Security: Doing Whatever is Needed... and Not a Thing More!

Omer Katz
Technion
omerkatz@cs.technion.ac.il

Benjamin Livshits
Imperial College London
b.livshits@imperial.ac.uk

Abstract—As malware, exploits, and cyber-attacks advance over time, so do the mitigation techniques available to the user. However, while attackers often abandon one form of exploitation in favor of a more lucrative one, mitigation techniques are rarely abandoned. Mitigations are rarely retired or disabled since proving they have outlived their usefulness is often impossible. As a result, performance overheads, maintenance costs, and false positive rates induced by the different mitigations accumulate, culminating in an outdated, inefficient, and costly security solution.

We advocate for a new kind of tunable framework on which to base security mechanisms. This new framework enables a more reactive approach to security allowing us to optimize the deployment of security mechanisms based on the current state of attacks. Based on actual evidence of exploitation collected from the field, our framework can choose which mechanisms to enable/disable so that we can minimize the overall costs and false positive rates while maintaining a satisfactory level of security in the system.

We use real-world Snort signatures to simulate the benefits of reactively disabling signatures when no evidence of exploitation is observed and compare them to the costs of the current state of deployment. Additionally, we evaluate the responsiveness of our framework and show that in case disabling a security mechanism triggers a reappearance of an attack we can respond in time to prevent mass exploitation.

Through a series of large-scale simulations that use integer linear and Bayesian solvers, we discover that our responsive strategy is both computationally affordable and results in significant reductions in false positives, at the cost of introducing a moderate number of false negatives. Through measurements performed in the context of large-scale simulations we find that the time to find the optimal sampling strategy is under 2.5 minutes in the vast majority of cases. The reduction in the number of false positives is significant, about 20% over traces that are about 9 years long (~9.2 million false positives).

I. INTRODUCTION

Much of the focus in the security community in the last several decades has been on discovering, preventing, and patching vulnerabilities. While both new vulnerability classes and new vulnerabilities are discovered seemingly every day, the exploitation landscape often remains murky. For example, despite buffer overruns, cross-site scripting (XSS), and SQL injection attacks (SQLIA) being heralded as the vulnerabilities of the decade [52], there is precious little published evidence of how commonly exploited XSS or SQLIA might be in practice; of course, there is a number of studies [37] on how vulnerability trends change over time. One of the studies we present in this paper suggests that, for example, XSS exploitation is not nearly as common as would be suggested by the daily stream of discovered vulnerabilities (found at www.openbugbounty.org or xssed.org).

Changing exploitation landscape: The security industry produces regular reports that generally present a growing number of vulnerabilities, some in widely-deployed software. It is exceedingly tempting to misinterpret this as a growth trend in the number of actual exploits. However, the evidence for the latter is scant at best. Due to a number of defense-in-depth style measures over the last decade, including stack canaries, ASLR, XRF tokens, automatic data sanitation against XSS and a number of others, practical exploitation on a mass scale now requires an increasingly sophisticated attacker. We see this in the consolidation trends of recent years. For example, individual drive-by attacks have largely been replaced by exploit kits [38], [23], [50]. In practice, mass-scale attacks generally appear to be driven by a combination of two factors: 1) ease of exploitation, and 2) whether attacks are consistently monetizable. This is clearly different from targeted attacks and APTs where the upside of a single successful exploitation attempt may be quite significant to the attacker.

Given the growing scarcity in exploitable vulnerabilities, there is some recent evidence that attackers attempt to take advantage of publicly disclosed attacks right after their announcement, while the window of vulnerability is still open and many end-users are still unpatched; Bilge et al. [17] report an increase of 5 orders of magnitude in attack volume following public disclosures of zero-day attacks. The situation described above leads to a long tail of attacks — a period of time when attacks are still possible but are increasingly rare. It is tempting to keep the detection mechanism on during the long tail. However, it is debatable whether that is a good strategy, given the downsides. We argue that the usual human behavior in light of the rapidly-changing landscape is inherently reactive, however, often not reactive enough.

A. Mounting Costs of Security Mechanisms

One of the challenges of security mechanisms is that their various costs can easily mount if unchecked over time.
• **False positives.** FPs have nontrivial security implications. According to a recent Ponemon Institute report, “The average cost of time wasted responding to inaccurate and erroneous intelligence can average $1.27 million annually.” Furthermore, “Of all alerts, 19% are considered reliable but only 4% are investigated.”

• **Performance overhead.** Our studies of scanning and filtering costs in Section IA1 show that while the IO overhead from opening files, etc. can be high, the costs of scanning and filtering increases significantly as more signatures are added to the signature set. When many solutions are applied simultaneously within a piece of software, the overhead of even relatively affordable mechanisms, such as stack canaries and ASLR, can be additive. There is a growing body of evidence that security mechanisms that incur an overhead of 10% or more do not tend to get widely deployed. However, several low-overhead solutions on top of another can clearly easily exceed the 10% mark.

The performance and false positive costs are in addition to maintenance and update costs, which are also difficult to predict. For example, analyzing malware, testing signatures, running honeypots, etc. [51], [50].

We argue that as a result of the factors above, over a long period of time, a situation in which we only add security mechanisms is unsustainable due to the mounting performance costs and accumulating false positives. This is akin to performing a DOS attack against oneself. In the limit, the end-user would not be able to do much useful work because of the overhead and false positive burden of existing software.

**Reluctance to disable:** At the same time, actively removing a security mechanism is tricky, if only from a PR standpoint. In fact, we are not aware of a recent major security mechanism that has been officially disabled. One of the obvious downsides of tuning down any security mechanism is that the recall decreases as well. However, it is important to realize that when tuning down a specific mechanism is driven by representative measurements of its effectiveness in the wild, this is a good strategy for dealing with mass attacks.

Targeted attacks, on the other hand, are likely to be able to overcome most existing defenses, as we have seen from Pwn2own competition, XSS filter bypasses, etc. We hypothesize that sophisticated targeted attacks are not particularly affected by existing defenses. However, reducing the level of defense may invite new waves of mass attacks, which can be mitigated by upping the level of enforcement once again. We therefore consider entirely taking out a security mechanism, rather than simply disabling or tuning it down, to be ill-advised.  

1) **Scanning and Filtering Costs:** To demonstrate our claims of the inefficiency and mounting costs of maintaining a large amount of outdated security mechanism, we turn to ClamAV, Snort, and Brave’s ad blocking engine.

- We installed the latest version of the ClamAV engine (0.99.2) and used it to scan a single file of 248 MB.
- To understand how the running time is affected by the size of the signature set, we ran the scan several times using different sized subsets of the ClamAV signature dataset. Figure 1a shows the obtained scan times, in seconds.
- We performed similar measurements using the Snort NIDS engine. Using the latest version of Snort (2.9.9.0), we scanned a collection of pcap files, which we obtained from [2], with signature sets of different sizes. Figure 1b shows the results of these measurements.
- Lastly, we used the ad-block engine of the Brave browser to the effect the ad-block rule set size has on the average scan time per url. We used rules from the EasyList and EasyPrivacy rule sets, totaling at 86,665 rules. Utilizing the Brave ad-block engine (4.1.1), we scanned a set of URLs containing 15,507 elements. We ran the experiment using different-sized subsets of the rule set. Figure 1c shows the obtained average scan times per URL, in milliseconds.

All three of the above figures clearly exhibits an approximately linear correlation between the rule/signature set size and the average scan time. These charts demonstrate the hidden cost over time of adding signatures and rarely removing them. This factor together with false positives argues for removing signatures more aggressively.

**B. Toward Tunable Security**

In recent years we have seen growing evidence that vulnerability statistics and exploit statistics are at odds. Nayak et al. report that despite an increase in reported vulnerabilities in the last several years, while the amount of exploitation goes down. Furthermore, only a portion of vulnerabilities (about 35%) actually gets exploited in a practical sense. Furthermore, vulnerability severity rankings are often misleading, as they do not necessarily correlate with the attractiveness or practicality of exploitation. Barth et al. advocate a reactive approach to security where previous attack patterns are used to decide how to spend the defender’s finite budget.

**Methodology:** In this paper, we experimentally prove the advantages of reactive security. We look at widely deployed security mechanisms, where the potential, for example, of a single false positive is amplified by the potentially vast installation base. A good example of such a system is an anti-virus (AV) engine or an IDS. The reactive approach to security is also supported by the number of zero-days that are observed in the wild and reported by Bilge et al. Our experimental evaluation in Section IV is based on 9 years of Snort signatures. We argue that a well-calibrated simulation is the best way we have to assess the reactive security mechanism proposed in this paper. We use an extremely valuable study of over 75 million real-world attacks collected by Symantec from 2015 to calibrate our simulation.

**Tunable security mechanism:** We propose an alternative: a tunable mechanism, guided by a strategy that allows the defender to selectively apply the mechanism based on internal and/or external sets of conditions. For example, a centralized server can notify the client that
(a) Using ClamAV (0.99.2) to scan a single 248 MB file.
(b) Using Snort (2.9.9.0) to scan a 4.1 GB pcap file.
(c) Using Brave’s adblock engine (4.1.1) to scan 15.5k URLs.

Fig. 1: Average scanning time as a function of the rule/signatures set size. The dashed lines represent linear fits to the measurement.

certain categories of attacks are no longer in the wild, causing the client to reduce their sampling rates when it comes to suspicious traffic. Signatures are thus retired when the threats they are designed to look for become less prevalent. For this to work, there needs to be a greater level of independence between the security mechanism and the policy, the kind of separation that is already considered a major design principle [9], [40].

Beyond signatures: It important to emphasize that while we primarily experiment with signatures in this paper, the ideas apply well beyond signatures. Specifically, most runtime security enforcement mechanisms, albeit not all, can be turned off, either partially or entirely. Mechanisms that rely on matching lists for their enforcement include XSS filters [15] and ad blockers [16], [42], [44], to name just a few. Similarly, one can apply XFI or CFI to some DLLs, but not others, that have not been implicated in recent attacks. Of course, the ability to adjust which DLLs are CFI-protected depends greatly on having a dynamic software deployment infrastructure, which we claim to be a desirable goal.

Matching today’s reality: In many ways, our proposal is aligned with practical security enforcement practices of adjusting the sensitivity levels for detectors depending on the FP-averseness of the environment in which the detector is deployed. The Insight reputation-based detector from Symantec allows the user to do just that [57]. Our ultimate goal here, of course, is to reduce the factors listed above, i.e. the false positive rate and the performance overhead.

C. Contributions

Our paper makes the following contributions:

• **Tunable.** We point out that today’s approach to proactive security leads to inflexible and bloated solutions over time. We instead advocate a novel notion of tunable security design, which allows flexible and fine-grained policy adjustments on top of existing security enforcement mechanisms. This way, the protection level is tuned to match the current threat landscape and not either the worst-case scenario or what that landscape might have been in the past.

• **Sampling-based approach.** For a collection of mechanisms that can be turned on or off independently, we propose a strategy for choosing which mechanisms to enable for an optimal combination of true positives, false positives, and performance overheads.

• **Formalization.** We formalize the problem of optimal adjustment for a mechanism that includes an ensemble of classifiers, which, by adjusting the sampling rates, produces the optimal combination of true positives, false positives, and performance overheads.

• **Simulation.** Using a simulation based on a history of Snort signature updates over a period of about 9 years, we show that we can adjust the sampling rates within a window of minutes. This means that we can rapidly react to a fast-changing exploit landscape.

II. Background

When it comes to malware detection, anti-virus software has long been the first line of defense. However, for almost as long as AV engines have been around, they have been recognized to be far from perfect, in terms of their false negative rates [61], [30], false positive rates, and, lastly, in terms of performance [39], [24].

Clearly, the choice of signature database plays a decisive role in the success of the AV solution. This is illustrated by the promises of SaneSecurity (http://sanesecurity.com) to deliver improved detection rates, by using the free open-source ClamAV detection engine and their own carefully curated and frequently updated database of signatures. For example, as of August 2016, they claim a detection rate of 97.11% vs only 13.82% for out-of-the-box ClamAV, using a database of little over 4,000 signatures vs. almost 250,000 for ClamAV.

While the issue of false negatives is generally known to industry insiders, the issue of false positives receives much more negative press. Reluctance to remove or disable older signatures runs the risk of unnecessarily triggering false positives, which are supremely costly to the AV
vendor, as reported by AV-Comparatives [53] (http://www.av-comparatives.org).

A. The Changing Attack Landscape

When the attacks for which some mitigation mechanism was designed are no longer observed in the wild, it might seem very alluring to remove said mechanism. However, in most real world scenarios, we are not able to fully retire mitigation techniques. Before disabling some mitigation mechanism, one should examine the reason these attacks are no longer being observed and whether this is simply due to the observational mechanism and data collection approach being faulty.

Today, large-scale exploitation is often run as a business, meaning it is driven largely, but not entirely, by economic forces. The lack of observed attacks might simply be associated with an increased difficulty in monetizing the attack. Given that the attacker is aiming to profit from the attack, if the cost of mounting a successful attack is too high compared to either the possible gains or alternative attack vectors, the attacker will most likely opt not to execute it as it is no longer cost-effective. We see these forces in practice as the attack landscape changes, with newer attacks such as ransomware becoming increasingly popular in the last several years while older attacks leading to the theft of account credentials becoming less common.

forces in practice as the attack landscape changes, with newer attacks such as ransomware becoming increasingly popular in the last several years while older attacks leading to the theft of account credentials becoming less common because of two-factor authentication, geo-locating the user, etc. To summarize, we identify two common cases where monetizing becomes hard.

- **No longer profitable.** The first is the result of causes other than the mitigation mechanism. For example, when clients are no longer interested in the possible product of the attack or if there are other security mechanisms in place that prohibit the usefulness of the attack’s outcome. In such cases, removing the mitigation mechanism in question will most likely not have a practical negative effect on the system since the attack remains not cost-effective.

- **Effective mitigation.** The other case is when the attack is not cost-effective due to difficulties imposed by the mitigation mechanism. In such cases, removing the mechanism will result in an increase in the cost-effectiveness of the attacks it was aimed to prevent. This might result in the reemergence of such attacks.

By sampling the relative frequency of attacks of a particular kind, we cannot always determine which case we are currently faced with. It may also be a combination of these two factors. However, there is growing evidence that attackers are frequently going after the low-hanging fruit, effectively behaving lazily [18].

We therefore suggest an alternative that acts as a middle ground by introducing sampling rates for all mitigation mechanisms. In the first case, the mitigation mechanism is no longer needed, therefore adding a sampling rate will not reduce the security of the system, but will provide fewer benefits than a complete removal. On the other hand, in the second case, the security of the system is somewhat lowered, but the statistical nature of the sampling rate maintains some deterrence against attackers.

B. Study of Snort Signatures

To test some of these educated guesses, we have performed an in-depth study of Snort signatures. Focusing on the dynamics of signature addition and removal, we have mined the database of Snort signatures, starting on 12/30/2007 and ending on 9/6/2016. Daily updates to the Snort signature database are distributed through the EMERGING THREATS mailing list archived at https://lists.emergingthreats.net, which we used to determine which signatures, if any were 1) added, 2) removed, or 3) modified every single day. Figure 2 presents statistics of Snort signatures obtained by exploring the dataset we collected by crawling the mailing list archive.

It is evident from the figure that there are many more signature additions than removals. These statistics support our claim that signature dataset sizes are growing out of control and becoming unsustainable.

Below we give several representative examples of signature addition, update, and removal.

**Example 1: Signature addition.** Figure 3 shows the addition of new signatures in response to observations of the ProjectSauron [21] malware in the wild. The connection between the malware and EMERGING THREATS signatures designed to prevent it is evident from the signature description.

**Example 2: Signature update.** In the case of the signature marked as 2011124, we see a false positive report about traffic on port 110 on 04/04/2016, which receives a response from the maintainers within two days:

```
we get quite a lot of false positives with this one due to the POP3 protocol on port 110, it would be great if port 110 or more generally POP3 traffic could be excluded from this rule
-- JohnNaggets - 2016-04-02

Thanks, we’ll get this fixed today!
-- Dariolf - 2016-04-04
```

The maintainers added port 110 the same day they responded, resulting in this signature revision 19:

```
alerts ftp BYPASS_NET (1,10,11,19,20,44,45,47,58,67,90,143,205) ->
any any (msg:"ET MALWARE Suspicious FTP kickoff on Local Port (spaced)";
Flow from Server, established, only_stream; content:"GET ";
depth:4; content:!["SMTP"; within:20;
reference:url,doc.emergingthreats.net/2011124;]
classtype:non-standard-protocol; sid:2011124; rev:19;)
```

**CVE Additions: Evaluation of the Delay:** Another question to consider is how fast signatures for known threats are added after the threats are discovered or publicly announced. To estimate that, we have correlated 176 CVEs to 40,884 EMERGING THREATS signatures. This process usually involves analyzing the comments embedded in the signature to find CVE references (for example, reference:cve,2003-0533). We have plotted a histogram (Figure 4) that shows the delay in days between the CVE (according to the NIST NVD database) and the signature introduction date. As we can see, many signatures are created and added the same day the CVE is disclosed. Sadly, in quite a significant percentage of cases, signatures are added two weeks and more after the CVE release date. What is perhaps most surprising is that many signatures are created quite a bit before the disclosure, in many cases the day before, and in some cases over a month prior to it. This is due to other information sources that lead to signature generation.
III. Optimally Setting Sampling Rates

In this section we set the stage for a general approach to selecting sampling rates in response to changes to the data. We evaluate these ideas with practical multi-year traces in Section IV. We start with a model in which we have a set of classifiers (in the context of Snort signatures discussed in Section II, each signature is a classifier) at our disposal and we need to assign a sampling rate to each of them, so as to match our optimization goals. These goals include higher true positive rates, lower false positive rates, and lower overheads. We formalize this as problem of selecting a bit-vector $\alpha$, indicating the sampling rate for each classifier.
A. Active Classifier Set

We assume that our classifiers send some portion of the samples they flagged as malicious for further analysis. This matches how security products, such as those from Symantec, use user machines for in-field monitoring of emerging threats. In the context of a large-scale deployment, this results in a large, frequently updated dataset, which consists solely of true positive and false positive samples. We can use this dataset to evaluate the average true positive, false positive, true negative, and false negative rates, induced by sampling rates for our classifiers. Specifically, our aim is to choose a sampling bit-vector \( \alpha \) that will keep the true positive and true negatives above some threshold, while keeping the false positive rate, false negatives, and performance costs below some maximum acceptable values. We found this formulation to be most useful in our evaluation.

Constraints: Formally, these goals can be specified as a set of inequalities, one for each threshold:

\[
\begin{align*}
TP(\alpha) &\geq X_p & (1a) \\
TN(\alpha) &\geq X_n & (1b) \\
FP(\alpha) &\leq Y_p & (1c) \\
FN(\alpha) &\leq Y_n & (1d) \\
\text{Cost}(\alpha) &\leq Z & (1e)
\end{align*}
\]

For each set sampling rate \( \alpha \) we can compute the average cost of executing the entire set of classifiers on an entry from the dataset as:

\[
\text{Cost}(\alpha) = P^T \cdot \bar{\alpha}
\]

Using this formulation we can:

- Define a budget, \( \text{Expenses}(\alpha) \leq \text{BUDGET} \), as a strict requirement from any sampling rate.
- Define our problem as a standard optimization problem with the objective \( \min \text{Cost}(\alpha) \).

Budget-aware objectives: Often when assessing the effect a security mechanism has on a company’s budget, a cost is assigned to each false positive and each false negative produced by the mechanism. These assessments can be used to minimize the total budgetary effect of the mechanism and expected expenses. Assuming \( \text{Cost}_{FP} \) and \( \text{Cost}_{FN} \) are the costs of false negatives and false positives respectively, we can express the expected expenses as:

\[
\text{Expenses}(\alpha) = \text{Cost}_{FN} \cdot FN(\alpha) + \text{Cost}_{FP} \cdot FP(\alpha)
\]

Using this formulation we can:

- Define our problem as a single-objective optimization problem with the objective \( \min \text{Cost}(\alpha) \).

Balancing true positives and false positives: In this scenario, we correlate our sampling rate optimization problem to a standard classifier optimization setting, such that our true-positive rate is equivalent to the classifier’s precision while the false-positive rate becomes the recall.

In such cases, a ROC curve induced by different sampling rates can be used to select the best rate. Taking some inspiration from the well-known F1-score, a similar score, \( F_{1sr} \), expressed in formula \( 6 \) can be used to transform our problem to a single-objective optimization problem.

\[
F_{1sr} = \frac{TP \cdot FP}{TP + FP}
\]
For efficiency, we split the process of classifier sampling rate optimization into two steps. Real-world data often contains classifier overlap, that is, samples that are flagged by more than one classifier. We split our dataset into batches based on the classifier overlap, so that the samples in each batch are flagged by the same set of classifiers. Each batch is associated with true positive and false positive counts. The first step consists of choosing the batches that are cost-effective.

### B. 0/1 Sampling

Based on the desired optimization objective and the estimated cost ratio between false negatives and false positives (if applicable), we proceed to define the problem of finding the optimal subset of sample batches as a linear programming problem. At this stage, since each batch is determined by a specific classifier overlap, there is no overlap between the batches. Therefore, the computation of the true/false positives/negatives becomes a simple summation of the associated true/false positive counts. For example, the total true positive count is the sum of true positives associated with batches that are determined as enabled (meaning they should be sampled) and the total false negative count is the sum of the true positive counts of disabled batches.

To encode this problem, we assign each batch \( b_i \) with a boolean variable \( v_i \), representing whether or not the batch should be active. We then encode the optimization goal using these variables and the associated counts. We use a linear programming solver called Pulp [5], which finds an assignment to \( \bar{v} = \{v_1, v_2, \ldots\} \) that optimizes the optimization objective. The output of this step is a division of the samples into enabled (meaning the classifier should sample them) and disabled samples.

When the dataset contains no classifier overlap, meaning each sample is sampled by exactly one classifier, the output of the first step can be used as the classifier sampling rates. In this setting, the batches essentially correspond to single classifiers and therefore disabled batches correspond to classifiers that are deemed not cost-effective according to the optimization objective. The optimal solution in this case would be to fully enable all cost-effective classifiers and fully disable the rest.

### C. Inferring Sampling Rates

In the second step of our solution, given a set of enabled samples and a set of disable samples as described in Section III-B, we infer sampling rates for all classifiers that will induce the desired separation.

The key insight we use to infer the classifier sampling rates is to express our problem in the form of factor graphs [41]. Factor graphs are probabilistic graphical models composed of two kinds of nodes: variables and factors. A variable can be either an evidence/observation variable, meaning it’s value is set, or a query variable, whose value needs to be inferred. A factor is a special node that defines the relationships between variables. For example, given variable \( A \) and \( B \), a possible factor connecting them could be \( A \rightarrow B \).

#### Example 3:
Consider the example factor graph in Figure 5. The graph consists of 8 variables: 3 named \( C_1–C_3 \) representing 3 different classifiers and 5 variables named \( S_1–S_5 \) representing samples. These variables are connected using 5 factors, \( F_1–F_5 \), such that \( F_i(C, S_j) = \forall C \rightarrow S_j \), where \( C \) is the set of classifiers with edges entering the factor.

The variables \( S_j \) are treated as observations, meaning their value is set, and the variables \( C_i \) are treated as query variables. The inference algorithm chooses at which probability is each \( C_i \) set to true, such that the factors satisfy the observations. If we set all observations \( S_i \) to true, the inference of the factor graph returns the trivial solution of always setting all \( C_i \) to true (meaning \( C_i \) is true with probability 1.0). When we set some \( S_i \) to false, the inference algorithm is able to provide more elaborate answers. For example, setting \( S_4 \) to false, results in probability 1.0 for \( C_1 \) and probability 0.5 to both \( C_2 \) and \( C_3 \).

Given the sets of enabled and disabled samples from the previous step, we translate the problem to a factor graph as follows:

1) For each classifier \( i \) we define a query variable \( C_i \);
2) for each sample \( j \) we define an observation variable \( S_j \) and a factor \( F_j \);
3) if sample \( j \) was set to be enabled we set \( S_j \) to true, otherwise to false;
4) we connect each \( S_j \) to its corresponding \( F_j \);
5) for every pair of classifier and sample \( (i, j) \), if classifier \( i \) flags sample \( j \) we connect \( C_i \) to \( F_j \).

Using this construction, we get a factor graph similar in structure to the graph in figure 5. The inferred probabilities for the query variables \( C_i \) are used as the sampling rates for the corresponding classifiers.

To solve the factor graph and infer the probabilities for \( C_i \), we use Microsoft’s Infer.NET [4], a framework for running Bayesian inference in graphical models. We evaluate the performance of the solver in Section IV.

#### D. Discussion

**Maintaining the dataset:** We intend to build our dataset using samples flagged as malicious by our classi-
This kind of dataset will naturally grow over time to become very large. Two problems arise from this situation.

The first problem is that after a while most of the dataset will become outdated. While we usually wouldn’t want to completely drop old samples, since they still represent possible attacks, we would like to give precedence to newer samples over older ones (which essentially should result in higher sampling rates for current attacks). To facilitate this we can assign a weight to each sample in the dataset. We represent these weights using $W \in [0, 1]^{[D]}$ and rewrite the formulas from (III-A) as:

\[
TP(\alpha) = \frac{\sum_{i=0}^{[D]} (W_i \cdot G_i \cdot Pr_i(\alpha))}{\sum_{i=1}^{[D]} (W_i \cdot G_i)} \tag{7a}
\]

\[
FP(\alpha) = \frac{\sum_{i=0}^{[D]} (W_i \cdot (1 - G_i) \cdot Pr_i(\alpha))}{\sum_{i=1}^{[D]} (W_i \cdot G_i)} \tag{7b}
\]

\[
TN(\alpha) = \frac{\sum_{i=0}^{[D]} (W_i \cdot (1 - G_i) \cdot (1 - Pr_i(\alpha)))}{\sum_{i=1}^{[D]} (W_i \cdot (1 - G_i))} \tag{7c}
\]

\[
FN(\alpha) = \frac{\sum_{i=0}^{[D]} (W_i \cdot G_i \cdot (1 - Pr_i(\alpha)))}{\sum_{i=1}^{[D]} (W_i \cdot (1 - G_i))} \tag{7d}
\]

While many different weighting techniques can be used, two examples are: (1) Assign weight 0 to all old samples, essentially dropping old samples from the dataset; (2) Assign some initial weight $w_0$ to each new sample and exponentially decrease the weights of all samples after each sampling rate selection. The second problem stems from the sampling rates themselves. Given 2 classifiers, $C_1$ and $C_2$, and their corresponding sampling rates, $\alpha_1$ and $\alpha_2$, if $\alpha_1$ is higher than $\alpha_2$ the dataset will contain more samples of attacks blocked by $C_1$ than by $C_2$. This creates a biased dataset that, in turn, will influence sampling rates selected in the future. This problem can also be addressed using the weights mechanism. One possible approach will be to assign weights in reverse ratio to the sampling rates (so $C_1$ will be assigned a higher rate than samples matching $C_1$). Other viable approaches exist and the most suitable approach should be chosen based on the setting in which the classifiers are used.

Minimum sampling rates: In Section (III-A) we’ve defined a sampling rate as $\alpha \in [0, 1]^{[C]}$. This definition allows for a complete disable of a classifier by setting it’s sampling rate to 0. In practice, since we can never be sure that an attack has completely disappeared from the landscape, it is unlikely that we will want to completely disable a classifier.

A possible approach to address this is by setting a minimal sampling rate for the classifier. Given that the attack for which this classifier was intended is extremely unlikely to be encountered we don’t want to apply the classifier to every sample encountered, however since the attack is still possible we should statistically apply the classifier to some samples to maintain some chance of blocking and noticing an attack (if one appears). Given an inferred sampling rate $S$, the minimal sampling rate can be introduced in many forms, such as

- a lower bound $L$ on the sampling rate assigned to each classifier ($S >= L$);
- a constant value $X$ added to the sampling rate ($S + X$);
- some percentage $Y$ reduced from the non-sampled portion ($S + (1 - S) \cdot Y$).

We note that the minimum sampling rate for each classifier should be proportional to the severity of the attacks for which it was intended. If the impact of a successful attack is minuscule, we may set a lower minimum sampling rate because even if we miss the attack the consequences are not severe. However, if the impact is drastic, meaning the severity of the attack is high, then we should set a higher minimum sampling rate as a precaution.

We can formalize the notion of minimal sampling rates as $MinSR \in [0, 1]^{[C]}$, which is based on a severity mapping $S \in [0, 1]$ (such that $S_j$ is the severity of the attacks for which classifier $C_j$ was intended), and use $MinSR_j$ as either $L$, $X$, or $Y$ from the examples above.

IV. EXPERIMENTAL EVALUATION

In this section we first describe our simulation design and then discuss both how much our approach helps with achieving optimization objectives such as reducing false positives, and how long it takes to solve the optimization problems on a daily or weekly basis.

A. Simulation Design

To evaluate the benefits of our approach we performed several simulations mimicking real-world anti-virus activity. For the purposes of our simulation, we collected detailed information from Snort signature activity summaries from 12/30/2007 until 9/6/2016, entailing signature additions, updates and removals, as shown in Figure 2. In total, we’ve collected information regarding 40,884 signatures.

Generating simulated malware traffic: We generate malware traffic traces (observed true positive and false positive samples) based on the collected Snort signature information. We base these traces on the following assumptions:

i Each signature was introduced to counteract some specific malware.

ii Nonetheless, some signatures might unintentionally flag malware other than the one it was intended for (resulting in classifier overlap).

iii The main purpose of signature updates is to address some false negatives, resulting in increased true positive and false positive observations.

The following design decisions are also incorporated into the trace generation:

i The decline in true positive observations count for a specific signature is modeled as a power law decay curve.

ii False positive observations count is modeled as a percentage of the true positive count (denoted as a simulation parameter $\theta$).

iii Amount of true positive traffic does not affect false positive observations.
Observations may be captured by more than one signature (referred to as “classifier overlap”). For more details, please see Section IV-A.

**Simulation scenario:** We aim to simulate a real world usage in our simulation. The scenario we are simulating is when *once every 3 days* our tool is applied to the latest observations and updates the sampling rates for all active signatures. New signatures might still be introduced between sampling rate updates and are set to full sampling until the next update. We believe this to be a reasonable setting that is quite likely to be implemented in practice.

Additionally, under some conditions, Infer.NET’s inference algorithm might fail. Such conditions are very rare (for only 1.5% of days either failed or timed-out). However, if they occur we allow the simulation to keep using the sampling rates computed on the last update, which we believe to be a solution applicable in practice.

We defined our optimization goal using a budget-aware objective. Assuming a known estimated cost ratio \( \beta \) between false negatives and false positives, we phrase the objective as \( FP + \beta \cdot FN \). We leave \( \beta \) as a parameter for the simulation.

Essentially, we set our goal to minimize the overall cost incurred by scanning. We note that, as Section IV-A mentions, there are many possible goals. Based on discussions with commercial vendors, we believe the overall incurred cost is a measure likely to be used in practice. Another reasonable goal is the total cost of scanning. In this setting each signature would have to be associated with a scanning cost the the system would look for a solution that either minimizes it or keeps it below some given threshold.

1) **Design Decisions:** The following design decisions are incorporated into the trace generation:

**Simulating the decline in true positives:** We use a power law decay curve to simulate the decline of a specific type of malware over time. Prior research on large-scale exploitation (75 million recorded attacks detected by Symantec sensors) in the wild suggests the power law as an accurate way to model diminishing exploitation rates [10].

We initialize the curve for an initial true positive count of approximately 500 observations per day and calibrate it to fit the lifespan of the signature intended for that malware. We filter out signatures which were added or removed outside of our sampling period, for which we cannot determine a life span, since we are unable to calibrate a proper decay curve for these signatures. We also eliminate temporary short-lived signatures (less than 7 days). Out of the 40,884 collected signatures, we are left with 3,029 signatures after filtering, which we use in the simulation. Figure 6 shows the number of active signatures for each day of our simulation.

We note that in many real-world cases, a signature is introduced only a few days after a malware appears in the wild and is removed at least a few days after the relevant malware disappeared from the attack landscape. We adjust the overall signature lifespan, introduction and removal dates accordingly to incorporate this insight into the attack model.

**Simulating false positives:** We model the amount of false positive observations as a percentage of the true positive observations remaining. We denote this percentage as \( \theta \), used as a parameter for the simulation.

As false positive observations originate solely from legitimate traffic which remains mostly unchanged, we determine that false positive observations should remain constant as long as the signature is not changed. We therefore update the false positive traces only when the signature is updated. The curve in Figure 7 shows an example of the number of true positive and false positive observation for Snort signature 2007705 for a set \( \theta \).

**Simulating classifier overlap:** From the collected signature information, we learn that, while there exists some overlap between signatures, most signatures only flag one kind of malware. To simulate overlap we randomly choose for each signature and each observation with how many other signatures it overlaps. We draw this value from the distribution shown in Figure 8 calibrated to match our collected signature information.

**B. Experimental Setup**

To compare different simulation conditions, we ran several simulations, each with a different combination of values for \( \theta \) and \( \beta \), both with classifier overlap and without. The simulations were executed on a Linux machine with 64 AMD Opteron(TM) 6376 processors, operating at 2.3GHz each, and 128 GB RAM, running Ubuntu 14.04. Each simulation was assigned the exclusive use of a single core.

**C. Precision and Recall Results**

By applying the sampling rates computed by our system, one can eliminate part of the false positives previously observed at the expense of losing part of the true positive observations. In Figure 10 we show the percentage of true positives remaining compared to the percentage of false positives remaining.

The dashed line across each of the figures symbolizes an equal loss of both false positives and true positives. The area above the dashed line matches settings in which less true positives are lost compared to false positives. This is the area we should strive to be in, since it represents a sampling which is relatively cost-effective. One can clearly see from the figures that, regardless of classifier overlap, all of our simulations reside above the dashed line.

Figure 9 show the classification precision and recall as a function of \( \theta \) for different values of \( \beta \), both with and without classifier overlap. The figures show that, regardless of overlap, both precision and recall drop when \( \beta \) and \( \theta \) rise. A rise of \( \theta \) means there are more false positive observations, which reduces the portion of observed true positives, thus affecting the overall precision and recall. Similarly, a rise of \( \beta \) means that relative cost of a false negative is higher than that of a false positive. Therefore, based on the optimization objective we set in Section IV-A.
it is only logical that the system will choose to allow for more false positives, rather than risking a false negative, thus again affecting both precision and recall.

Adapting to the situation: From the aforementioned figures, we learn that the effectiveness of applying sampling rates depends greatly on the operating scenario. In some cases, where for example false negatives are extremely expensive (as might be the case for corporate datacenters), the sampling rates remain rather high and thus the overall true positive and false positive counts remain mostly unaltered. On the other hand, when false negatives are relatively cheap (as is often the case for private, user owned desktops), we can expect our system to determine sampling rates that are relatively low.

We believe our system is especially well suited for large-scale services such as web-mail providers. In this scenario, each user can set its own willingness to accept risk, i.e. the subjective cost of a false negative. Doing so will allow the service’s servers to greatly reduce their scanning workload, which will have a tremendous effect on the overall server performance as the amount of data scanned by these servers is huge. Such services would like obtain the greatest benefit from our approach.

D. Solution Times

We recognize that for a system such as the one proposed in this paper to be applicable to real world scenarios, it is required that solving and computing new sampling rates be very fast and cheap. Long solving times mean the system would not be able to quickly adapt to changing landscapes and respond by setting new sampling rates in a timely fashion.

Figure 11 shows a cumulative distribution of the total solving times (both PuLP and Infer.NET) measured during our simulations for each day. The figure shows that over 80% of simulated days were solved in under 20 seconds. The day which took our system the longest to solve took less than 5 minutes (285 seconds to be exact).
Fig. 9: Classification precision and recall as a function of \( \theta \) for different values of \( \beta \) with and without classifier overlap.

Fig. 10: Percentage of true positives remaining compared to percentage of false positives eliminated with and without classifier overlap. Different setting for FP-threshold and cost ratio correspond to different points on the curves.

Fig. 11: Cumulative distribution of overall solution times (PuLP + Infer.NET).

This tells us that using this kind of system in a responsive manner is indeed feasible.

Figure 12 shows the average solving time needed for each day of our simulation. We first note that the solving times for PuLP (represented by the blue line) are extremely low, constantly below 1 second. When there is no classifier overlap, the solution provided by PuLP is sufficient as the sampling rates for the classifiers. This means that when there is no overlap, solving is extremely fast. Also, there is a clear correlation between Infer.NET solving time and the number of active signatures, both following the same trends. This correlation is interesting as it indicates that (1) solving time can be anticipated in advance, and (2) we can accelerate the solving of days with many active signatures using a “divide-and-conquer” approach, meaning we can split them to smaller batches and solve each one separately.

E. Experimental Summary

Reduction in false positives: Regardless of classifier overlap, when comparing the reduction in the number of false positives to that of true positives, we find that our responsive optimization technique removes more false positives than true positives, both in terms of percentages (19.23% compared to 12.39% without overlap; 20.13% compared to 11.96% with overlap) and in terms of absolute values (9,286,530 compared to 8,002,871.5 without overlap; 9,225,422.6 compared to 8,065,888.6 with overlap). The reduction in absolute values is surprisingly significant, considering that the highest value of \( \theta \) in our simulations was set to 25% of the true positive rate. In settings with classifier overlap, applying sampling rates is more beneficial than in settings...
V. Limitations

We acknowledge that our approach has the following limitations.

Code complexity: The adoptive approach may increase development and maintenance costs to developers or security researchers, because a new mechanism for introducing the sampling rates will need to be implemented. We also note that debugging might prove more difficult since, in addition to the inputs introduced to the system, the sampling rates used would also have to be taken into account, leading to possible non-determinism.

When it comes to the issue of long-term cost of enforcement, we remind the reader that our approach doesn’t remove signatures, it merely disables them.

Adaptive attacker countermeasures: Most security mechanisms entail new opportunities for attackers and our approach is no exception. An attacker familiar with the working of a system utilizing our approach could attempt to use it to her advantage. With the approach in this paper, classifiers are no longer always applied and any attack has some probability to get through the classifiers if it is not sampled. Using this knowledge, the attacker can attempt the same attack several times, hoping that at least one instance will be overlooked.

Additionally, classifiers for uncommon attacks would be sampled at lower rates. An attacker can deliberately use outdated vulnerabilities, which are likely not sampled frequently to increase her chances of a successful attack. The attacker can use a variety of attacks to force a high sampling rate on all classifiers. This would at most cause the system to revert to the current default situation, in which all classifiers are always on.

Using one or more of the approaches outlined above, the attacker can temporarily increase her chances of success. Doing so will increase the amount of observed attacks for the relevant classifiers, thus triggering an increase in respective sampling. As a result, we anticipate that the window of vulnerability will be small, and that relatively few users will be affected.

VI. Related Work

Reactive vs. proactive Security: There has been some interest in comparing the relative performance of proactive and reactive security over the years. Barth et al. [14] make the interesting observation that proactive security is not always more cost-effective than reactive security. Just like in our paper, they support their claim using simulations. Barreto et al. [13] formulate a detailed adversary model that considers different levels of privilege for the attacker such as read and write access to information flows.

Blum et al. [19] demonstrate that optimizing defences as if attackers have unlimited knowledge is close to optimal when confronted with a diligent attacker, with limited knowledge regarding current defences prior to attacking. Such attackers are more realistic, thus supporting our results highlighting the benefits of tunable security.

Classifiers designed to detect malicious traffic or samples are often affected by an issue known as “Concept drift” [65]. Researchers have proposed a number of ways to address concept drift through retraining classifiers. For instance, Soska and Christin [27] present techniques that allow to proactively identify likely targets for attackers as well as sites that may be hosted by malicious users.

Several researchers have proposed generating new signatures automatically [10], [15], [22], [54], [66]. Signature addition seems to largely remain a manual process, supplemented with testing potential AV signatures against known deployments, often within virtual machines. Automatic signature generation will likely improve security but will worsen the false positive and performance issues addressed in this paper.

Exploitation In the Wild: Nayak et al. [45] highlights the lack of a clear connection between vulnerabilities and metrics such as attack surface or amount of exploitation that takes place. They use field data to get a more comprehensive picture of the exploitation landscape as it is changing. None of the products in their study had more than 35% of their disclosed vulnerabilities exploited in the wild. These findings resonate with the premise of our paper.

One of the better ways to understand the exploitation landscape is by consulting intelligence reports published by large security software vendors. Of these, reports published by Microsoft [13] and Symantec [58] stand out, both published on a regular basis. A recent report from Microsoft [63], [64] highlights the importance of focusing on exploitation and not only vulnerabilities. The current approach to software security at Microsoft is driven by data. This approach involves proactive monitoring and analysis of exploits found in-the-wild to better understand the types of vulnerabilities being exploited and exploitation techniques being used.

Bilge et al. [17] focus on the prevalence and exploitation of zero-days. They discover that a typical zero-day attack lasts 312 days on average and that, after vulnerabilities are disclosed publicly, the volume of attacks exploiting them increases by up to 5 orders of magnitude. These findings
were important in designing credible simulations in this paper.

Economics of Security Attacks and Defenses: Herley et al. [35] point out that, while it can be claimed that some security mechanism improves security, it is impossible to prove that a mechanism is necessary or sufficient for security, meaning there is no other way to prevent an attack or that no other mechanism is needed. They also make a similar observation stating that one can never prove that a security mechanism is redundant and not needed. These observations put into words the frame of mind that resulted in the current overwhelming number of active security mechanisms. We try to address this problem using the proposed sampling rates.

A report by the Ponemon Institute [49] estimated the costs of false positives to industry companies. The estimation was based on a survey filled by 18,750 people in various positions. While the numbers portrayed in the report are not accurate, they do paint an interesting picture. The average cost of false positives to a company was estimated at 1.27 million dollars per year. These estimations include the cost analyzing and investigating false positive reports as well as the cost of not responding in time to other true positive reports.

Models of Malware Propagation: Arbaugh et al. [12] introduced a vulnerability life-cycle model supported by case studies. The introduced model is different than the intuitive model one would imagine a vulnerability follows. We relied on the insights presented in this paper in designing our models for trace generation.

Many works have focused on modeling malware propagation. Bose et al. [20] study several aspects crucial to the problem, such as user interactions, network structure and network coordination of malware (e.g. botnets). Gao et al. [28] study and model the propagation of mobile viruses through Bluetooth and SMS using a two-layer network model. Fleizach et al. [26] evaluate the effects of malware self-propagating in mobile phone networks using communication services.

Garetto et al. [29] present analytical techniques to better understand malware behavior. They develop a modeling methodology based on Interactive Markov Chains that captures many aspects of the problem, especially the impact of the underlying topology on the spreading characteristics of malware. Edwards et al. [25] present a simple Markov model of malware spread through large populations of websites and studies the effect of two interventions that might be deployed by a search provider: blacklisting and depreferencing, a generalization of blacklisting in which a website’s ranking is decreased by a fixed percentage each time period the site remains infected.

Grottke et al. [33] define metrics and models for the assessment of coordinated massive malware campaigns targeting critical infrastructure sectors. Cova et al. [21] offer the first broad analysis of the infrastructure underpinning the distribution of rogue security software by tracking 6,500 malicious domains. Hang et al. [34] conduct an extensive study of malware distribution and follow a website-centric and user-centric point of view. Kwon et al. [60] analyzed approximately 43,000 malware download URLs over a period of over 1.5 years, in which they studied the URLs’ long-term behavior.

VII. Conclusions

Securing today’s complex systems does not come free of charge. The most common cost is performance. Using three security mechanism examples, anti-virus signatures, Snort malware signatures, and ad-blocking lists, we show that the cost of security enforcement (measured in terms of latency) often grow linearly with the number of policies that are involved. It is therefore imperative to devise ways to limit the enforcement cost.

In this paper we argued for a new kind of tunable framework, on which to base security mechanisms. This new framework enables a more reactive approach to security, thus allowing us to optimize the deployment of security mechanisms based on the current state of attacks.

Based on actual evidence of exploitation collected from the field, our framework can choose which mechanisms to enable/disable so that we can minimize the overall costs and false positive rates, while maintaining a satisfactory level of security in the system.

Our responsive strategy is both computationally affordable and results in significant reductions in false positives, at the cost of introducing a moderate number of false negatives. Through measurements performed in the context of large-scale simulations, we find that the time to find the optimal sampling strategy is mere seconds for the non-overlap case, and under 2.5 minutes in 98% of overlap cases. The reduction in the number of false positives is significant (about 9.2 million, when removed from traces that are about 9 years long, 20.13% and 19.23%, with and without overlap, respectively).
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