Reducing Malware Analysis Overhead with Coverings

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Abstract—There is a growing body of malware samples that evade automated analysis and detection tools. Malware may measure fingerprints ("artifacts") of the underlying analysis tool or environment, and change their behavior when artifacts are detected. While analysis tools can mitigate artifacts to reduce exposure, such concealment is expensive. However, not every sample checks for every type of artifact—analysis efficiency can be improved by mitigating only those artifacts most likely to be used by a sample. Using that insight, we propose MIMOSA, a system which identifies a small set of "covering" tool configurations that collectively defeat most malware samples with increased efficiency. MIMOSA identifies a set of tool configurations which maximize analysis throughput and detection accuracy while minimizing manual effort, enabling scalable automation for analyzing stealthy malware. We evaluate our approach against a benchmark of 1535 labeled stealthy malware samples. Our approach increases analysis throughput over the state of the art on over 95% of these samples. We also investigate cost-benefit tradeoffs between the fraction of successfully-analyzed samples and computing resources required. MIMOSA provides a practical, tunable method for efficiently deploying analysis resources.

Index Terms—Malware analysis, covering sets, artifact mitigation

1 INTRODUCTION

Malware continues to proliferate, significantly eroding user and corporate privacy and trust in computer systems [34], [43], [44], [63]. Malwarebytes Threat Landscape reported a 13% increase in malware targeting businesses in 2019 [42]. SonicWall detected around 10 billion malware attacks in 2019 [59]. Although Symantec notes a 61% decrease in the number of new malware variants between 2017 and 2018, the distribution of specific samples like Adware/InstallCore increased 360% from 2018 to 2019 [42], [64]. Keeping abreast of this large volume of malware requires effective scalable malware analysis techniques.

Once a malware sample has been detected and analyzed, automated techniques such as signature matching can quickly identify other copies. Understanding novel malware samples, however, requires lengthly analysis using both automated and manual techniques [23], [73]. Analysts frequently execute samples under laboratory setups [19], [68] using virtualization. This includes not only virtual machine monitors like VMWare [67], Xen [21], and Virtual-Box [47], but also tools that depend on virtualization such as Ether [18], HyperDbg [24], or Spider [16]. Executing the malware sample in a controlled environment allows the analyst to observe its behavior safely. If malware causes damage, the damage is limited to the virtualized environment, which can be destroyed and restarted to analyze subsequent samples. Virtualization is now a lynchpin of computer security and analysis applications [?], [5], [30], [38], [51].

As these malware analysis methods have matured, malware authors have in turn adopted evasive, or *stealthy*,

techniques to avoid or subvert automated analysis [11], [61], [62]. Chen et al. [11], for example, reported that 40% of malware samples hide or reduce malicious behavior when run in a VM or with a debugger attached. Stealthy malware techniques include anti-debugging [9], [11], [22], anti-virtualization [6], [52], and anti-emulation [54]. These methods detect a particular feature, or *artifact*, of the analysis environment which allows the malware to determine if it is being analyzed. When an artifact is detected, the malware can avoid executing its malicious payload, thereby hiding its true function from the analyst. Table 1 summarizes common artifacts, derived from Zhang et al. [74]. Studying the behavior of stealthy malware requires that the analyst mitigate the artifacts by configuring the environment in a way that prevents detection by the malware. Over time, malware authors have discovered a wide diversity of artifact types, which has increased the time required to manually determine the best mitigation strategy for each malware sample. This process has proven difficult to automate.

Given current trends, we expect that malware authors will continue discovering new artifacts, forcing analysts to develop new mitigations, leading to continued escalation of the complexity and cost of conducting malware analysis. Balzarotti *et al.* describe how stealthy malware samples check for evidence of analyses and behave differently when they are present [7]. They classify stealthy malware by running samples under multiple environments and using the differences between those runs, especially in terms of patterns of system call execution, to characterize evasive behavior. For example, if a sample is executed under both VMWare [67] and VirtualBox [47], and the VMWare instance does not exhibit malicious behavior, one can conclude that the sample detects VMWare-specific artifacts (e.g., [49]). Many techniques, from machine learning [50] to symbolic execution and traces [26] to hybrid dynamic analyses [40], among others, have been proposed to tackle this problem of environment-aware malware—even as new black hat approaches for more insidious stealthy evasion (e.g., [45], [65]) are proposed as well.

This paper presents MIMOSA¹ to address the need for high-throughput, low-overhead automated analysis of stealthy malware. MIMOSA's key insight is that any malware sample is likely to use a small set of artifact mitigation strategies out of the large set of possible mitigations. We propose using *coverings* to find a small set of analysis configurations that collectively cover (mitigate) the techniques used by most stealthy malware samples while minimizing the cost of each individual analysis configuration. MIMOSA can be used as part of an automated malware analysis or triage system to help detect and understand new stealthy malicious samples.

We extend the previous state-of-the-art to consider both the cost and coverage of artifact mitigation strategies. Given the popularity of stealthy malware and the increasing number of anti-stealth techniques, the question is no longer whether or not evasion should be mitigated, but which set of techniques should be used for a particular sample. Since samples often use combinations of artifacts to evade detection [62], this is not a simple decision. First, each stealth mitigation technique comes with associated costsdevelopment time, deployment time, CPU time, memory and disk utilization, runtime overhead, etc.-compared to a bare-metal or bare-VM setup. These costs are critical because the rate at which new malware is deployed [66] combined with the time and resources required to complete each analysis has led to a situation in which analysis time can be a bottleneck [10]. Second, some stealth mitigation techniques supplant or subsume others but with different costs. For example, an API call can be hooked to read VMWare-specific registry keys to prevent malware targeting that registry key from detecting the environment. Such a strategy is more efficient than using an alternate approach to hide the registry key.

To summarize, the main contributions of this paper are:

- A new algorithm for identifying a low-cost set of artifact covering configurations;
- MIMOSA, a system for selecting and deploying covering combinations of artifact mitigations to maximize analysis throughput and accuracy;
- An empirical study of 1535 labeled stealthy malware samples from the wild, demonstrating that MIMOSA achieves high coverage of stealthy malware and high automated analysis throughput; and
- Open-source software that provides a unified framework for conducting scalable evasive malware analysis. We release the codebase of MIMOSA under the following Github repository for public access: github.com/AdaptiveComputationLab/MIMOSA.

1. MIMOSA: Malware Instrumentation with Minimized Overhead for Stealthy Analysis.

2 BACKGROUND

We call malware *stealthy* if it actively seeks to detect, disable, or otherwise subvert malware analysis tools. Stealthy malware operates by checking for signatures, or *artifacts*, associated with various analysis tools or techniques. For example, a malware sample may invoke the isDebuggerPresent Win32 API call to determine whether a debugger is attached to the process—if a debugger is attached, the sample may conclude that an analyst is instrumenting it and change its behavior accordingly. There are many different types of artifacts exposed by the wide variety of analysis tools and frameworks used today. Briefly, stealthy malware samples use artifacts as heuristics to determine if they are under analysis, and change their behavior to subvert the tool.

Stealthy, evasive malware has been studied extensively [10], and is of increasing concern in industrial settings, with companies such as Minerva and Lastline marketing solutions for detecting stealthy malware. In addition, stealth is often a property gained through the use of packers [1], [2], [55] that can systematically change malware statically to evade detection and subvert analysis. Thus, there is a need for defensive methods that can keep up with the escalating arms race with malware.

An *artifact* is information about the execution environment that a malware sample can use to determine if it is running non-natively. For example, if a malware sample checks whether a debugger is attached to it, that sample may behave differently in an attempt to conceal its true behavior from an analyst using the debugger. For any given artifact, there can be multiple *artifact mitigation strategies* for preventing exposure of the artifact to the sample. Each such strategy comes with an associated (1) *mitigation cost*, which captures overhead, development effort, or other economic disadvantage, and (2) generality, or *artifact coverage*, which is the fraction of stealthy samples defeated by the strategy.

We consider three broad malware analysis methods:

- 1) *manual analysis*, in which a human analyst reverse engineers, modifies, and analyzes the sample. This laborious process can take many hours of effort per sample.
- 2) *bare metal analysis*, in which the sample is run natively rather than in a VM and thus exposes no artifacts to the sample but also incurs risk to the host environment.
- 3) *combined environment analysis*, in which the sample is run in multiple disparate environments so that the sample is exposed to disjoint sets of artifacts.

In this paper, we focus on the third approach, namely combined environment analysis. Earlier work [7], [36] used observed differences between runs in disparate environments to determine which artifacts are used by a stealthy malware sample. Historically, however, such approaches have not involved many analysis environments, instead focusing on case studies that compare runs between limited numbers of virtualization environments. Given the growing number of malware mitigation techniques, there is a need for techniques that enable fine-grained control over the artifacts exposed by the analysis environment. By precomputing a set of configurations that can be tested in parallel and reused for different malware samples, we hypothesize that MIMOSA will both increase coverage and analysis scalability of stealthy malware.

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 TABLE 1

 Example artifacts used by stealthy malware [74].

Artifact Name Artifact Description	
Hardware IDVMs have devices with obvious strings (e.g., "VMWare Hard Drive") or sRegistry KeyWindows VMs have telling registry keys (e.g., unique dates and times assCPU behaviorVMs may not faithfully reproduce CPU instructions.Resource constraintMalware analysis VMs may be given sparse resources (e.g., <20GB hard or	specific identifiers (e.g., MAC address). sociated with VM creation). disk) d redefined names (e.g., vmtoolsd in VMWare).

3 MOTIVATING EXAMPLES

In this section, we consider two artifact families commonly used by stealthy malware to detect an analysis environment: debugger-related API calls and hard disk capacity. For each artifact family, we highlight multiple mitigation strategies an analyst might use defeat such evasion, and we illustrate how each strategy can have a different cost and effectiveness. These tradeoffs motivate MIMOSA's design.

At one extreme, the analyst could run the sample on a bare metal machine without virtualization, exposing the fewest artifacts (high coverage). This strategy has high cost because it precludes parallel analyses involving multitenant VMs and it can be expensive to recover from the malware payload. At the other extreme, the analyst might use a single mitigation strategy (low overhead). Recall that stealthy malware operates by executing myriad checks for such artifacts, sometimes six or more [62], so this approach is likely to have low coverage. Even if the single mitigation strategy chosen defeats one check, it is unlikely to defeat all of them. As a third alternative, the analyst could apply every known mitigation strategy simultaneously. However, in practice, a single sample rarely checks for the majority of known artifacts.² The third alternative is also not practical because some mitigations are incompatible: they may require specific VMs or incompatible hardware configurations, and combining all possible mitigations will often incur unacceptable overheads. Given a set of available analysis tools, MIMOSA can produce sets of configurations that occupy different points in the cost-coverage space.

3.1 Debugger Presence Artifact Family

Some stealthy malware samples explicitly check for the presence of standard debugging software. Analyzing stealthy malware requires tools that do not expose related artifacts to the malware sample under test. In some cases, this can be trivial. For example, we can mitigate the isDebuggerPresent API call by hooking it and returning a spoofed value so that, from the malware's perspective, it appears as though no debugger is attached. Such a hook is fairly simple and requires low runtime overhead (indeed, some debuggers used for malware analysis, such as OllyDbg [72], offer an option to hook this API call). However, sometimes this is ineffective: other techniques exist, beyond that single API call, that can be used by malware to determine the presence of a debugger (e.g., isRemoteDebuggerPresent or fields in process control structures). We could employ one of many strategies to mitigate this "debugger presence" artifact family:

- 1) do nothing, risking exposure to samples that invoke any API calls related to debugger presence;
- 2) hook one or more API calls within the OS;
- 3) run in an instrumented virtual machine that does not directly attach a debugger to the sample; or
- 4) use a physical machine to preclude exposure.

Strategy (2) is attractive because hooking these API calls would incur relatively low runtime overhead. However, hooking API calls like this requires development effort specific to the platform being used for analysis. Moreover, deciding to hook API calls may introduce subsequent mechanisms for determining the presence of a different artifact. For example, hooking API calls in Windows requires modifying a process data structure, which could itself be checked by the malware. Alternatively, we could opt to run the sample in another environment such as an instrumented virtual machine (e.g., Ether [18]), but this would incur more significant runtime overhead, reducing efficiency. In brief, moving from strategy (1) to strategy (4) increases the coverage of stealthy malware samples, but at a greater cost.

3.2 Hard Disk Capacity Artifact Family

As a more complex example, many stealthy samples will check the size of the hard disk. If the hard disk capacity is below some threshold, the sample may conclude that it is executing in a resource-constrained virtual machine for automated analysis. Depending on the guest OS, there may be a variety of API calls that would, either directly or indirectly, measure the available hard disk space. Based on our experience, pafish and some other loaders check for a threshold of 60GB, and if the hard drive size is less than this value, they consider it as a potential analysis environment. An analyzer has several strategies for addressing this "hard disk capacity" artifact family:

- do nothing, risking exposure to samples that look for specific hard drive capacities;
- 2) hook one or more API calls associated with disk space;
- 3) externally hook the API call from a hypervisor context,
- allocate a larger virtual hard disk to a virtual machine used for malware analysis; or

^{2.} Advanced Persistent Threats are an exception, which we exclude from consideration.



Fig. 1. A simplified illustration of our MIMOSA workflow, consists of four major engines including Covering algorithm, VMCloak [33], Dispatcher, and Detox.

5) run the sample on a physical machine to preclude artifact exposure.

Strategy (2) is cheaper in terms of analysis cost, but requires more effort to research and understand each of the (potentially many) associated API calls (e.g., in addition to measuring disk size directly by querying disk information, a malware sample could write a large amount of data and check if the OS raises an exception once space is depleted). On the other hand, strategy (4) requires resources and effort at runtime, restricting the number of parallel VMs that could be used for malware analysis. Finally, we could instead allocate an entire physical analysis machine for the sample, which would successfully mitigate all artifacts in the disk space family for the largest subset of malware, but also inhibits analysis scalability.

These examples show how multiple mitigation strategies can exist for the same artifact family, how those strategies can have different costs, and how those strategies can vary in coverage or effectiveness. However, although we have thus far presented them in linear lists, the conflicts we demonstrated mean that a more nuanced representation is merited. For example, for the debugging presence artifact family, strategies (3) and (4) conflict and cannot be employed simultaneously. These observations motivate our adoption of the lattice data structure (to address coverage and conflict concerns) and our extension of the covering array algorithm (to address coverage and cost concerns).

4 PROPOSED WORKFLOW

In this section, we describe the workflow we envision to support. We seek to make the automated analysis of stealthy malware more efficient. Current techniques either rely on human creativity (e.g., debugging with IDA Pro [28] or OllyDbg [72]) or heavy-weight analysis techniques that incur significant overhead (e.g., MalT [74] or Ether [18]). Moreover, differencing approaches, such that of as Balzarotti *et al.* [7], execute a sample in multiple instrumented environments and use the difference in runs to determine which artifact is used by the sample, potentially wasting resources.

Given a list of available artifacts, the strategies available for mitigating them, and a cost model, MIMOSA's objective is to select a small set of configurations, which can be deployed in parallel on a given malware sample. That is, given a fixed number of available servers, each will be configured to mitigate a different specific subset of artifacts, with lower total cost, e.g., runtime, to lower analysis latency compared to existing methods. Once the covering configurations are identified, MIMOSA deploys each of the configurations as a separate instance of an instrumented VM. MIMOSA manages the VMs to gather logging information and support malware analysis.

MIMOSA's high-level workflow is illustrated in Figure 1 with details given in Figure 2. In Step 1, we apply our covering algorithm (Algorithm 1), which takes (1) a list of artifacts, (2) corresponding costs for each artifact (Section 5.1), and (3) a set of mitigation strategies for each artifact (Section 5.2) as input. The algorithm returns a covering set of configurations for designing and deploying different virtual machines. Each covering is represented as a vector of bits, where each element indicates whether that artifact should be mitigated in the server's configuration.

The cost model can include a multitude of factors, as determined by the analyst, including VM run-time, memory usage, development time of the mitigation, etc. MIMOSA uses our covering algorithm (Section 5.3) to determine a set of mitigation configurations for each server in a malware analysis cluster based on the cost model.

Next, these coverings are realized in a malware analysis cluster by configuring specific virtual machines. The VM-Cloak module receives the set of configurations generated previously and maps VM snapshots to nodes in the cluster. VMCloak is MIMOSA's custom VM provisioning and deployment framework. Coverings may entail specific virtualization backends (e.g., QEMU vs. VirtualBox), hooking API calls, or modifying the guest kernel (e.g., network drivers).

With a configuration established for each server in the analysis cluster, MIMOSA next allocates samples to servers. We assume access to a suite of hypervisors and hardware resources that can be configured a priori to realize the set of mitigations specified by the covering. As described in Section 6.2, we implemented 13 such hypervisor and hardware configurations (Table 3), managed by our dispatcher module to spin up and spin down analysis resources as samples are processed.

Each sample is then executed as a process within each configuration. As the process runs, MIMOSA collects API traces and VM state logs through Virtual Machine Introspection (VMI) and determines heuristically determine whether the sample is executed successfully. These heuristics are stored in the Detox engine, which correlates process and VM execution logs to infer more semantic patterns. In particular, Detox detects if the process exits, if certain network communication patterns exist, or if certain process names are created. We conclude that a sample has been executed successfully if it runs to termination under each environment. Section 6 uses well-labeled corpus of stealthy malware to evaluate MIMOSA's effectiveness.

5 ALGORITHMIC APPROACH

A key insight of our approach is that efficient analysis of malware samples must balance two competing factors: the number of artifacts that are mitigated and the cost of deploying multiple mitigations. Because stealthy malware uses artifacts to evade detection, it is desirable to mitigate as many artifacts as possible to minimize the chance of disclosing to the sample that it is being analyzed. However, mitigating all artifacts simultaneously imposes unreasonable costs, so the goal is to find sets of *configurations*, where each configuration



Fig. 2. MIMOSA workflow: In step ①, we develop a set of known artifacts, a set of known mitigation strategies, and a cost model for each artifact, all of which serve as input to our algorithm. In step ②, our covering algorithm generates a set of mitigation configurations for each server in a particular cluster. Generated configurations are inputs to our VMCloak engine that provisions VMs that mitigate subsets of artifacts. In step ③, a malware sample repository, a list of configurations and corresponding VMs are passed to the Dispatcher. In step ④, the Dispatcher spawns and manages the analysis of VM instances based on those provisioned by VMCloak. We record API call traces, which are analyzed to inspect and monitor VM state. In Step ⑤, our Detox engine correlates the collected API logs and VMI using heuristics to determine whether the malware sample was detected by one of the VM instances or not.

is a subset of the available artifact mitigations. The idea then is that each configuration can be run simultaneously, will individually be relatively inexpensive to deploy, but collectively most malware samples will be defeated by at least one configuration.

Given a set of artifact mitigation strategies (configurations) and a model that assigns a cost to each strategy, we describe an algorithm for efficiently selecting a set that maximizes coverage while minimizing cost. At a high level, there are three main components:

- The analyst decides on a cost model. Any non-negative cost function can be used. For example, the model might include development effort and analysis efficiency, combined linearly to compute a total cost.
- 2) For each artifact family, each mitigation strategy is represented as a configuration. Each configuration has an associated cost, computed via the cost model.
- 3) The **covering algorithm** then selects from the many possible configurations to produce a small set that optimizes the trade-off between cost and coverage.
 - We next describe each component in more detail.

5.1 Cost Model

Abstractly, we model cost as a function mapping each artifact mitigation strategy to $\mathbb{R}_{\geq 0}$. Our approach operates regardless of how this cost function is defined, but we consider, and provide qualitative details for, two exemplar cost functions: development time and analysis efficiency (Section 6).

If a mitigation strategy is known (e.g., from a published paper) but an implementation is not available, the analysis organization incurs a software development cost to implement it. Software engineers must be paid to design, implement, test and deploy the mitigation. A full discussion of software engineering costs is beyond our scope [27], but we note that there are many organizations or situations in which developer time is an expensive, limiting resource compared to abundant server, cloud, or compute time.

Given an available set of implemented mitigations, a second cost is the overhead of deploying them. There are a number of relevant metrics here such as throughput and energy consumption. Given the rate at which new stealthy samples are discovered [36], [66] and the costs associated with zero-day exploits, rapid analysis response is often paramount. Given a fixed computing budget, if one approach admits analysis after 100 time units and another approach only admits analysis after 800 time units, the former is preferred. For example, consider a scenario in which ten servers are available. One could deploy heavyweight tools (such as Ether [18], BareCloud [36], or MalT [74]) on all ten servers; this would produce a suitable analysis but is not efficient: it would take a long time for an analysis to run to completion. Alternatively, one could deploy lighter-weight systems such as LO-PHI [61] or VMI-based introspection. This would be more efficient, but risks detection by samples in the input corpus, at which point the analysis fails.

Note that while more expensive mitigations usually have higher coverage, this is not always the case. For example, if a cost model is used that captures only developer-hours, then the mitigation strategy of hooking API calls is both more expensive (it requires a developer to write code) and less effective than using an alternative analysis environment (which may require little developer time in such a model).

5.2 Selecting Artifacts and Mitigations

First, we enumerated a number of potential artifacts commonly used by our corpus of stealthy malware samples on Windows systems (Section 6.1). We followed existing literature [10], [74] and the pafish tool [48] to group these artifacts into a taxonomy of categories. We consider nine artifact families for a total of 39 specific artifacts, which together for a representative sample of indicative behavior of stealthy malware.

For each artifact, we implemented several mitigation strategies across a number of hypervisor backends. The mitigation strategies ranged in complexity from straightforward scripting (e.g., synthetic mouse movements) to more complex patches to the hypervisor source code (e.g., to hook kernel API calls made within the guest). Table 2 lists each artifacts we considered in our prototype, and the Appendix shows several example mitigation implementations.

As new artifacts are discovered in the future and exploited by adversaries, mitigations can be implemented and added to MIMOSA incrementally. However, our current implementation includes the artifacts exploited by our representative dataset of 1536 manually analyzed stealthy samples. The cost analysis and coverings construction, however, generalizes regardless of artifact behavior or exploitation.

5.3 Generating Coverings

Next, we present our algorithm for generating a set of lowcost covers. Let $\mathcal{A} = \{A_1, \dots, A_n\}$ be the set of *n* artifacts, and $\mathcal{C} = \{C_1, \dots, C_s\}$ be the set of configurations. Let S_1, \dots, S_p be the set of samples observed. For each sample S_i , we associate with it a set of *behaviors* $B(S_i)$, which is a subset of the artifacts \mathcal{A} . For each configuration C_j , we associate it with a set of *mitigations* $M(C_j)$, which is also a subset of the artifacts \mathcal{A} .

Our goal is to construct a binary array (called a *covering*), where each of the rows corresponds to a configuration, and each of the columns corresponds to an artifact, with the following property. For any sample S_i , there are configurations $C_{j_1}, \dots, C_{j_\ell}$ for which $B(S_i)$ is a subset of $M(C_{j_1}) \cup \dots \cup M(C_{j_\ell})$; in other words, for any sample, there are some configurations that together fully mitigate the sample. In terms of the array itself, suppose that $B(S_i)$ involves the columns b_1, \dots, b_m . Then the union of all rows r in these columns has a 1 in each entry, where 1 in column b_i indicates that configuration r mitigates the artifact b_i , and 0 otherwise. If the property is not maintained, we generate an array that mitigates as many samples as possible (high coverage), while also having the cost(s) of the chosen configurations be as low as possible.

In addition, we maintain a set of *desirably high* (DH) and *desirably low* (DL) characteristics, where each configuration has a valuation for each of these. For a covering corresponding to a set of configurations, the measure for the covering of the same characteristic may be the average from each configuration, the total, or some other measure. For example, if the characteristic is measuring the deployment time, then the total deployment time for a set of configurations is the total over all of their deployment times. In general, we want to generate a set of configurations such that the covering's DH characteristics are as large as possible, and the DL characteristics are as low as possible. For the deployment time example, this would be a DL characteristic; coverage would be a DH characteristic. Because different

TABLE 2 Summary of mitigated artifacts in MIMOSA. We categorize artifacts according to conceptual similarity.

Artifact Family	Mitigation Examples
VM-specific Registry Keys	Hook RegOpenKeyEx API Hook RegQueryValueEx API Remove offending keys from guest (e.g., HARDWARE\ACPI\DSDT\VBOX_) Use alternate VM Run on bare metal
Mouse / Keyboard / Video Detec-	Spoof peripheral input
	Replace spoofed driver files (e.g., VBoxMouse.sys) Use higher resolution (e.g., >800x600) Pass through graphics adapter
Internal Timing	Hook instructions that read MSRs Hook GetLastInputInfo API Hook GetTickCount API Virtualize time stamp counter (TSC) Run on bare metal
Device Properties	Spoof device names Allocate bridged network Hook Device Query APIs Hook I/O APIs Allocate more virtual CPUs Modify BIOS, system, baseBoard, chassis, and OEM Strings Change NIC MAC address Use alternate VM Run on bare metal
Drive capacity check	Hook CreateFile API Hook DeviceIoControl API Hook GetDiskFreeSpaceExA API Hook WriteFile API Hook GetDriveTypeA API Hook GetVolumeInformationA API Allocate Large virtual disk Allocate physical disk
Memory capacity check	Hook GlobalMemoryStatusEx API Allocate larger VM guest Run on bare metal
Hooked API detection	Externally Hook APIs (e.g., hook hypercalls) Use hardware breakpoints Run on bare metal
Retrieving CPU Vendor Name	Patch VMM Change VM config Run on QEMU full system emula- tion
Process / Drive Name Detection	Patch VMM Change VM config Run on QEMU full system emula- tion
Invalid Instruction Behavior	Patch VMM Use alternate VM Run on bare metal

characteristics can have different impacts on a system, we aim to produce a collection of coverings such that none of them "overshadow" any other one.

Next, we walk through the algorithm. First, we will discuss generating a covering of all the considered configurations and artifacts relevant for any sample. For each configuration and artifact, we mark whether or not the configuration mitigates the artifact; the array corresponding to the covering is the natural one. We determine the cost and coverage of each configuration in turn. Next, we generate all subsets of configurations; suppose these subsets are S_1, \dots, S_k . We say that a subset of configurations S_i dominates another subset S_j if the following properties hold:

- S_i 's DH characteristics are all at least those of S_j ,
- S_i 's DL characteristics are all at most those of S_j , and
- either (1) some DH characteristic of S_i is strictly larger than that of S_j, or (2) some DL characteristic of S_j is strictly smaller than that of S_j.

The *Pareto front* of the subsets is the collection of subsets S such that none of the subsets dominates any other in S, which can be found by *non-dominated sorting* [15].

This algorithm is not efficient because it examines every subset, which takes exponential time in the number of configurations. We give an optimization that improves the running time in practice, contingent on the following assumption. Suppose that all of the DH and DL characteristics (other than coverage) are *monotonic*, which means that if a new configuration c is added to a set of configurations S, then $S \cup \{c\}$ cannot have larger DH characteristics nor smaller DL characteristics than those of S. For example, adding a configuration does not decrease the total deployment time, so this is a monotone DL characteristic. Note that coverage as defined here is always monotone.

Let A_i be all subsets of size *i*, and suppose all noncoverage characteristics are monotone. Let a_i be a subset in A_i , and let *c* be any configuration not in a_i . If the coverage of $a_i \cup \{c\}$ is more than a_i , then we need to observe some subset in A_{i+1} (because $a_i \cup \{c\}$ is one such subset). However, if the coverage does not increase for any subset in A_i with any new configuration c_i then we can terminate the algorithm because (1) the coverage does not increase, and (2) the characteristics are monotone. We give a more detailed description in Algorithm 1. In practice, all of the characteristics we have used are monotone, and the algorithm benefits because most configurations in the Pareto frontier had fewer than four configurations, a significant improvement over the brute-force strategy. We present and discuss various points of Pareto frontiers derived from this algorithm in Section 6.

An advantage of our algorithm is that it is highly likely that a configuration will cover the artifacts employed by any observed sample. The construction of Algorithm 1 produces minimal subsets of configurations (i.e., deleting any configuration from any subset will cause coverage to decrease). Indeed, as demonstrated in Section 6, most of the points found on the Pareto frontier involved a very small number of configurations. **Algorithm 1:** Pareto Generation of Configurations via Coverings when the characteristics are monotone.

Generate the covering C with rows R as							
configurations, and columns as (monotone)							
characteristics.							
PreviousCoverage $\leftarrow \emptyset$. PointsToConsider $\leftarrow \emptyset$.							
for $i = 1$ to $ R \operatorname{\bar{do}}$							
NewCoverage $\leftarrow \emptyset$.							
for each subset S of size i of R do							
Add the coverage of <i>S</i> to NewCoverage, and							
both the coverage and costs of <i>S</i> to							
PointsToConsider.							
Call the <i>parent</i> of <i>S</i> to be every subset of <i>S</i> of							
size $ S $ -1 (i.e., deletion of a single element).							
end							
if the coverage of each subset in NewCoverage is the							
same as its parents in PreviousCoverage then							
Exit this loop.							
end							
else							
$ $ PreviousCoverage \leftarrow NewCoverage.							
end							
end							
Output the Pareto frontier of PointsToConsider							
using non-dominated sorting.							

6 **EMPIRICAL EVALUATION**

MIMOSA adapts coverings to choose artifact mitigation strategies that enable the accurate and rapid analysis of stealthy malware that would otherwise take significant effort to analyze and understand. In this section, we present results from two empirical evaluations of MIMOSA.

We begin by introducing an indicative use case (see Section 4). Consider an enterprise that desires to use a set of servers with finite capacity for automated malware classification and triage. We assume that low-latency analysis of stealthy samples is paramount: given a fixed set of computing resources, we want the analysis of a given sample to complete as quickly as possible (e.g., to support subsequent human analysis, defense creation, signature generation, etc.). We further assume that the input samples are stealthy, and the analysis tool must mitigate the artifacts exposed to each sample to prevent subversion. Although it might be possible to use all servers available to the enterprise to mitigate all potential artifacts, this is not an efficient use of resources and does not provide the lowest analysis latency. Instead, we apply our algorithm to determine which sets of artifacts are to be mitigated by each server. This minimizes the latency of analyzing each sample across all available servers while maximizing the combined analysis power of all available servers.

To evaluate our approach, we consider three research questions:

- **RQ1 Coverage** Does MIMOSA produce artifact mitigation configurations that effectively covers stealthy malware samples?
- **RQ2 Scalability** Does MIMOSA produce artifact mitigation configurations that admit low-cost, high-



Fig. 3. Distribution of malware samples in our dataset according to the number of unique artifacts employed. For example, more than 600 of our 1535 samples employed a single artifact. The graph is not cumulative.

throughput automated stealthy malware analyses?

RQ3 Efficiency — What tradeoffs exist in the resource costs and coverage space among the configuration sets produced by MIMOSA?

We first discuss the corpus of malware we used in our evaluation. Then, we discuss each research question in turn.

6.1 Malware Corpus Selection

We consider stealthy malware that targets Windows. Of the many available malware corpora, only a few focus directly on stealthy malware, in part because they are so difficult to analyze automatically. We studied two of these in detail (BareCloud [36] and an anonymous security company) and found that they the labels were inadequate for our purpose because they did not label the specific artifacts used by each sample. A sample might be labeled "device id detection," for example, rather than listing the specific device it checked for. Instead, we obtained a set of 1535 unique samples from independent security researchers, which are analyzed according to the artifacts they use. This dataset consists only malware samples that have been manually identified as stealthy and curated precisely. Other work has used larger malware databases for similar experiments [8], [13], but as mentioned above these datasets are not labeled with enough specificity for our study.

Figure 3 shows that each individual malware sample in our corpus uses between one and five evasion techniques, thus confirming our hypothesis that most malware considers only a few artifacts and supporting our design decisions for MIMOSA. In addition, we show a taxonomy of malware families in our corpus in Figure 4.

We categorized the samples based on the artifacts they are looking for in the system, summarized in Figure 5. Among these artifacts, checking for BIOS and SCSI device metadata were common. Additionally, many of our samples checked for the existence of specific processes (e.g., helper programs for in-guest clipboard access, video acceleration, etc.). We categorized which specific process was used by each stealthy malware sample, shown in Figure 6. In particular, Xen service (xenservice.exe) is the most frequentlychecked process among other processes used.



Fig. 4. Taxonomy of malware samples contained in the corpus, which includes samples of several popular families such as Lethic (Trojan), Ny-maim (Trojan), and InstallCore (Potentially Unwanted Program (PUA)).



Fig. 5. Frequency of artifacts detected by samples in the malware dataset.

6.1.1 Pafish

In addition, we used pafish [48], an open source tool that enumerates common checks used by stealthy malware, to determine whether a given configuration could provide coverage over specific artifacts. Pafish is well-suited to this task because it can be configured to check or ignore specific artifacts. We used pafish to confirm the sets of artifacts mitigated by each configuration before we applied each configuration to malware samples in our dataset.



Fig. 6. Distribution of process names checked for by stealthy malware.





Fig. 7. Success and failure counts for each tested configuration, when run against the 1535 stealthy malware samples.

6.2 RQ1: Coverage — Artifact Mitigation

In this experiment, MIMOSA assigns artifact mitigation strategies to analysis servers. We say that the *configuration set size* is the number of configurations combined together — this is an input parameter that represents the number of distinct configurations that the user is willing to run concurrently. For example, if more servers are available for analysis, a larger configuration set size can be selected. We say that a stealthy malware sample is successfully analyzed if at least one configuration in the configuration set produced by MIMOSA mitigates all of the artifacts it uses.

For each configuration, we represent artifact coverage as a bit-array in which each set bit implies that that particular artifact has been successfully mitigated in the environment. Table 3 gives details about each configuration instance.

We use VMWare, VirtualBox, KVM, and QEMU backends for virtualizing guests to complete an analysis of each sample. We use 13 different configurations across each of these backends for conducting analyses. Each configuration implements a subset of mitigations against each class of artifacts. For example, the gemu_patched_conf1 contains intentionally low RAM size (< 1GB), exposing the RAM detection family of artifacts, but also contains custom patches that remove all QEMU-related hardcoded strings throughout the source. In contrast, the VMWare_conf2 configuration employs the VMWare Tools suite for faster execution, exposing process names (i.e., of VMWare Tools). Broadly, we designed and implemented these configurations by considering the families of artifacts exposed by our dataset (Section 6.1) and the expected complexity in mitigating each artifact family across each virtualization backend.

We compute whether at least one configuration covers each evasive sample by analyzing traces of API call invocations, including arguments passed to each call and the corresponding output. We developed a module ("Detox" engine in Figure 2) to wrap and unify multiple Virtual Machine Introspection (VMI) APIs, including Icebox [3], PyReBox, DRAKVUF [39], and VMWare VProbes [69]. Thus, we collect multiple API trace logs for each sample for each configuration, based on the virtualization backend used. Next, we aggregate these API trace logs to bridge the semantic gap [29], [57]: doing so allows reconstructing higher abstraction API traces invoked against the guest OS.

Given each trace of each sample, we confirm detection results based on the malware's behavior across all configurations. Specifically, we follow the malware execution trace up to the point when it starts to create, manipulate, or remove a memory section, segment, or page using APIs such as NtCreateSection, NtMapViewOfSection, or NtSetContext. Then, we compare these results against ground truth established in our corpus to ensure that the malicious process executed completely. If the analysis differs from the ground truth (e.g., if the sample detects the environment and hides its behavior), we say that configuration does *not* cover the sample. If there exists at least one configuration that *does* cover the sample, we call that sample covered. We show the detection rate of each configuration across our entire corpus of malware in Figure 7.

6.2.1 RQ1 Result Summary

Our mitigation strategies and corresponding configurations provide varying coverage levels across an indicative dataset of 1535 stealthy malware samples, allowing us to explore the trade-off space between coverage provided by analysis tools and the cost of deploying those tools or acquiring analyses. In Figure 8, we show a the level of coverage achieved by our approach compared to other approaches versus configuration set size. Specifically, we measure the coverage achieved by a set of configurations of a specific size for (1) Random — a randomly-generated coverage vector,

TABLE 3

CON	nguration	. Note that some con	ngurain	ons supp	ontum	differi	ng ar	tifact mitiga	tions.	Jy_U	Unin	Call De lui				, yieit	Jing
Index	Backend	Configuration	Process	Debugger	CPUID	RDTSC	CPU #	# Invalid Inst.	TickCount	HCI	BIOS	5 File Check	HDD - SCS	I Disk size	Memory	MAC	ACPI
1 2	KVM	qemu_patched_conf1 qemu_patched_conf2	√ √	\checkmark	-	_	√ √	\checkmark	_	\checkmark	\checkmark	-	- ~	_	- ~	√ _	√ √
3 4 5	VMWare	vmware_conf3 vmware_conf2 vmware_conf2_vmtools	√ √ -	√ √ √		- - -	✓ - ✓	√ - -	- - -	\$ \$ \$	√ - -	_ ✓		- - -	- ~ ~	✓ - -	✓ ✓ ✓
6 7	KVM	qemu_legacy_conf1 qemu_legacy_conf2	\$ \$	√ √	_	_	✓ _	√ √		<i>\</i> <i>\</i>	√ ✓	√ √	_	_	√ -	√ _	√ √

 \checkmark

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List of tested configurations and the artifacts they mitigate. Each column corresponds to whether a specific category of artifact is mitigated in that configuration. Note that some configurations support different backend (e.g., qemu_legacy_conf1 can be run in both KVM and QEMU), yielding differing artifact mitigations.



vbox_conf1_guestadditions

vbox_conf2_guestadditions

vbox_conf1

vbox conf2

qemu_legacy_conf1 qemu_legacy_conf2

8

10

11

12

13

Virtualbox

QEMU

Fig. 8. Proportion of stealthy malware samples covered for different configuration set sizes for various techniques. Random indicates a randomly-generated coverage vector. Semi-random represents a randomly-selected subset of our 13 configurations. King-of-the-Hill represents the best single configuration from our set of 13. Our approach achieves higher levels of coverage compared to the best available single configuration.

(2) Semi-random — a randomly-selected configuration from our set of 13 configurations (shown in Table 3), (3) Kingof-the-Hill (KoTH) — the best single configuration from our set of 13 configurations, and (4) MIMOSA, the set of configurations selected by our approach. For this set of experiments, we averaged 10 trials.

We view KoTH as the baseline for automated malware analysis systems that do not use our approach (e.g., companies that pick the "best" sandbox they can, and scale it up to multiple machines in a cluster). Our approach achieves 97% coverage when combining five configurations, compared to KoTH, which achieves 65% coverage. This suggests our approach can generate configurations of malware analysis environments that can apply to most stealthy malware samples in an indicative corpus.

6.3 RQ2: Scalability — Automated Analysis

We also evaluated our approach with respect to malware analysis throughput. Because our approach also considers the relative costs (e.g., overhead, disk utilization) of each configuration, we can measure our system's effectiveness at scale. For example, if a given configuration *does not* cover a given sample, that configuration wastes time and resources attempting to execute that sample. Thus, we can compute the amount of resources *wasted* by considering the total resources consumed by configurations executing samples that were not covered by those configurations.

~

We measure the time wasted by a configuration using virtual machine introspection (VMI) to reconstruct events that occur within each configuration guest environment from low-level execution traces collected for each sample. We compared these execution traces against ground truth execution traces gathered for each sample (provided as part of our malware dataset). Each sample's collected and ground truth traces were compared using the trace merging algorithm introduced by Virtuoso [20], VMWatcher [31], and VMWare VProbes [69]. For each sample in each configuration, we report the time t at which the measured and ground truth traces diverged - where a sample's anti-analysis technique caused the execution to differ from the ground truth. If the traces never diverge, then we conclude the sample was covered. Thus, for each uncovered sample and configuration, we report the time wasted as the difference between time t and some maximum timeout (configured as 2s here; state-of-the-art typically uses 5s timeouts [39]).

Figure 9 shows a comparison of time wasted of various approaches versus configuration set size, as described in Section 6.2.1. Our approach spends 3X less CPU time executing samples that *are not covered* by configurations. As a result, our approach can scale analysis of malware samples 3X over state-of-the-art by accurately analyzing a higher proportion of samples in less time.

6.4 RQ3: Efficiency — Analysis Tradeoffs

In this section, we consider tradeoffs between analysis resource cost and stealthy malware sample coverage. Recall that a stealthy malware sample is *covered* if all of the artifacts it uses are mitigated. We evaluate coverage with respect to two cost functions: memory utilization and disk throughput. Both are relevant for scalable automated malware analysis.

We analyzed each of the 1535 stealthy malware samples. For each sample, we determined which set of configurations would mitigate the artifacts used by that sample, then measured how much of a resource was used during that sample's execution. In particular, we measured disk throughput (bytes per second) and memory utilization (approximated



Fig. 9. Average analysis time wasted executing each sample for sets of different configuration sizes. Random refers to a randomly-generated coverage vector. Semi-random refers to a random subsets of our 13 configurations. King-of-the-Hill represents the best single configuration selected from our 13 configurations. Our approach wastes the least amount of time failing to execute stealthy samples, enabling higher automated analysis throughput.

by measuring average free bytes during execution). We used MIMOSA to generate a Pareto front by considering which subsets of configurations would require which levels of resource to achieve a particular degree of coverage.

Table 4 shows the Pareto front and indicative points for the memory utilization cost function. As an example, the point with the highest coverage (i.e., 1432 out of 1535 samples analyzed successfully) required an average of 718MB during execution, while the configurations with lower coverage (e.g., 1020 samples) used only 316MB of memory. Overall, this graph shows how to balance the tradeoff between malware analysis tool configurations with respect to memory usage.

Similarly, Table 5 show the Pareto front for the disk throughput cost function. As before, there is a tradeoff between how many samples are covered and the disk usage is required to obtain analyses per sample.

6.5 RQ3 Tradeoffs Summary

MIMOSA enables finding a Pareto-optimal point that provides accurate stealthy malware analyses while minimizing the resource allocation required to obtain those analyses.

7 DISCUSSION

In this section, we discuss (1) potential threats to the validity of the experimental results, (2) using MIMOSA for controlling an adaptive malware analysis system, and (3) potential future improvements that can be made to cost functions.

7.1 Threats to Validity

First, we characterized artifact families according to conceptual similarity. The artifact families ultimately inform what structure the corresponding covering takes. There is no standard method for classifying artifacts in this manner—the effectiveness or utility of MIMOSA could change depending on the specific assumptions we made about which artifacts are categorically similar.

TABLE 4 Indicative points in the Pareto front comparing samples covered with memory utilization.

Configuration Set	Samples A Covered	Avg. Available Memory(MB)
vbox_conf2 vbox_conf1 qemu_legacy_conf1 qemu_patched_conf1 vmware_conf3 qemu_legacy_conf2 qemu_legacy_conf1 vbox_conf2_guestadditions vbox_conf1_guestadditions	1432	718
vmware_conf3	1020	316

TABLE 5 Indicative points in the Pareto front comparing samples covered with disk throughput.

Config Set	Samples A Covered	Avg. Disk Write (KBytes/sec)
vbox_conf1 qemu_legacy_conf1 qemu_legacy_conf2	1432	397
qemu_legacy_conf2	1044	209

Second, our experimental approach for RQ2 measured execution time only while the sample was actively executing. In practice, there are other considerations that have impact on the overall efficiency of malware analysis (e.g., restoring clean virtual disks, reloading the OS image, etc.).

Third, although our evaluation incorporated 1535 stealthy malware samples from the wild, we produced configurations whose costs were measured in isolation (e.g., we measured CPU utilization separately from memory utilization). Additional engineering effort is required to construct a production-quality end-to-end system that uses the configurations produced by MIMOSA to apply to a real set of hardware.

7.2 Remarks on Adaptability

MIMOSA takes as input a set of modeled mitigation strategies and associated costs, and it produces as output a coverage-optimal, low-heuristic-cost array of strategies. This approach can be extended to adapt over time to changes in the distribution of stealthy malware. For example, if new artifacts are discovered or if the costs associated with mitigating each one changes with technology, our overall approach and algorithms will still be applicable as a tool for finding cost-optimal analysis configurations.

As a specific example, recent work leveraged "wear and tear" of virtual machine environments [46]. In essence, malware samples can look for evidence that an environment is "aged." An analyst that spins up a vanilla VM image may fall victim to a sample that detects if the environment is pristine and newly-created. That is, the perceived "age" of the virtualized environment is the artifact. Malware campaigns like Dyre and Dridex use heuristics like (1) investigating the clipboard for evidence of random strings associated with normal use, and (2) registry keys to track historical use of common prorgrams (e.g., Microsoft Word). We do not include such artifacts in our prototype coverage calculation because our dataset did not contain samples that exploited wear and tear artifacts; however, they can be readily incorporated by implementing a corresponding mitigation. For example, our prototype currently moves random files to the Desktop, Recycle bin, and Temp directories, and it also injects decoy entries in the Registry. We could introduce this as a full mitigation in our framework: the coverings vector would be augmented to reflect this new artifact so that it is covered in the optimally-generated configurations.

7.3 Remarks on Cost Functions

MIMOSA currently considers optimizing for cost, which can be captured in several ways: CPU utilization, memory utilization, and runtime overhead with respect to latency. However, these one-dimensional approaches may admit coverings that are difficult to interpret. For example, in a cluster of 10 servers, assigning nine servers to do no mitigation (minimal cost) and one server to run bare metal (maximal coverage) is a well-formed solution.

We also discussed a second parameter that captures *benefit*: coverage of stealthy malware samples is important for acquiring faithful, interpretable analyses. For example, if we know a mitigation strategy will cover 90% of stealthy malware, we may be willing to pay a higher cost to use that strategy because of its overall coverage. On the other hand, a strategy that only covers 2% of stealthy malware in the wild may be disregarded. While we examined the costbenefit space in our evaluation, future work will include a multidimensional heuristic search to find optimal coverings with respect to more complex cost functions.

8 RELATED WORK

Various projects have focused on detecting and evading analysis systems in both x86 executables [12], [53], [54], [56] and mobile devices (e.g., Android [32]). In this section, we discuss this work in three categories: (1) malware detection using behavioral analysis, (2) malware analysis using virtual machine infrastructure, and (3) malware analysis using bare-metal machines.

8.1 Stealthy Malware Detection

Current stealthy malware analysis techniques generally rely either on human creativity (e.g., debugging with IDA Pro [28] or OllyDbg [72]) or heavy-weight analysis tools that incur significant overhead (e.g., MalT [74] or Ether [18]). Moreover, differencing approaches, such that of as Balzarotti *et al.* [7], work by executing a sample in multiple instrumented environments and use the difference in runs to determine which artifact is used by the sample, potentially wasting resources.

Balzarotti *et al.* [7] demonstrate the ability to detect evasive behaviors by running malware in various runtime environments and comparing their system calls. Lindorfer *et al.* [41] later employed a similar technique, but used various malware sandboxes and scored their evasive behaviors. HASTEN [37] specifically focuses on stalling malware, which is a particularly difficult evasion technique to analyze because the malware appears benign for an extended period of time. TriggerScope [25] similarly examines Android programs which mask there malicious behavior until a certain *trigger* is observed. Our technique leverages a combination of multiple environments that separately mitigate different artifact families, instead providing environments that are more likely for the sample to execute faithfully.

Our approach is conceptually related to SLIME [14], an automated tool for disarming anti-sandboxing techniques employed by stealthy malware. SLIME runs a sample many times, each time configuring the environment to explicitly expose certain artifacts to the sample. In contrast, our approach seeks to minimize the total cost of execution (or the resources consumed) to either identify or analyze the sample under test. In addition, we introduce a novel structure called a covering that helps identify the optimal configuration for an analysis system.

8.2 Virtual Machine Analysis

Ether [18] is a malware analysis framework based on hardware virtualization extensions (e.g., Intel VT). It runs outside of the guest operating systems, in the hypervisor, by relying on underlying hardware features. BitBlaze [58] and Anubis [4] are QEMU-based malware analysis systems. They focus on understanding malware behavior, instead of achieving better transparency. V2E [71] combines both hardware virtualization and software emulation. Hyper-Dbg [24] uses the hardware virtualization that allows the late launching of VMX modes to install a virtual machine monitor, and run the analysis code in the VMX root mode. SPIDER [17] uses Extended Page Tables to implement invisible breakpoints and hardware virtualization to hide its side-effects. DRAKVUF [39] is another VMI-based system capable of both user and kernel-level analysis.

We note that recent work has investigated changes to the sandboxing environment to give it the appearance of age or use [46]. For example, a dearth of Documents, Downloads, event logs, or installed software could be a hint that the sample is not executing in a real, vulnerable environment. Although our current prototype does not address samples exhibiting such "age" checks, as discussed above, we could readily incorporate it. As with other new or yet-undiscovered artifacts, our overall framework would not change. One would simply implement a configurable mitigation against that new artifact and include it as a strategy used by our coverings algorithm.

8.3 Bare-metal Analysis

BareBox [35] is a malware analysis framework based on a bare-metal machine without any virtualization or emulation techniques, which is used for analyzing user mode malware. Follow up work, BareCloud [36], uses mostly uninstrumented bare-metal machines, and is capable of analyzing stealthy malware by detecting file system changes. Willems *et al.* [70] propose a method for using branch tracing, implemented on a physical CPU, to analyze stealthy malware. LO-PHI [60] is a system capable of both live memory and disk introspection on bare-metal machines, which can be used for analyzing stealthy malware. MalT [74] uses System Management Mode to instrument a bare-metal system at the instruction level, exposing very few artifacts to the system. While LO-PHI and MalT both have high deployment overheads, they also expose very few artifacts to samples under test; thus, either could conceptually serve as our highest coverage (and highest cost) configuration.

9 CONCLUSION

Stealthy and obfuscated malware is expanding rapidly. As the security arms race continues, malware authors use increasingly sophisticated techniques to subvert analysis. The large volume of new malware released every year makes automated analysis increasingly mandatory to identify and understand new malware samples. Techniques to address the volume of stealthy malware are critical.

In this paper, we introduced coverings, a novel way of representing the problem of analyzing stealthy malware efficiently, and a prototype implementation called MIMOSA. We studied a broad set of artifacts exposed by analysis environments and the mitigation strategies required to prevent malware samples from using those artifacts to subvert detection. We modeled the mitigations using a partially ordered structure according to the number of artifacts mitigated and the cost associated with deploying that strategy. We developed 32 such mitigation strategies. We presented an algorithm that finds the lowest-cost selection of mitigation strategies to implement while guaranteeing a total coverage of the artifacts. Finally, we empirically evaluated MIMOSA using 1535 stealthy malware samples from the wild. We found that MIMOSA can find mitigation strategies that reduce the overhead and memory utilization associated with mitigating all artifacts considered.

10 ACKNOWLEDGMENTS

We thank Giovanni Vigna, Christopher Kruegel, and Hojjat Aghakhani for graciously providing the well-labeled corpus of evasive malware samples used in our evaluation. This work would not be possible without the tireless engineering effort invested to construct such a dataset, so we are grateful for members of the community who share data to improve the state-of-the-art.

We also thank the anonymous reviewers for their valuable comments and suggestions, and the Avira company, Alexander Vukcevic, Director of Protection Labs and QA, and Shahab Hamzeloofard for helping us with determining provenance of our malware samples.

We gratefully acknowledge the partial support of NSF (CCF 1908633, 1763674), DARPA (FA8750-19C-0003, N6600120C4020), AFRL (FA8750-19-1-0501), and the Santa Fe Institute. Any opinions, findings, and conclusions in this paper are those of the authors and do not necessarily reflect the views of our sponsors.

The opinions in the work are solely of the authors, and do not necessarily reflect those of the U.S. Army, U.S. Army Research Labs, the U.S. Military Academy, or the Department of Defense.

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