There is little overlap in terms of a detecting both network-based and host-based features of malware in a hybrid malware detection model, and thus in a realistic scenario, would excel at detecting one type or family of malware, but would fail at detecting another.

Network-based Detection

Some malware families require a connection to a command and control[1] server in order to grab data needed for delivering its payload. After the victim is infected, it establishes a connection to a server under the attacker's control. Through this connection, the attacker can issue direct commands to the malware and extract data. Researchers have proposed different methods that seek to determine the presence of a malware by trying to detect and classify these connections.

Modern malware tends to use DGAs[2] to establish a channel to its C2 server using subdomains instead of hard coded IPs to prevent defenders from blocking the specific IP or domain used by a family of malware.

Salehi and others (2018) studied and showed success in detecting ransomwares based on their use of DGAs for subdomains. They identified 3 classes of features: gibberish domains, the frequency of requests to different domains and re-generation of domains by the algorithm. Their detection engine is supplemented by a black/white list module to reduce false positives. Zhang utilized deep learning algorithms to use one-hot encoding[3] for their DGA detection features (Zhang, 2020, 464).

[1] Also known as C2 or C&C - a method of controlling multiple infected hosts through a centralized server.
[2] Domain Generation Algorithm - instead of using a static IP to create a C2 channel, pseudorandom generated subdomain names are used.
[3] A method of encoding non-rankable items into a numeric order (such as colours)

Most of the research for detecting DGAs is under the assumption that the traffic is in plain text (Patsakis, Casino and Katos, 2019) however there are several protocols being evaluated to offer encrypted DNS services. These approaches are good at detecting network-based feature of malware, but their limitation is around their easiness of tampering by attackers.

Patsakis, Casino and Katos (2019) developed indicators of compromise that could distinguish legitimate DNS from those generated by a malware DGA. They identified that DGAs tend to generate domains of similar length and therefore the response packets tend to be similar in length, they also noticed that DGAs queries have a cyclical component that is possible to detect through a statistical analysis (Patsakis, Casino and Katos, 2019, 4). While these methods might work currently, the behaviours seem to be easily modified by attackers.

Research has also been conducted in detecting malware directly through its network traffic. Zhu and others (2018) proposed a model to detect Remote Access Trojans[4] that looks at the TCP[5] headers, they selected 4 features based on RAT's different traffic pattern. For example, benign applications tend to send as much data as possible as soon as the connection is established, RATs might show what they called early-stage, a period of time where noticeable idle time is present between packets (Zhu, 2018, 1008). This model has a good baseline for detecting RATs, and can be modified to detect C2 traffic for malware.

Alhawi, Baldwin and Dehghantanha (2018) proposed a model to detect ransomware on Windows machines called NetConverse. They manually selected 13 features from traffic conversations[6] but their model cannot detect ransomware using real-time data.

[4] Also known as RATs - allows an attacker to remotely control a machine over a network or the Internet
[5] Transport Control Protocol - used for transporting data over a network, the internet.
[6] Defined as the bidirectional traffic for a 5-tuple flow (from an source ip:port to a destination ip:port on the same protocol)

In contrast, Almashhadani and others (2019) created a working prototype with two network detectors, one packet-based and a second flow-based for the Locky ransomware family. The features were selected both manually and through the WEKA[7] feature selection tool. The features revolved around 3 aspects of the network traffic: a distinguishable use of RST, ACK-flagged[8] packets to terminate connections, its use of POST[9] requests and DGA-generated subdomains. This paper provides a good basis for network feature-based detection of malware, but does not test other malware families aside from the Locky ransomware family.

In order to obfuscate their presence, some malware variants encrypt their traffic. Premrn explores creating a device capable of detecting encrypted C2 channels using a machine learning model (Premrn, 2020, 5). They manually selected 6 features from the connection logs (instead of traffic capture) (Premrn, 2020, 54). Their model presented a high False Positive Rate which would make it unsuitable for day-to-day operations, so, they proposed integrating it with some kind of IP whitelisting to reduce false positives (Premrn, 2020, 90).

Modi (2019) also explored detecting malware through encrypted traffic, instead of just using connection statistics they also selected features related to the TLS[10] hand-shake and the certificate used (Modi, 2019). They propose to increase the model efficiency by adding an additional detector of DGAs (Modi, 2019, 68). Overall, their model is limited in capability because it can only classify if the sample is ransomware or not, and it cannot perform multiclass classification to attribute the ransomware to a specific family or as a general malware.

[7] Waikato Environment for Knowledge Analysis, an open-source data mining and machine learning tool
[8] Flags used to terminate a TCP connection - stands for Reset, Acknowledge
[9] POST is one the methods used in for HTTP traffic
[10] Transport Layer Security - a protocol that encrypts internet traffic

In summary, the approaches we reviewed have the limitation in that they do not account for host-based features, so if malware was to exist on a host that does not communicate with an external host, this approach would be ineffective.

Host-based Detection

While most ransomware families need to contact their C2 server, about a third do not require C2 traffic, in such cases detecting it through network traffic is not viable (Berrueta et al, 2019). Host-based methods are also harder to evade, while attackers can and do change malware behaviour to obfuscate their presence, ultimately there are action the malware need to perform to accomplish its objective which cannot be hidden (Almashhadani et al, 2019, 47057).

Arabo and others (2020) proposed a system to detect ransomware that used two detection modules: One that uses machine learning and the other based on manually configured thresholds. The machine learning features were selected around the malware resource usage (CPU, RAM and disk access). Their machine learning model was only partially successful in detecting the ransomware (Arabo et al, 2020, 294), as it does not consider if the malware was not particularly resource intensive, or used other resources such as networking.

Bae, Lee and Im (2018) explored using machine learning to detect ransomware through Windows Native API[11] invocation sequences when a file is executed (Bae, Lee and Im 2018, 4). They proposed a classification model called Class Frequency - Non-Class Frequency (CF-NCF). This classification model focuses around how many times something shows up in a certain class (benign, malware and ransomware), instead of the traditional Term Frequency - Inverse

[11] Application Programming Interface - a means for software to allow interaction with itself through predefined functions or tasks.

Document Frequency that looks how many times the term shows up in a document (Bae, Lee and Im 2018, 4). This approach is limited as it does not utilize other API function calls for malware detection, as well as not utilizing network-based features on the host for C2 detection.

In comparison to the previous paper, Hirano and Kobayashi (2019) proposed a framework to detect ransomware that collects I/O requests through a hypervisor[12] instead of the OS to make the framework portable. They selected 5 features related to the read/write characteristic of the encryption process ransomware use (Hirano and Kobayashi, 2019). This enables usage with any operating system instead of just Windows exclusively in the previous paper.

Some researchers select their features manually, according to their knowledge of the dataset and the malware behaviour, others however use automated tools to extract numerous raw features from the system and then use an automated algorithm (heuristics), such the Chi-squared test method[13] and fine tune the final feature set used by their machine learning model.

For example, Sethi and others (2019) put forward a framework where raw features are extracted from a sandbox's report when a file is executed and then the chi-squared test is used to select features for the detection model, they create two models, the first one classifies the executable in benign/malware, when a malware is detected a second model classify the malware family (Sethi, et al, 2019). This approach to host-based malware detection provides a good framework for the host-based component of our hybrid malware detection model, and future work can be done using other malware families and network-based features.

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[12] A means of running one or several virtual computers on one or more physical computers
[13] A test used to determine the differences between a theoretical model and actual data, in this case used to refine the accuracy of the model

Shhadat and others (2020) looked at the impact the heuristics can have in the model accuracy. They expanded on the work of Chumachenko (2017) that used a similar framework than Sethi, et al (2019) of extracting features from a sandbox. Shhadat et al (2020) used a different heuristic to select the features (cross-validation). While the models that used decision-tree and Random forest saw no significant change, models using Naïve Bayes saw significant improvement (Shhadat, et al, 2020).

Jethva (2019) suggested a hybrid host-based malware detection model. Their solution has two detectors, one based on a ML model using heuristics (chi-squared test) to narrow the features (Jethva, 2019, 43); and the other based on the combination of file entropy (encrypted files show higher entropy) and the presence of file signatures (magic numbers) to help distinguish benign compressed files that also show high entropy (Jethva, 2019, 34).

The lack of labelling datasets may prove to be a limitation on research datasets. Noorbehbahani and Saberi (2020) looked into the use of semi-supervised methods. They used 5 supervised heuristics to extract the feature set and then used semi-supervised classifiers to identify ransomware (Noorbehbahani and Saberi, 2020). The main limitation of this approach is that the utilized unsupervised feature selection accuracy was very poor, which makes it unfeasible to use by itself and would improve by implementing it in a hybrid malware detection scheme.

In summary, the literature around host-based detection mainly suggests that there is a limitation with most approaches in that only host-based features are considered, whereas the detection rate would improve if network-based features were also implemented.

Conclusions

In conclusion, we reviewed the state of the art within the topics of malware detection in network-based and host-based environments using machine learning. In a network-based environment, the state of the art revolves around detecting malware through its communication with C2 servers, primarily using DNS subdomains generated by a DGA. In our review, we identified a gap within only focusing on network features on malware. As we identified in the host-based detection section, a third of ransomware does not actually communicate over the network. In a host-based environment, the state of the art revolves around utilizing detectors to detect malicious processes, and through file-based features such as invocation of file API function calls or file signatures. However, we observed limited development through using other functions, such as cryptography functions, or opening network connections on a host. We believe there is a gap in knowledge surrounding combining network-based and host-based features into a hybrid malware detection scheme using machine learning, and is our focus going forward.

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