Against All Odds: Winning the Defense Challenge in an Evasion Competition with Diversification

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Abstract—Machine learning-based systems for malware detection operate in a hostile environment. Consequently, adversaries will also target the learning system and use evasion attacks to bypass the detection of malware. In this paper, we outline our learning-based system PEberus that got the first place in the defender challenge of the Microsoft Evasion Competition, resisting a variety of attacks from independent attackers. Our system combines multiple, diverse defenses: we address the semantic gap, use various classification models, and apply a stateful defense. This competition gives us the unique opportunity to examine evasion attacks under a realistic scenario. It also highlights that existing machine learning methods can be hardened against attacks by thoroughly analyzing the attack surface and implementing concepts from adversarial learning. Our defense can serve as an additional baseline in the future to strengthen the research on secure learning.

I. INTRODUCTION

Machine learning is a powerful tool for detecting malware. The capability to automatically infer and generalize patterns from data allows detecting newly emerging malware. However, machine learning itself introduces a considerable attack surface, as previous work in adversarial learning unveils. Possible attacks range from exploiting the preprocessing stage [34, 41], poisoning the training data [e.g., 8, 18, 26], stealing the model [37], to misleading the prediction [e.g., 9, 10].

As a result, it is vitally important to consider machine learning-related attacks in addition to the underlying security problem. The 2020 Machine Learning Security Evasion Competition [46] focuses on the threat of evasion attacks with Windows Portable Executable (PE) malware. This competition provides a unique opportunity: It allows researchers to take the role of a defender or attacker in a real scenario without perfect knowledge. Defenses can be examined against evasion attacks from independent real-world attackers.

Our defense PEberus got the first place in the defender challenge, resisting a variety of sophisticated attacks. Our solution is based on diversification and consists of three main concepts. First, various heuristics address the semantic gap. This gap between the semantics of a PE program and its feature representation allows relatively simple functionality-preserving attacks. Second, multiple classification models use distinct feature sets to classify malware reliably while considering targeted attacks against the model. A stateful defense finally detects iterative attacks that exploit the API access to the classifier. Although our solution fends off the majority of attacks in the competition, it is limited to static analysis, and thus a few attacks based on obfuscation succeeded. Note that the use-case is Windows PE malware, but our insights and concepts are generally usable for other security domains as well.

In this paper, we outline the design of our defense. After providing background information about the contest and PE malware detection (§II), we analyze the attack surface of machine learning-based malware detection from a practical and theoretical point of view (§III). This provides the basis for our defense in §IV. We describe the results and insights from the competition in §V, and conclude the paper in §VI.

II. BACKGROUND

Before examining the attack surface and our defenses, we briefly introduce background information on the competition, the structure of Windows PE files, existing approaches to detect malware, and the threat of evasion attacks.

A. Microsoft’s Evasion Competition

The Machine Learning Security Evasion Competition by Microsoft [46] focuses on the robustness of machine learning against evasion attacks in the context of malware detection. The contest is structured in two challenges.

We participated in the defender challenge. The participants need to develop their own solution to detect Windows PE malware without any restrictions on the used dataset, features, or learning method. Yet, a valid solution needs to fulfill three requirements: (a) the maximum false positive rate is 1%, (b) the minimum true positive rate is 90%, (c) the system must report a decision within five seconds. The competition organizers regularly check these conditions on a holdout set that is unknown to the participants.

In the subsequent attacker challenge, participants need to bypass the detection of the developed defenses from the first round for 50 Windows malware samples. Only a black-box API access with a binary output is provided without further knowledge about the defenses. The attackers have any freedom to manipulate the PE file, but with the requirement to preserve the functionality. This is tested by a dynamic analysis for the submitted adversarial samples. The maximum PE file size for all submissions is 2 MiB.

1The defense is publicly available at https://github.com/EQuiw/2020-evasion-competition.
The detection of PE malware requires a basic understanding of the file format. Figure 1 illustrates the general PE structure. It can be divided into three parts: the header, the sections, and the overlay. All PE files start with a DOS header. Another header follows that contains the actual information for a PE file, such as the type of the target machine (e.g., x64) or a timestamp of creation. The section table describes each section, including its size and address in the PE file and memory. Padding can be necessary to meet the file alignment, resulting in a slack space between sections. A section can be, for instance, executable code, an export or import table to link the PE file with libraries, or data (e.g., strings used by the code section). Finally, additional special sections, such as a debug section, might be added at the end of a PE file and are often referred to as the overlay.

C. Windows Malware Detection

The research on new methods for malware detection based on machine learning techniques is still a lively field in security, as these approaches have the ability to derive malicious patterns and relations from large datasets automatically [e.g. 3, 24, 27, 30]. Due to these capabilities, learning-based methods can better cope with the increasing number of emerging malware than traditional, signature-based approaches.

As a result, researchers have proposed a large number of different learning-based methods for malware detection throughout the past few decades. These methods can be broadly divided into approaches based on static [21, 24, 30] and dynamic [4, 6, 22, 25, 35] analysis. For instance, an early approach that applies machine learning to detect malicious PE files has been presented by Kolter and Maloof [24] in 2006. Their method uses boosted decision trees trained on statically extracted byte n-grams of a PE file. Similarly, BitShred [21] clusters n-gram features to perform large-scale malware triage. In contrast to these approaches, which are mainly based on static analysis, there are also a number of approaches that rely on dynamic analysis [4, 5, 6, 22, 25, 40]. Due to the prediction time constraint of five seconds, we refrained from incorporating them into our defense.

A recent learning-based detection method for Windows malware is the so-called Ember classifier, which uses handcrafted features and yields high detection rates, even outperforming related, deep learning-based approaches [1]. The Ember classifier builds the foundation for some of the defenses presented in this paper (see §IV) due to the provided data. In the following, we describe some of the details on the Ember classifier and the features it uses.

**The Ember classifier.** The Ember classifier has been trained on a large corpus of Windows PE files, containing more than 1 million applications in total. Unfortunately, the binaries are not publicly available due to legal restrictions. However, the authors of Ember have released all features extracted from this corpus, enabling other scientists to reproduce the results and use the data for further research.

The Ember feature set comprises eight groups of raw features, which can be broadly divided into two different feature categories: parsed features and format-agnostic features. The parsed feature sets include various features extracted after parsing the file, including basic information derived from the headers as well as imported and exported functions. In contrast, the format-agnostic features can be extracted without parsing the file. These feature sets include simple statistics about printable string characters and byte histograms.

To derive distinct patterns for malicious and benign applications, the extracted feature sets are first mapped into a common feature space. Afterward, a Gradient Boosted Decision Tree (GBDT) model is trained on the feature vectors with LightGBM [17].

D. Evasion Attacks With Structured Data

Our focus in the competition lies on evasion attacks against learning methods, where an adversary tries to manipulate a sample, such that it is misclassified. Unlike the commonly studied image domain, programs are a structured input and any manipulation needs to keep the functionality. The action space is limited, i.e., bytes in a PE file cannot be changed arbitrarily in general. To create real adversarial examples for malware, an adversary needs to consider multiple constraints, such as defining possible manipulations, keeping the functionality, and preserving the inconvincingness [see 31]. In general, the attacker faces the challenge that problem and feature space have no one-to-one correspondence [see 33]. The PE file needs to be changed in its input or problem space, but the machine learning method operates in a feature space. Consequently, finding the optimal solution while keeping all constraints is challenging. It has a direct impact on the attacker’s capabilities.

Although various rather advanced attack strategies are already discussed [e.g. 31, 33, 42], we identify that current attacks often use rather simple, yet considerably effective weak spots in learning-based systems. These weak spots simplify a real-world attack and need to be considered as well.

Finally, we note that various evasion techniques against malware detection exist that do not directly target machine learning [e.g. 28, 36, 39]. For instance, adversaries can obfuscate the control flow, data location or data usage and so deceive the feature extraction from a static analysis [28].
Our learning-based system needs to detect Windows PE malware while an attacker is targeting the learning-based system itself. It is thus important to analyze the attack surface first. In the following, we examine the attacker’s capabilities being relevant for the competition before introducing our learning-based system as a defense in the next section.

An adversary has to change the features to create adversarial examples. As described in §II-D, the challenge is to manipulate a PE file without compromising its functionality. Such an attack can be divided into two components, as Figure 2 illustrates: (i) the file modification (where and how a PE file can be changed), and (ii) the attack algorithm (how to combine modifications for evasion). Both need to be combined accordingly, such that the adversary finds a sequence of modifications that lead her to the benign class.

A. File Modification

A prevalent modification strategy in the literature and previous competitions against learning methods is to add unused content in areas that are not relevant for the functionality of a program [e.g. 15, 45]. In particular, adversaries exploit the semantic gap, that is, the discrepancy between extracted features and the actual processed part of a PE file [20]. Although this is a rather brittle attack procedure, it has a considerable advantage: Changing or adding content in unused areas relieves the adversary from implementing modifications that keep the program functionality. At the same time, the classifier is influenced by these areas. Therefore, the semantic gap as a weak spot of a learning-based system can have a considerable impact on its security.

In the context of PE files, an adversary can exploit or create unused areas at multiple locations [15]. As Figure 3 highlights, it is possible to enlarge the DOS header, to fill the slack space at the end of each section, or to append bytes to the overlay, i.e., to the end of the PE file. Another possibility is to add a new unused section that the adversary can fill [2].

A rather simple, yet effective way is then to inject content from benign samples into the unused areas to overload the malicious traits [45]. For instance, adding a large number of strings extracted from a benign Windows file can successfully evade the default Ember model [45]. More general, this attack represents a mimicry attack that manipulates an input such that it mimics the characteristics of a particular target class [16].

Another way is to rewrite the features. An attacker can be expected to try exploiting weak spots in the features first. For example, the model may focus on a few features only, or the model uses features that are simple to change, such as the timestamp in a PE header. Anderson et al. [2] introduce further modifications, such as packing/unpacking, rewriting section names, and manipulating the header checksum.

B. Attack Algorithm

An attacker can proceed in different ways to find the combination of modifications that evade the learning-based system. Recall that we operate in a black-box scenario in the competition. Still, the black-box access is enough to find promising modifications by iteratively querying the system [e.g. 2, 13, 32, 33, 42]. For instance, attacks based on Monte-Carlo tree search can evaluate the impact of modifications multiple steps ahead by using a search tree [see 33].

It is reasonable to expect that an attacker can also learn an own local surrogate model from a similar training dataset or feature set due to some domain knowledge [7]. This can reduce the number of queries considerably. Identified weak spots in a surrogate model may allow an attacker to create evasive samples that transfer to the original model under attack [29, 38]. In our case, multiple of our models are based on the Ember feature set. We can therefore assume that an adversary also tries promising directions on an own Ember model and verifies them with the black-box access to our defense. This was indeed the case for attackers in the competition (see §V).

With a surrogate model, an attacker can use white-box attacks to compute evasive samples. Computing a gradient, for instance, has the advantage of finding the direction towards the benign class. Still, the gradient from the feature space needs to be mapped back to a valid file modification in the problem space. Kolosnjaji et al. [23] examine such a method to create a valid byte modification. Yet, this attack builds on the semantic gap, so that the byte modification does not need to consider the functionality of the PE file.
Fig. 4: Overview of our learning-based system that detects Windows PE malware and considers an attacker targeting the learning-based system itself.

IV. DEFENSES

Equipped with a basic understanding about the attacker’s capabilities, we are ready to proceed with our developed approach PEberus. The overall design concept is diversification. Our system consists of multiple defenses, each addressing different attack strategies outlined before. A PE file is classified as malware if any of the system’s components considers it as malicious. Therefore, an attacker needs to exploit weaknesses in all components in order to successfully trick the system. Figure 4 gives an overview of the defenses and their combination. In the following, we describe the concept of each defense in more detail. Table I provides a summary of our approach.

A. Malware Classification

We start with introducing three different approaches to detect malware. This ensemble increases the diversity, so that not only the malware detection can be improved, but also an attacker has to evade different feature sets at the same time.

**Ember-based Model.** Our first and main defense is based on Ember [1] due to its high detection performance and the provided features from a large corpus of data. Yet, we exclude the header feature group in all models to reduce the attack surface. Preliminary tests show that these features, such as a timestamp, can be easily manipulated by an adversary. This, in turn, can considerably affect the classification performance. Moreover, we rely on various regularization strategies of the learning algorithm to prevent the model from focusing on a few features only.

We train a GBDT model using xgboost [12]. In particular, our default model is trained on all Ember features extracted from the 2017 corpus, except for the header features. Also, we add multiple variations of this model to our ensemble. In this way, we can mitigate various attack strategies and still use the Ember feature set from the large corpus of data.

Our first variation is to truncate the input by using the virtual size, that is, the binary size after mapping the file into memory. Only the bytes up to the virtual size of a PE file are passed to the feature extraction. The intention is to reduce the impact of attacks that add malicious bytes to the overlay. Furthermore, we remove strings in the byte stream passed to the byte histogram and byte-entropy histogram feature set from Ember. The idea is to reduce the impact of adding strings from benign samples on the histogram distribution.

Our second variation uses only a reduced feature set from Ember. In particular, we only consider the section, import, export, general file, and string groups. In the latter group, we do not use the printable string histogram. In this way, we remove all histogram parts that are vulnerable to feature addition attacks. Moreover, the data directory group is not considered as well, as preliminary tests showed its vulnerability against feature manipulation.

Our third variation uses the same features as the second variation, but is trained on the 2018 corpus. It adds new knowledge about more recent malware. In principle, we could train a GBDT model on the combined 2017 and 2018 dataset, but we learned two models to reduce training time.

**Monotonic Skipgram Model.** Although the previous variations mitigate the impact of feature addition attacks, our next model is invariant to such attacks by design. To this end, we use the concept of monotonic classification [19]. With a monotonic model, an increase in feature value can only increase the malware score, so that more benign features cannot lower the classification score. Unfortunately, this leads to a lower detection performance in general [19]. Still, monotonic models can serve as an additional line of defense against feature addition.

As features, we use skipgrams extracted over the bytes of a PE file. In principle, skipgrams are n-grams, but with gaps between each token. Figure 5 underlines the concept. The absolute count of each skipgram is used, so that the model is based on the presence of features [11]. The relative frequency, for example, is not used. A normalization allows decreasing monotonic malware features by adding other features. We train a monotonic GBDT model with xgboost based on an own collected dataset of 22,000 benign and malicious PE files.
Signature-based Model. The third component is based on Yara rules\(^2\) that capture the characteristics of well-known malware as detection signatures. In particular, we extract all matched rules on our collected PE file dataset and keep only those rules that are solely present in malware. The system assumes malware if any of the kept rules is matched. Note that these rules have the disadvantage of being manually crafted signatures. Although they provide only a small increase in detection performance, they serve as a backup by capturing malware patterns directly.

B. Semantic Gap Detectors

As an additional line of defense, we try to reduce the semantic gap, so that the adversary is forced to perform more complicated changes than adding features in unused areas. To this end, we implement detectors to check if an attacker exploits a semantic gap. We consider the following three approaches. Our slack space scanner assumes an attack if the space between sections is filled with non-zero bytes. The reason is that the slack space of benign samples is expected to just be filled with zeros, such that the sections match with the file alignment. Our overlay scanner computes the ratio of the overlay to the overall file size. A considerably high ratio indicates that an attacker may have appended bytes to the overlay. Finally, our duplicate scanner detects an attack if two or more duplicate sections are present, excluding empty sections. We assume that benign files have rather unique sections. This idea reduces the attack surface by preventing the attacker from adding the same benign content repeatedly.

Note that these are rather simple heuristics and only cover prevalent semantic gaps. Still, they raise the bar for a successful attack, which has also been confirmed throughout the competition (see §V). Our detectors motivate a more systematic analysis to close the semantic gap between extracted features and the processed parts of a PE file, enforcing the attacker to change used code then.

C. Stateful Defense

The attackers in the competition operate in a black-box scenario with access to a binary classification output. Thus, they may need to use iterative attack algorithms as described in §III-B. The attackers send specifically crafted samples and observe the respective binary output over multiple iterations. This, in turn, motivates a stateful defense that monitors incoming sequences of queries for evasion patterns.

For the sake of simplicity, we adapt the stateful nearest-neighbor detector already given by the competition. The overall idea is to check if a similar, previously submitted file has been considered malicious. In particular, the detector saves each sample classified as malware in a history buffer. For a sample under investigation, the detector checks if it is sufficiently similar to a previous malicious one. If the distance to the nearest neighbor from the history buffer is smaller than a defined threshold, the detector assumes an attack. To obtain the distance between two PE files, we calculate the \(L_1\) distance on the histogram and byte-entropy features from Ember. In contrast to the competition’s solution, we do not truncate the PE file to limit the number of sections or bytes per section.

Another approach is to save any input (i.e., benign or malicious) in the history buffer to check if the system is probed with a sequence of similar inputs. We decide against this strategy to lower the risk of our solution being rejected due to a high false positive rate, as this rate must not exceed \(1\%\) throughout the competition. The competition organizers may regularly submit benign samples to validate the solution, so that benign samples once stored in the history buffer can create false positives in these checks.

We finally note that stateful defenses can considerably impede iterative attacks, and thus should be explored further. Different stateful strategies have already been successfully applied in multimedia security that are transferable to machine learning [see 32].

D. Combination of Defenses

Our system consists of a diverse set of defenses, including different machine learning models, semantic gap detectors, and a stateful defense. Figure 4 shows this combination. The input file is first passed to the semantic gap detectors. If they detect a malicious change, the system classifies the input as malware. Otherwise, we use our ensemble of classifiers, including the four Ember-based GBDT models, a monotonic skipgram model, and a signature-based classifier. We use max voting to combine all predictions, so that an attacker has to evade all models for a successful attack. With a positive malware classification, we pass the input to the stateful defense in order to save it in the history buffer, and return the malware classification. With a benign prediction from the ensemble, the stateful defense finally checks if the input sample is too similar to a previous one. If so, the system predicts malware.

V. COMPEITION RESULTS

In the competition, five attackers participated. They attacked three defense solutions: (i) our defense, (ii) the one from the team ‘needforspeed’ [44], and (iii) an Ember-based baseline given by the competition [43]. To be accepted to the attacker challenge, a defense has to detect regular malware reliably on an unknown holdout set (see §II-A).

Each submitted attack sample is checked if it evades any defense before its functionality is validated, i.e., it has the same behavior as the original malware sample. A defense is
Table II: Results from defender challenge in terms of evasion rate

| Rank | Defense                        | Relative Evasion Rate |
|------|--------------------------------|-----------------------|
| 1.   | Our defense PEberus            | 23 %                  |
| 2.   | needforspeed [44]              | 58 %                  |
| 3.   | Ember-based baseline [43]      | 94 %                  |

ranked according to its relative evasion rate, that is, the fraction of all validated samples that evade the particular defense.

Results. Table II shows the results from the defender challenge. Our solution got the first place with a relative evasion rate of 23%, compared to 58% and 94% for the other defenses. Thus, our defense considerably increases the robustness against attacks, and withstands different attackers.

Analysis. A closer look on the attacks provides further insights. Only the team ‘needforspeed’ [44] succeeded against our system for all 50 samples. This team uses a dropper with a single-byte XOR encryption and Base64 encoding to hide the payload. Our system cannot cope with these kinds of obfuscations, as it solely builds upon features extracted through static analysis, making it difficult to reconstruct the encrypted content.

Further attackers are less or not successful. Using self-signed certificates [47] succeeds only for 18% of the files. Adding content from benign files to the overlay or a new section guided by genetic programming [14] leads to no successful sample against our defense.

All in all, most attackers seem to have constructed their samples with no concept of learning in the back. For instance, they target the static analysis by hiding the payload [44] or add self-signed certificates [47]. Thus, current attacks are so far rather expert-driven attacks than systematic attacks on a learning model. Finally, the competition also underlines that an attacker can exploit some knowledge even in a black-box scenario. The adversaries used own local models and domain knowledge first to enhance and test their attacks before making queries [e.g. 44]. This explains the rather small number of 741 API queries of the leading attacker ‘needforspeed’. Yet, the more robust a learning-based system becomes, the more we can expect adversaries to systematically send queries in the future.

VI. CONCLUSION

Modern learning-based systems for malware detection do not only have to identify malware reliably. Also, they should be robust against attackers that target the system itself. The Microsoft Evasion Competition is an excellent opportunity for security researchers to analyze and reduce the attack surface of state-of-the-art learning-based detection methods.

Our defense for the competition is based on diversification to consider multiple attack scenarios. In particular, we address the semantic gap, use various classification models, and apply a stateful defense for iterative attacks. Our defense shows that existing machine learning methods can be hardened against attacks by analyzing the attack surface thoroughly and implementing concepts from adversarial learning.

However, we also find that our system is still prone towards obfuscation methods, as it solely builds upon features extracted throughout a static analysis. While many attack strategies have been successfully fended off by our model, including the exploitation of the semantic gap, circumventing the system by encrypting the malicious payload has been successful. To counter such attacks, extending the system with a dynamic analysis should be considered in the future.

ACKNOWLEDGMENT

We acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under the research grant RI 2469/3-1, and by the German Ministry for Education and Research as BIFOLD - Berlin Institute for the Foundations of Learning and Data (ref. 01IS18025A and ref 01IS18037A). Furthermore, we would like to thank Christian Wressnegger for supporting us with additional data.

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